Ref. Ares(2025)10451930 - 28/11/2025

TEALHELIX

SMART LABELS
INCLUSIVE SOLUTIONS

DELIVERABLE 2.5

Data Scraping Report

University of St. Gallen

26 / 11 / 2025

Funded by
the European Union

This project has received funding from the European Union's Horizon Europe Research and Innovation programme under Grant Agreement number no. 101136955 and from the Swiss State Secretariat for Education, Research and Innovation (SERI). Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or European Research Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

Project funded by

Schweizerische Eidgenossenschaft
Confédération suisse
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Swiss Confederation

Federal Department of Economic Affairs, Education and Research EAER
State Secretariat for Education, Research and Innovation SERI

This work is dedicated to the memory of Justina Baršytė, our project coordinator, whose vision and commitment were invaluable to this project.

PROJECT INFORMATION

PROGRAMME	Horizon Europe
TOPIC	HORIZON-CL6-2023-COMMUNITIES-01-6
TYPE OF ACTION	HORIZON Research and Innovation Actions
PROJECT NUMBER	101136955
START DAY	1 September 2024
DURATION	48 months

DOCUMENT INFORMATION

TITLE	Data scraping report
WORK PACKAGE	2
TASK	2.4
AUTHORS (Organisation)	Michal Elhanan (University of St. Gallen), Prof. Dr. Reto Hofstetter (University of St. Gallen)
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DATE	26/11/2025

DISSEMINATION LEVEL

PU	Public, fully open	x
SEN	Sensitive, limited under the conditions of the Grant Agreement	
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Classified C-UE/EU-C	EU CONFIDENTIAL under the Commission Decision No2015/444	
Classified S-UE/EU-S	EU SECRET under the Commission Decision No2015/444	

DOCUMENT HISTORY

VERSION	DATE	CHANGES	RESPONSIBLE PARTNER
V0.1	06/11/2025	First draft is ready for internal review	UniSG
V0.2	18/11/2025	Reviewer's feedback	KUL/VilniusU
V.0.3	26/11/2025	Revisions based on reviewers' feedback	UniSG

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ABBREVIATIONS

API	Application Programming Interfaces

Executive Summary

This report details the comprehensive data collection and initial analysis conducted in Task 2.4, aiming to analyse the current state of behavioural aspects in online media environments concerning food, agriculture, and sustainability.

Data Collection and Scope: Data was collected from X (Twitter), Bluesky, TikTok, and Instagram using respective Application Programming Interfaces (APIs) (atproto, twttr API, TikTok Research API, and HikerAPI). The data collection process employed a recursive search-term expansion method initialized by researcher suggestions and terms gathered from ChatGPT based on the sustainability indicators defined in TealHelix Work Package 3. Data collection aimed primarily at content uploaded in 2024, although Instagram data lacked time frame filtering. The final dataset consisted of 173,010 posts: 128,442 from TikTok, 27,575 from Bluesky, 14,272 from Instagram, and 521 from X. The textual data was filtered to include only English texts that discussed both (1) food/agriculture/food supply chain and (2) sustainability indicators (e.g., environmental sustainability, health, animal welfare, affordability, workers' conditions, or geographical accessibility). Ultimately, 64.41% (over 50k posts) of the English posts discussed both required categories.

The key KPI for this task is achieving the highest possible F1 score. This KPI was achieved with an average F1 score for classifying texts into each sustainability indicator of 0.906.

Key Findings on Engagement and Sentiment (Textual Data):

• Engagement (Log Engagement): Posts discussing animal welfare and environmental aspects of eating and cooking food received the highest average engagement, while posts discussing workers' conditions and affordability received significantly less engagement.

• Platform Differences: X (Twitter) exhibited the highest average engagement, while Bluesky showed the lowest.

• Sentiment: Instagram was found to be the most positive platform, while Bluesky and X were the most negative. Discussions surrounding workers' conditions and affordability had a strong negative sentiment, while food supply chain, food, and health discussions showed a strong positive effect on sentiment.

• Temporal Trends: Content posted between 20:00 and 22:00 received the highest engagement, while content posted around 08:00–09:00 received the lowest.

Key Findings on Visual Data (Instagram):

• Engagement: Posts featuring images with a higher ratio of red trended toward higher engagement, while a higher ratio of green and yellow trended toward lower engagement. Images related to "food," "posters animal welfare," and "posters other" were associated with high engagement.

• Colour Distribution: Generally, images were dominated by red and orange, were low in saturation, and very bright, possibly reflecting the use of bright colours in posters to capture attention.

The findings can support researchers, policymakers, and practitioners in sustainability, food, and agriculture by highlighting how content related to sustainability indicators is engaged with and perceived online. Insights on engagement, sentiment, and visual features can inform more effective

communication strategies, campaigns, and label designs, and provide a foundation for future studies and platform-specific adaptations.

1. Data Collection

The objective of task 2.4 is to analyse the current state of behavioural aspects in online media environments. To this end, a comprehensive data collection of online social media platforms was conducted. Data was collected from X (Twitter), Bluesky, TikTok and Instagram. X, Instagram and TikTok were chosen for being well know globally with a high levels of user content uploads with ~500 million posts/day[1], over 67 million posts/day[2], 16,000 posts/minute[3] respectively. Bluesky was chosen because of the recent events and controversies regarding X, which led to a fast growth in Bluesky and the seemingly political divide between the platforms[4], using data from both platforms might create a more balanced view. Data were collected using APIs, An API is a structured interface that allows one program to request and receive data or services from another system over the web. APIs allow access to data in a standardized, machine-readable format. APIs are used to systematically collect large volumes of data, while respecting platform rules and rate limits, not all APIs are official platform APIs, in our data collection 2 of the APIs used were 3rd party APIs. Data from Bluesky were collected using their own open API, atproto[5], from X using twttr API[6], from TikTok using their own research API[7], and from Instagram using HikerAPI[8]. We chose to use existing APIs, since the specific APIs chosen allow access to all required data that we could get by using R or python libraries (such as Selenium), which are data publicly accessible from the browser, and are more robust and reliable. In the data collection process, we have queried search terms relevant to food, agriculture, and sustainability, we did not query specific users or influencers. The queried search terms were collected in a recursive search-term expansion process (see section 2.1.2). To concentrate on up to date and relevant content, when possible, data uploaded in 2024 were collected.

1.1 Search Terms Curation Method

1.1.1 Initial Search Terms List

The starting keyword list was created using a short list of well known, basic terms suggested by reading through various online content connected to the subject and looking for repeating short phrases (for example: food sustainability, animal welfare and ethical eating), and a list of search terms collected from ChatGPT using the prompt: "suggest short search terms to find posts that talk about each of the descriptions:" followed by the descriptions from the sustainability indicators defined

[1] https://www.dsayce.com/digital-marketing/tweets-day/

[2] https://edgedelta.com/company/blog/how-much-data-is-created-per-day

[3] https://sproutsocial.com/insights/tiktok-stats/

[4] https://www.washingtonpost.com/technology/2024/11/14/x-social-media-bluesky-threads/

[5] https://atproto.blue/en/latest/

[6] https://rapidapi.com/davethebeast/api/twitter241

[7] https://developers.tiktok.com/products/research-api/

[8] https://hikerapi.com/

in TealHelix Work Package 3, this resulted in a list of 44 search terms listed in Appendix A. Any such, short list can't be comprehensible, for this reason we developed the recursive search-term expansion algorithm (see section 2.1.2), this algorithm allows us the collection of a high number of varied search terms. In contrast, existing research usually uses a minimal amount of, 1 or 2, search terms.[1], while our algorithm returned hundreds.

1.1.2 Recursive Search-Term Expansion

The initial list of search terms was used to launch the recursive search-term expansion process, developed for in this task for the collection of a high number of posts, and using search terms that were not identified by the authors previously, this allows for lower bias in search term selection. We then made multiple requests to the Bluesky and X APIs. For each search term and for each platform, we issued 12 requests, one for every month of 2024. From each API response, we collected the top 100 posts for that search term in the corresponding month. The threshold of 100 was chosen since, in most of the platforms data were collected from, it is the highest number of results that can be returned in a search, it was used for all platforms for consistency and in order to not give any platform a higher presence for technical reasons. The ranking of the top posts is done by the platforms themselves and the formula for calculation is not shared by the platforms, it is speculated that the ranking is highly correlated with the engagement the post received. It is important to note that each platform might have a different algorithm that decides which posts will be ranked higher, but since the other option is to order the retrieved data by date of posting and seeing that social media engagement is usually very low and long tailed, this is the best possible way for us to collect posts that were somewhat impactful and engaged with. Also, different search terms from a specific platform on a specific date might return some overlapping posts, so the overall number of posts collected is always equal to or smaller than $N(search\ terms) * 12(months) * 100$.

All collected posts were used to generate a new list of search terms. The text of each post was pre-processed: it was tokenized (i.e. the process of breaking text into discrete units, or tokens, such as words, for computational analysis or natural language processing), stop words were removed, and the remaining words were stemmed (i.e. the computational process of reducing words to their root or base form to unify variations of the same term for text analysis). From this processed text, all N-grams (i.e. contiguous sequence of N words, extracted from a text corpus, commonly used in computational linguistics and text analysis to model language patterns) of length N=2,3 were generated and counted. N-grams were then filtered based on three criteria:

1. N-grams already present in the previously used search terms were removed.
2. N-grams that were not frequent enough, defined as appearing in fewer posts than the cube root of the total number of posts, were removed. This threshold was chosen to not be too high so that in early iterations an extremely low number of new search terms will be added, and on the other hand not too low so in later iteration, when a very large dataset already exists, only N-grams that are substantially common will be considered.

---

[1] Ozcan, Sercan, et al. "Social media mining for ideation: Identification of sustainable solutions and opinions." Technovation 107 (2021): 102322.

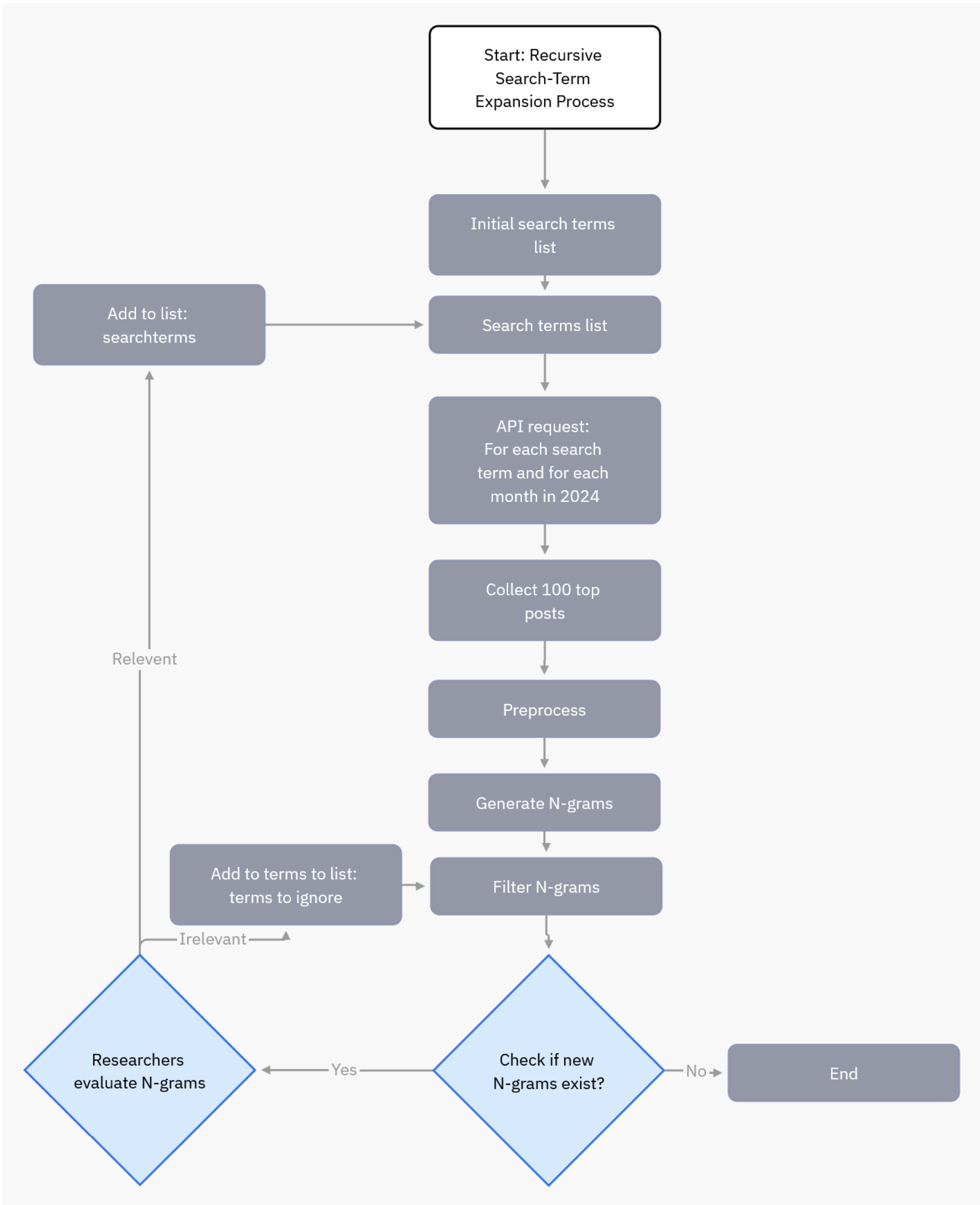
Ballestar, Maria Teresa, Miguel Cuerdo-Mir, and María Teresa Freire-Rubio. "The concept of sustainability on social media: A social listening approach." Sustainability 12.5 (2020): 2122.

Brzustewicz, Paweł, and Anupam Singh. "Sustainable consumption in consumer behavior in the time of covid-19: Topic modeling on twitter data using lda." Energies 14.18 (2021): 5787.

3. N-grams appearing on the "ignore" list of search terms were also excluded.

Each N-gram was assessed for its relevance to both sustainability, and food or agriculture. N-grams deemed relevant had one of their original forms, not stemmed and with stop words, added to the search-term list, while those deemed irrelevant were added to the ignore list. The newly accepted search terms were then used to collect additional posts. All posts, both previously collected and newly obtained, were used to identify further potential search terms. This iterative process continued until no additional N-grams were found that were both sufficiently common and relevant. Note that N-grams that were not frequent enough in an earlier stage could become more common in later stages and therefore may still be considered for inclusion as potential search terms. A list of the 102 search terms collected is found in Appendix A. A flowchart of the process can be seen in Figure 1.

Figure 1: Flowchart for recursive search-term expansion process



The starting search terms and the search terms collected from Bluesky and X were used to initialize the process for TikTok. The same algorithm of recursive search-term expansion was used, changing the selection of the 100 videos for each query each month to be random since TikTok doesn't allow to search for top content, it allows only to order the content by time of upload or randomly. The text from the video description was used as the post text. TikToks' API doesn't allow access to the videos themselves, but only to the metadata of the video, so we could not collect and analyse the video data. A list of the 357 search terms collected is found in Appendix A.

Instagram does not allow to search by search terms, only by hashtags. For this reason, to initialize the algorithm, all hashtags from data collected in Bluesky, X and TikTok were collected and were evaluated the same way new search terms are evaluated. To create a list to initialize the algorithm with, a list with the 312 initial search term hashtags is provided in Appendix A. We collected only posts that include images (image or carousel), not posts containing videos. The text from the caption was used as the post text. Instagram doesn't allow searching within specific time frames, the top 100 posts per hashtag search term were collected regardless of the time at which they were uploaded. This limitation might create bias towards proportionally higher engagement posts on Instagram. On the other hand, this results in fewer posts, a maximum of 100 rather than $12(months) * 100$ per hashtag search term. In addition, the date in which the posts were created could be before 2024, during 2024, or after 2024. Furthermore, most Instagram posts do not include a caption text, and were used only in the image analysis. These limitations might skew the analysis of text originating from Instagram, specifically when looking at the overall number of posts from Instagram, the engagement levels on the platform or the temporal trends on the platform. The same algorithm was used for recursive search-term expansion, using hashtags instead of N-grams. A list of the 166 hashtags search terms collected is found in Appendix A.

2. The Data

At the end of the data collection process, we have collected data from 521 X posts, 27,575 Bluesky posts, 14,272 Instagram posts, and 128,442 TikTok posts 110 and 5732 of the posts on Bluesky and Instagram, respectively, did not have texts in them. The High variance between the number of posts collected on the different platforms can be a result of the different levels of user activity between the platforms and specifically different levels of user activity regarding food sustainability on the different platforms. All the posts on X and TikTok had text, and all Instagram posts included images.

We collected the parallel features from all retrieved social media uploads, regardless of platform. Images were collected from Instagram only. Table 1 shows all the collected data, from which platform it was collected, and any deviations if they were necessary.

Table 1: Details of collected features per platform

When name of the feature on the platform deviates from the feature name it is given in brackets

Feature	X (Twitter)	Bluesky	Instagram	TikTok
Post ID	V	V (CID)	V (PK)	V
User ID	V	V (DID)	V (User PK)	V (User name)
Time of creation	V	V	V	V

Post text	V	V	V (Caption text)	V (Video description)
Like count	V (Favorite count)	V	V	V
Share count	V (Retweet count)	V (Repost count)	X - Instagram does not allow access to this data	V
Reply count	V	V	V (Comment count)	V (Comment count)
Type (Image/Carousel)	X	X	V	X
Number of images	X	X	V	X
Images	X	X	V	X

The data was split into two data sets: (1) Visual dataset – containing all the data from Instagram, (2) Textual dataset – containing all posts from any of the four platforms, that contain texts, filtering all posts that do not contain text. Notice that Instagram posts that also contain text appear in both datasets, in the textual dataset they do not contain the visual info, and in the visual dataset they do not contain the post text.

2.1 Data Filtering

The Textual dataset was further filtered to contain only English texts that discuss issues relevant to both sustainability and food or agriculture. The dataset was not filtered by country for incomplete or non-existing country data for the different platforms, in a short test, before the full data collection, all platforms that do have country level data, had had incomplete data, and specifically a very low number of posts with country data, further filtering for only relevant countries would have led to a very small dataset which would have resulted in very limited analysis results.

2.1.1 Filtering Non-English Texts

The original data included texts in multiple languages, but mostly in English. The dominance of English texts can be explained by the general and global tendency to use English in online environments. This tendency is strengthened by using English search terms in the querying stage. Additionally, the second most common language on each platform is far less frequent than English, and the remaining non-English content is spread across many different languages, each represented by only a small number of posts. We used the Langdetect[1] library to detect the language of each post. There are 487, 26,435, 4,505 and 95,386 English posts, and only 33, 999, 1,224 and 32,666 non-English posts in 11, 34, 45 and 51 languages, the next most common language is Japanese, German, Spanish, and Indonesian, with 9, 394, 200 and 6,321 posts on X, Bluesky, Instagram, and TikTok, respectively. We filtered out all non-English posts.

[1] https://github.com/shuyo/language-detection

2.1.2 Filtering Irrelevant Posts

In the second filtering stage we filtered out posts that don't discuss subjects relating to the TealHelix project. We kept only posts that discuss both (1) food and its production (agriculture and food supply chain) and (2) sustainability as defined by the sustainability indicators described in the sustainability indicators defined in TealHelix Work Package 3. To do so we created a classification model for each of the following: food, agriculture, food supply chain, environmental sustainability, health, workers conditions, animal welfare, affordability, geographical/physical accessibility. Each Model classify texts as discussing (True) or not discussing (False) a specific subject. The last category (geographical/physical accessibility), is not part of the sustainability indicators, but in data collection and cleaning the data we had gotten the impression that this subject is being talked about frequently ("food deserts", for example, is a search term that came up from each of the platforms), and we believe it is important to have a better look at this subject as well. To train and evaluate the model we annotated a smaller dataset using zero shot classification.

Zero shot classification

The first stage in creating the classification model was to create a training and testing data set. This was done by zero-shot classification using chat-GPT. We have used batch analysis with the model "gpt-3.5-turbo" and the prompt:

"For the given post, return true or false for these categories:

Food (eating, cooking, diet)

Agriculture (farming, crops, livestock)

Environmental Sustainability (climate, renewables, pollution)

Health (well-being, medicine, nutrition)

Workers' Conditions (labor rights, safety, pay)

Animal Welfare (humane treatment, cruelty)

Affordability (cost, price, accessibility)

Food Supply Chain (production, transport, distribution)

Geographical/Physical Accessibility (location, proximity, infrastructure)

Output JSON exactly as:

```
{
"Food": true/false,
"Agriculture": true/false,
"Environmental Sustainability": true/false,
"Health": true/false,
"Workers' Conditions": true/false,
"Animal Welfare": true/false,
"Affordability": true/false,
"Food Supply Chain": true/false,
"Geographical Accessibility": true/false
}"
```

We sent a request for each of the Bluesky and X posts and received the results.

To test the results, we had hand annotated a random subsample of 50 posts. Research has shown that when comparing models, evaluating around 50 annotated examples is often sufficient, since human judgments and performance metrics stabilize with relatively few samples, providing a reliable estimate of overall quality. In zero-shot classification, we are, essentially, comparing the model's predictions to human-labelled ground truth rather than another model, so using 50 annotated posts should be sufficient. The lowest agreement between the hand-annotated categories and the AI-annotated categories was 41 out of 50 for the food category, and the highest was 50 out of 50 for workers conditions category. Specifically, because this is used for filtering, and we have a very large dataset, we do not mind over-filtering, so false negatives, have lower significance for our use case. If we count only false positives as mistakes, we get the lowest agreement at 42 out of 50 for the health category, all other categories have an agreement of at least 45 out of 50. We had used zero shot classification instead of hand annotation since we required a large and complicated annotated dataset. We annotated approximately 28,000 posts, each post had 9 different classification annotation was required for. If we give each human rater 5 posts, which is 45 overall classifications, we will not want to give a high number of annotation tasks per rater to not cause burnout and lower the quality of annotations. Requiring 10 raters for each piece of content, we will need 56,000 raters. If we annotate a small number of posts, for example 10% of the data, we will still need 5,600 annotators. On the other hand, seeing that many of the discussed topics appear only sparsely, using such a low number of annotated posts might cause us to overlook certain topics. At the same time, humans also frequently disagree in such annotation tasks.[1], in similar rates to the rate of disagreement found in the annotated subsample. For these reasons the approach most applicable to our scenario is zero shot modelling.

Support vector classification

Though it is technically possible to continue using the zero-shot method for future use this is expensive, time-consuming, and relies on external factors for consistency. For this reason, we used the data set created in section 2.3.2.1 to train and test a new classification model for each category. We embedded the posts texts using the all-MiniLM-L6-v2.[2] embedding model that is intended for sentences or short paragraphs, so is fitting to use to embed posts. For each category, we had trained its own support vector classification (SVC) model, using the scikit-learn SVC model. A random sample of 20% of the annotated data was used for testing the model. Using the testing set, we had computed the weighted average F1 score and the false negative rate for each model. The weighted average F1 score is a metric used to evaluate classification performance across multiple classes, considering both the F1 score of each class and the number of true instances in that class. Specifically, it computes the F1 score for each class, then multiplies each by the proportion of instances of that class in the dataset and finally sums these weighted scores. This ensures that the overall metric reflects the classifier's performance more accurately in datasets with class imbalance, giving more influence to classes with more samples while still incorporating all classes. We had also computed the weighted average F1 for the naïve model. The naïve model assigns all posts the most common classification in the training set. A naïve model that always predicts the most common class

[1] Braylan, Alexander, Omar Alonso, and Matthew Lease. "Measuring annotator agreement general-ly across complex structured, multi-object, and free-text annotation tasks." Proceedings of the ACM Web Conference 2022. 2022.

[2] https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2

in the training set is often used as a baseline because it establishes a minimum expected performance, if a more complex model cannot beat this, then it has not learned anything useful. Such a "majority-class" or "ZeroR" baseline is widely recommended for evaluating classifiers, especially in imbalanced-class settings.[1]. For the Naïve case the false negative scores were not computed, since when using this kind of model it tends to the extreme, for example, if the most common label is false the false negative rate will be 0, and if it is true it will the same as the rate of posts with a false label (posts that do not discuss the specific category). The results can be seen in Table 2.

Table 2: F1 scores for the trained model and for the Naïve model, and the false positive rate for the trained model, for each category

Sustainability indicators defined in TealHelix Work Package 3, are shown in Bold.

Category	F1-score	Naïve F1-score	False positive rate
Food	0.85	0.37	0.09
Agriculture	0.88	0.49	0.04
Environmental Sustainability	0.87	0.48	0.05
Health	0.84	0.59	0.04
Workers' Conditions	0.97	0.97	0
Animal Welfare	0.93	0.77	0.02
Affordability	0.92	0.89	0.01
Food Supply Chain	0.86	0.75	0.02
Geographical Accessibility	0.89	0.84	0.01

Notice, that for the workers' conditions category the F1 scores for both models are 0.97. This is due to the low number of posts discussing this subject, specifically, in the test set, only 107 out of 5280 posts discuss workers conditions. The SVC model was able to predict some of these posts as true, but because of the small number and the rounding we don't see the difference between the 2 models in the F1 score. The small, but still existing, difference in F1 Scores for the affordability and geographical accessibility categories is due to a similar but weaker effect, with only 404 and 569 posts, respectively, discussing these subjects.

The SVC model was then applied to classify all posts. After classification, the dataset was filtered so that only posts with at least one subject labelled true in each of the following category groups were retained:

1. Food: food, agriculture, or the food supply chain.

[1] https://datalab.utk.edu/bas474/chapters/classification/Assessment.html

2. Sustainability: environmental sustainability, health, worker conditions, animal welfare, affordability, or geographic accessibility.

Out of 81,062 English posts, 69.78% discussed sustainability, 83.09% discussed food, and 64.41%, which is over 50k posts, discussed both.

The key performance indicator (KPI) for this task is achieving the highest possible F1 score. The reported F1 score is the average across the classification models for the sustainability indicators, with an average F1 score of 0.906, substantially higher than the naive models' average F1 score of 0.74.

3. Feature engineering

The directly collected data detailed in Table 1, needed to be processed into more meaningful features. These features are:

1. Overall engagement: the sum of the like, share and reply counts.
2. Log engagement: the log transformed overall engagement, $ln\ (1 + overall\ engagement)$.
3. Hour of day – the hour (0-23) in which the post was created.
4. Months since January 2024 – how many months before or after January 2024 the post was created.
5. Day of week – the day in the week (0=Monday, 6=Sunday) in which the post was created.
6. Month – the month in the year (1-12) in which the post was created
7. Week of year – the week of year (0-51) in which the post was created.
8. Is weekend – whether the post was posted on weekend (Saturday or Sunday) or not.
9. Part of day – the part of day (05:00-11:59=morning, 12:00-16:59=afternoon, 17:00-20:59=evening, 21:00-4:59=night) in which the post was created.

In our analysis, we look at the overall engagement and not at each engagement type specifically. That is, since the distribution of the like, share, and reply counts is very skewed, and many posts have no engagement in terms of shares or comments. Table 3 shows statistical aggregation of these features and the log engagement feature, showcasing that it is significantly less skewed than the original data. This is due to it being an integration of all three engagement options and it being log transformed. For this reason, using the log engagement feature will give us clearer, more understandable results.

Table 3: Summary statistics for the engagement data

Statistical measure	Like count	Share count	Reply count	Log engagement
25%	2	0	0	1.38
50%	11	0	0	2.64
75%	38	1	2	3.78
Max	1,346,353	164,039	18,690	14.22

Mean	353.35	32.58	8.71	2.7
STD	7507	1060	126	1.86
IQR	36	1	2	2.4
Skewness	93	102	80	0.8

More features were created specifically for the textual and the visual analysis.

3.1 Textual features

Further features calculated from the posts text:

1. Food agriculture and sustainability indicators category classification – 9 features, one for each category in Table 2.
2. Number of words – the number of words in the post text
3. Topic group – the assignment of this feature is described in section 3.1.1.
4. Number of hashtags – the number of hashtags in the text.
5. Number of Emojis – the number of emojis in the text.
6. Distinct hashtags – hashtags appearing in the post text that are also distinctive to a topic group. The assignment of this feature is described in section 3.1.2.
7. Distinct Emojis – emojis appearing in the post text that are also distinctive to a topic group. The assignment of this feature is described in section 3.1.2.
8. Sentiment compound – This is a single score representing the overall emotional tone of the post text, calculated using VADER[1] sentiment analysis. The score ranges from -1 to 1, where -1 indicates very negative sentiment (e.g., anger, sadness), 1 indicates very positive sentiment (e.g., joy, approval), and 0 represents a neutral or balanced sentiment. A positive score suggests that the post expresses favorable or optimistic content, while a negative score indicates unfavorable, critical, or pessimistic content.

3.1.1 Topic clustering

A main feature created from the posts texts is the text topic groups. This allows us to discover emergent topics discussed online that were not previously identified. The clustering model was fitted to the Bluesky and X posts and later applied to all posts. To construct the final topic model, we followed a two-stage approach. First, we performed an initial topic analysis on the full Bluesky and X dataset to identify the broad thematic structure. This analysis revealed one dominant cluster containing a large share of the posts. In the second stage, we fitted a separate topic model exclusively on the posts within this dominant cluster to obtain a more fine-grained thematic decomposition. Further methodological details for each stage are presented in the following sections.

[1] https://vadersentiment.readthedocs.io/en

Initial topic model

To fit the initial model, we used the all-MiniLM-L6-v2 embedding model, which was also used for the SVC, seeing that we know it captures the essence of the posts' texts from our previous results. To create the model, we used the Bertopic[1] library. The model chosen used a UMAP dimension reduction model (number of neighbors=15) and a HDBSCAN clustering model (mini-mum cluster size=15), resulting in 17 topics, and an outliers group. Different parameters and models were tested, and their results were evaluated by the researchers. The chosen models showed the clearest, distinct, and not too specific topics. Table 4 describes the initial topic clusters.

Though there are some topics that seem to relate to similar subjects, larger minimum cluster sizes didn't always cluster these topics together, and on the other hand, hurt the clearness of other topics. For this reason, after fitting both topic models, the researchers grouped similar topics together.

Table 4: Topic description for the initial topic model

Topic	Number of posts in topic	3 most Representative words
-1 (Outliers)	456	-
0	14305	farming, agriculture, waste
1	412	gaza, insecurity, food insecurity
2	195	https snackdeals, snackdeals, snacks
3	116	ai, agriculture, future
4	91	cashapp, motel, raymondkennon
5	67	billion, apartheidisrael, gazagenocide
6	61	flu, bird, bird flu
7	53	nutri score, nutri, score
8	51	turkey, turkeys, thanksgiving
9	40	bees, bee, pollinators
10	37	soup, mona lisa, mona

[1] Grootendorst, Maarten. "BERTopic: Neural topic modeling with a class-based TF-IDF procedure." arXiv preprint arXiv:2203.05794 (2022).

11	35	cooking, carbon footprint https, forgoing steaks
12	31	fav, height, color
13	24	sounded like, free range way, range way
14	20	Ukraine, russia, war
15	16	hemp, cannabis, fibre
16	16	best organic, best organic baby, baby food pouches

Since Topic 0 contains more than 14k posts, while the next biggest topic contains only 412 posts, and after searching for parameters for the dimension reduction and clustering models that will mitigate the high variance in cluster sizes unsuccessfully, we decided to fit another model.

Secondary topic model

The secondary model was fitted using only the posts from cluster 0 of the initial topic model. We used a larger embedding, all-mpnet-base-v2.[1], which is also intended for short texts, similarly to the initial topic model we had used a UMAP dimension reduction model (number of neighbors=5, minimum dist=0.0) and a HDBSCAN clustering model (minimum cluster size=15, minimum samples=5), resulting in 47 topics and an outlier group. Different parameters and models were tested, and their results were evaluated as in the initial topic model stage. Table 5 describes the secondary topic clusters.

Table 5: Topic description for the secondary topic model

Topic	Number of posts in topic	3 most Representative words
0.-1 (Outliers)	3669	Meat, insecurity, eggs
0.0	8449	climate, permaculture, org
0.1	379	eggs, free range, dozen
0.2	173	chickens, free range, range chickens
0.3	160	fish, aquaculture, ocean
0.4	106	milk, raw, raw milk
0.5	99	diet, weight, lose

[1] https://huggingface.co/sentence-transformers/all-mpnet-base-v2

0.6	69	cat, cats, food water
0.7	64	great, museum, pretty
0.8	63	recall, costco, salmonella
0.9	51	sugar, amp, salt
0.10	51	today, drop, trip
0.11	46	dog, pet food, pet
0.12	45	games, music, gardening
0.13	44	water use, groundwater, use water
0.14	44	rfk, rfk jr, jr'
0.15	42	worms, soil, earthworms
0.16	37	dream, food forest, acres
0.17	35	biochar, https buff ly, https buff
0.18	34	bluesky, hello, excited
0.19	34	chinese, chinese food, restaurant
0.20	33	rice, rice organic, meatless
0.21	33	medicaid, cuts, medicare
0.22	32	drink, alcohol, warm
0.23	30	thanksgiving, thankful, happy thanksgiving
0.24	28	recipe, turn, https www theguardian
0.25	27	fungi, scientific, form
0.26	26	money, groceries, just don’t
0.27	25	bsky social, bsky, color
0.28	25	power, food water, supplies
0.29	24	alpine boreal forest, alpine boreal, boreal

0.30	24	glyphosate, mexico, gmo
0.31	23	mice, beetle, smell
0.32	23	protein, nutrition, calories
0.33	22	butter, grass fed, grass
0.34	21	fuel, jet, nfu
0.35	21	coli, cucumbers, recalled
0.36	19	medicine, diet rich, msg
0.37	19	favorite, favorite food, chocolate
0.38	19	water agriculture, watercress, retain
0.39	18	workers, immigrants, food tables
0.40	18	birthday, dinner, lovely
0.41	18	aquaponics, fish, aquaculture
0.42	18	mushrooms, mushroom, foraging
0.43	17	delivery, fast food, fast
0.44	17	dems, rights, healthcare
0.45	16	access food medicine, food medicine, medicine
0.46	15	biodiversity, tools, restoring biodiversity

Cluster 0.0 is still significantly larger than other topics, but further clustering resulted in overly specific clusters, many of which are clusters of posts from a single user, so no further analysis was done.

Notice that some clusters show representative words that are relevant to the US and not the EU, such as Costco or RFK jr, this might suggest bias in the data towards the US and UK markets. While this might be true another explanation stems from the fact that the difference between the countries in the EU is much higher than the difference between the states in the US, so in the EU there is a larger number of retailers and political events, leading to a lower number of mentions for each of them, even though the overall number of posts regarding similar topics might be similar, so US relevant phrases will be the most common in the cluster.

Grouping the clusters

Many clusters in both model topics seem to be connected. For this reason, we had gathered them into groups, considering the sustainability indicators from the “TealHelix Sustainability Indicators” document, and the hierarchy of topics in the models. Table 6 shows the groups and the topics within them.

Table 6: Grouping for the topics from initial and secondary topic models

-

Group name	Topics	Example post
War food insecurity	1, 5, 14	Sudan atrocities and famine at ‘breaking point,’ UN and U.S. say: War has triggered the world’s worst displacement crisis, with 8.5 million people forced to flee their homes and 18 million people facing acute food insecurity.
Markets shops deals	2, 16, 26, 29	$3.09 Kraft Real Mayo Classic Mayonnaise Spread – 12 fl oz Bottle, Made with Cage-Free Eggs: Price: $3.09 (as of Apr 29, 2024 14:56:07 UTC – Details)… https://snackdeals.shop/2024/04/29/3-09-kraft-real-mayo-classic-mayonnaise-spread-12-fl-oz-bottle-made-with-cage-free-eggs/
Environmental agriculture and supply chain	3, 6, 9, 15, 0.0, 0.3, 0.13, 0.15, 0.16, 0.17, 0.25, 0.30, 0.38, 0.41, 0.42, 0.43, 0.46	The alliance is centred on collaboration to accelerate innovation across EIT's four Humane Endeavours: - Health and medical science - Food security and sustainable agriculture - Climate change and clean energy - Government innovation in the age of artificial intelligence.
Affordability	4, 0.21, 0.44	I really hate to post this but I'm unable work and haven't been able to afford food, bills and necessities for a bit bc I hate asking for help.
Health	7, 0.4, 0.5, 0.9, 0.32, 0.36	Very timely! The US Food and Drug Administration finalized the rule governing “healthy” claims on labels

		yesterday—though I'd be curious if they're as effective as Nutri-Score.
Animal welfare	8, 13, 0.1, 0.2, 0.33	I'm getting turkey and rabbit feet in my order this time to see how long they last. The farms involved all practice regenerative agriculture so these aren't feedlot cows or battery birds.
Environmental eat and cook	11, 0.20, 0.24	@TheEconomist: Beef emits 31 times more CO_2 per calorie of food than tofu does. By cooking so many cows, humans are cooking themselves, too. Forgoing steaks may be one of the most efficient ways to reduce our carbon footprint https://t.co/ThPBV8aKih 👇
Introduction post	12, 0.12, 0.18, 0.22, 0.27, 0.37	Name: Max Height: 5'6" Sexuality: Man I don't know Sign: Crablion Piercings: None
Current affairs	10, 0.14, 0.34, 0.45	We want healthy and sustainable food! So we're going to waste some food by… throwing it at a painting?
Pet food	0.6, 0.11	I can't own a dog until I own my first house. I'm paranoid about the nasty shit that the FDA lets pass into foods. Sadly the organic healthier options for pet food are wildly expensive.
Recall	0.8, 0.35	The FDA reclassified the recall for eggs sold at Costco stores over possible salmonella to their highest risk level. The Nov. 27 recall is for 10,800 retail units of organic, pasture-raised, 24-count eggs, sold under Costco's Kirkland Signature brand by New York–Handsome Brook Farms.
Workers conditions	0.39	Farmworkers 'ensure that we have food on our tables and sustain our agricultural industry – and they too have been in legal limbo for years

		because politicians have refused to come together and fix our broken immigration system.’
Other	0.7, 0.10, 0.19, 0.23, 0.28, 0.31, 0.40	Oh my god, this is a portrait of heaven that I haven't seen since I was in college.
Outliers	-1	BILLY VANILLY Skin SUPER-Food – invigorating, refreshing, 100% Organic, Vegan, 30/60ml https://tuppu.net/6157c4bc
Secondary outliers	0.-1	Come on down to LV-426 for your free-range, grass-fed, all-organic dronification needs. Grass-fed beef fed marines, but there's grass in the chain somewhere.

Notice that introduction posts don’t usually discuss food and sustainability in detail, but can still mention these subjects, and for this reason many of them remained after filtering. For example, one of the posts in the introduction posts group says:

“Looking for new online peeps ;) My interests and such: Permaculture, Gardening, TTRPGS […] Vegan, Plantbased, Movies, #promosky".

Finally, all posts were processed using the two-stage topic modeling approach. Each post was initially assigned the topic identified in the first-stage analysis. For posts labeled as topic 0 in the initial analysis, the topic assignment from the second-stage model was used instead. Finally, each post was mapped to its corresponding topic group.

3.1.2 Emojis and hashtags

All emojis and hashtags were extracted from each post. In addition to creating the features representing the total number of emojis and hashtags per post, two additional features were generated based on TF-IDF analysis. First, we identified the emojis that were most distinctive to each topic group. Using this set of distinctive emojis, we then created a feature for each post that lists only the emojis present in the post that are part of the distinctive set, regardless of the post’s assigned topic group. In other words, a post from topic group A could include emojis that are distinctive to topic group B, and these would still be captured in the feature. The same procedure was applied to hashtags: for each post, a list was created containing only the hashtags that appear in the set of hashtags identified as distinctive across all topic groups. These features, therefore, represent, for each post, the presence of emojis and hashtags that are considered distinctive in at least one topic group, providing a way to incorporate topic-specific patterns into the analysis while allowing overlap across groups. Table 7 shows the distinctive emojis and hashtags per group.

Table 7: The most distinctive emojis and hashtags for each topic group

-

Group name	Emojis	Hashtags
War food insecurity	PS, 🍉, 🟢, SD, 💚	#GazaGenocide, #ApartheidIsrael,

		#GenocideJoeBiden, #Gaza, #palestine
Markets shops deals	🍫, 🍅, ✨, *,*	#deals, #snacks, #food, #furryart, #furry
Environmental agriculture and supply chain	🌱, ✨, 🌾, 💚, 🌍	#fyp, #regenerativeagriculture, #gardening, #permaculture, #SustainableFarming
Affordability	⬇, 💸, 🚨, 💕, ✔	#homeless, #mutualaid, #hungry, #foodinsecurity, #Homelessness
Health	✨, 💪, 🥩, 🥛, 🌱	#nutrition, #dairy, #healthylifestyle, #health, #food
Animal welfare	🐓, 🐔, 🥚, ☑️, ✨	freerangechickens, #chickens, #pasturedpoultry, #chicken, #backyardchickens
Environmental eat and cook	🌱, ✨, 🌾, 😋, ☑️	#meatlessmeals, #meatlessmonday, #vegetarian, #plantbased, #vegan
Introduction post	🌺, ▫️, 👉, 🌱, ☑️	#cakeporn, #biscoffcannoli, #nutellacannoli, #vanillacustard, #dessertsofinstagram
Current affairs	us, 🎨, 🌱, 💚, 🏰	#MonaLisa, #rfkjr, #louvre, #monalisa, #maha
Pet food	🐾, 🐶, 💚, 🫐, 😅	dogtreats, #dogfood, #dogsoftiktok, #petfood, #pets
Recall	⚠️, 🔥, ✔, 🚨, 🥒	#recall, #salmonella, #FoodSafety, #texasranch, #costco
Workers conditions	no emojis in posts from this topic group	#notillfarming, #smallfarm, #farmlife, #호주, #현실남매
Other	🔥, ✨, 📍, 🍖, ⭐	#fyp, #eatlocal, #jalanjalan, #foodie, #fypシ
Outliers	✨, 🌱, 🐔, 🐓, 🥚	#freerangechickens, #farmlife, #fyp, #chickens, #pastureraised

Secondary outliers	🌱, ✨, 🌾, 💚, 🌍	#fyp, #regenerativeagriculture, #farmlife, #SustainableFarming, #farming

3.2 Visual Features

Visual features were computed on 2 levels: (1) image level, (2) aggregated post level, this is due to many posts being carousel-type posts that include multiple images. First, the image level features will be explained, then the aggregated post level features.

3.2.1 Image level features

Visuals can be split into two aspects: (1) the physical elements in the image, in other words the “what” of the visual and (2) the style of the image, in other words the “how” of the visual. We use Image topic groups to analyse the physical elements of the images. Analysing style is highly complicated, we chose for this work to analyse the color distribution within the images, which is an important aspect of style.

The following features were calculated for each image:

1. Color distribution, in HSV format (Figure 2 shows the distribution bins used):
    a. Distribution of hue – 16 features for 16 bins. The value in each bin is the ratio of pixels in the image with hue values within the bin edges.
    b. Distribution of saturation – 16 features for 16 bins. The value in each bin is the ra-tio of pixels in the image with saturation values within the bin edges.
    c. Distribution of values (lightness) – 16 features for 16 bins. The value in each bin is the ratio of pixels in the image with lightness values within the bin edges.
2. Image topic group – the assignment of this feature is described in the following section.

Figure 2: HSV bins visualization

Each element of the HSV is presented while holding the others two elements fixed.

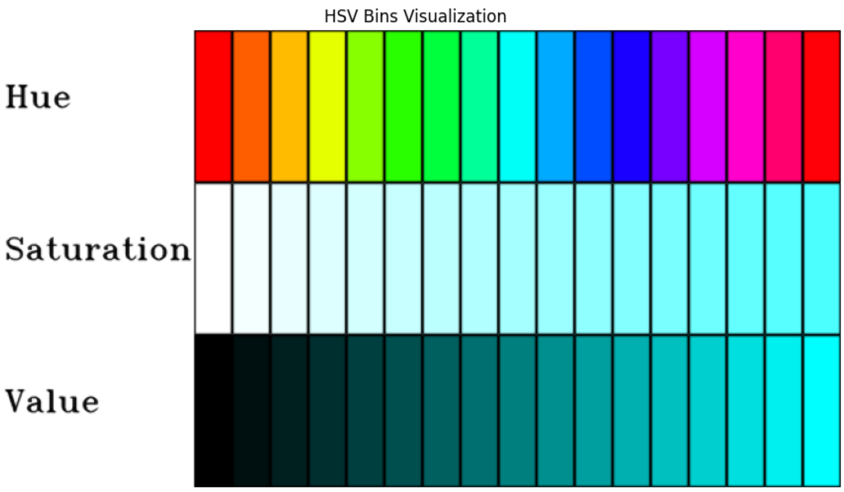


Image content topic clustering

We have fitted a multimodal topic model to all images. Many images had texts on them, we used the easyocr library[1] to retrieve the texts from the images. Then we used the clip-ViT-B-32[2] to create embeddings for each image and for each text retrieved from the image. If the image did not have text on it then the embedding of the image was used as is. If the image had text on it then its embedding was calculated as: multimodal embedding=0.25*text embedding+0.75*image embedding, the text embedding was given a low weight due to the somewhat low quality of the text retrieval results. We didn't account for the captioning text, since it is analysed with the texts from the other platforms.

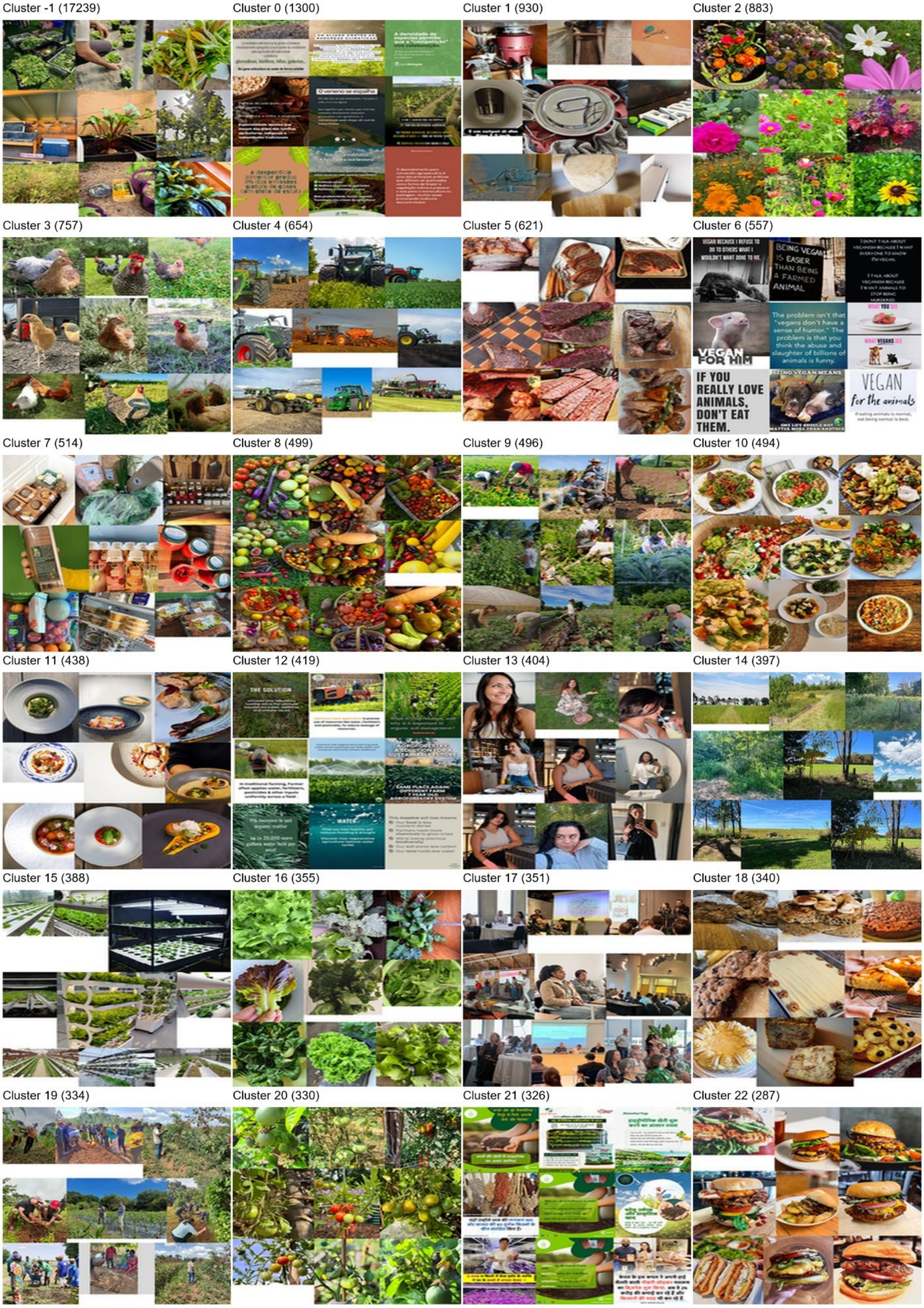
We used these embeddings for topic analysis using Bertopic with UMAP dimensionality reduction and HDBSCAN clustering model with the default parameter, and a minimum topic size of 40. This resulted in 99 image clusters and an outlier group. Figure 3 shows representative images from the biggest 24 clusters, the other clusters are shown in Appendix B.

Figure 3: Representative images from the 24 biggest image topic clusters

size of cluster in parenthesis. Cluster -1 is the outliers group.

[1] https://github.com/JaidedAI/EasyOCR

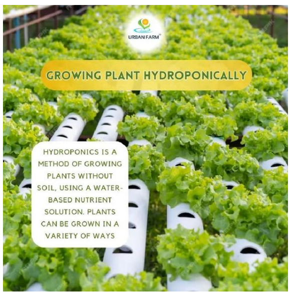
[2] https://huggingface.co/sentence-transformers/clip-ViT-B-32

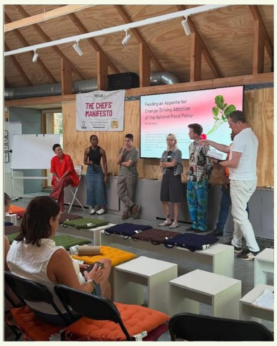


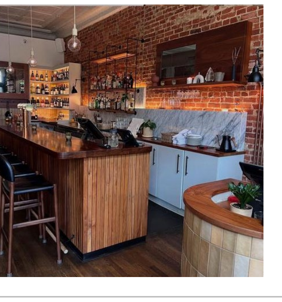
We had then grouped the clusters together into 20 image topic groups. Table 8 shows the groups and the topics within them.

Table 8: Grouping for the image topics model

-

Image group name	Image topics	Example images
Outliers	-1	
Posters agriculture	0,12,21,40,68	
Flowers	2,67	
Farm animals	3,33,44,49,50,84,73	
Tech agriculture	4,15,54,64	

Food	5,10,11,18,22,30,46,72,75,77,93	
Posters animal welfare	6,89	
Produce	7,8,16,20,24,38,39,51,70,78,79,95	
People farm work	9,19	
People other	13,17,57,60,69,90	

Nature	14,47,86	
Posters other	23,63,85,94,48	
People food work	25,29	
Posters food	26,27,28,6,36,37,41,42,55,71,82,97	
Restaurant	31,80	

Agriculture	32,34,61,92	
Pets	35,99	
Other	45, 52, 56, 59, 62, 65, 87, 88, 91, 96, 83, 98, 1, 66,53	
People children	58, 76, 81, 84	
Alcohol	43,74	

All Images were processed using the image topic model and each image was mapped to its corresponding image topic group.

3.2.2 Aggregated Post level features

Unlike the textual features, the aggregated post level data for the features for each image do not contain the category classifications, since most of the posts collected from Instagram did not have a caption text so we can't apply the SVC model on them.

The post level data also include the following aggregated features:

1. Number of images in the post.

2. Ratio of images in each image topic group – 20 features on for each of the 20 image topic groups. The value is calculated as: $\frac{Number\ of\ images\ of\ group\ i\ in\ post\ j}{Number\ of\ images\ in\ post\ j}$
3. Dominant topic group – the topic group that with the highest ratio.
4. Average colour distribution: $3(colour\ features\ in\ HSV) * 16(bins) = 48$ features averaging the colour distribution of all images in the post.

4. Results

In this part we will describe the main results of the data analysis. We will discuss the textual data and later the visual data. For each modality we will describe the distribution of the log engagement value, the temporal features and the modality specific features, then we will discuss how they affect or are affected by the log engagement, compound sentiment and temporal trends for the sustainability indicators (for the textual data).

Due to the large amount of data the differences are usually significant within $p<0.01$ and even $p<0.005$, since we are using pairwise significance tests, we have hundreds of significant results, for brevity and ease of read we will not discuss the significance level of the results further. Only some of the significant results will be shown and discussed, non-significant results will not be discussed. The effect sizes are also small, this is with line with current research[1] on interventions on social media, but since we have a large amount of data the effects are still significant. For this reason, and again for brevity and ease of read, we will not discuss the effects sizes, only direction or comparison when relevant.

It is also important to note that this is exploratory research, and no causal effect could be inferred.

4.1 Textual Data Analysis

4.1.1 Feature distribution

We divide the data into 3 types: categorical, numerical and temporal data. Table 9 shows the summary statistics for the categorical data.

Table 9: Statistical summary for the textual data categorical features

Feature	Unique values	Mode	Cardinality	Evenness
Platform	['Bluesky', 'Twitter', 'Instagram', 'TikTok']	TikTok	4	0.504
Agriculture	[False, True]	TRUE	2	0.988
Affordability	[False, True]	FALSE	2	0.144
Environmental	[False, True]	TRUE	2	0.993

[1] Aridor, Guy, et al. "Experiments on social media." (2024).

Sustainability				
Food Supply Chain	[False, True]	FALSE	2	0.655
Geographical Accessibility	[False, True]	FALSE	2	0.295
Animal Welfare	[False, True]	FALSE	2	0.749
Workers' Conditions	[False, True]	FALSE	2	0.006
Health	[False, True]	FALSE	2	0.983
Food	[False, True]	TRUE	2	0.926
Group	['enviromental_agricalture_supplly_chain', 'secondary_outliers', 'current_affairs', 'health', 'pet_food', 'outliers', 'other', 'markets_shops_deals', 'animal_welfare', 'war_food_insecurity', 'affordability', 'introduction_post', 'enviromental_eat_cook', 'recall', 'workers_conditions']	enviromental_agricalture_supplly_chain	15	0.491

Evenness is a measure of how uniformly the data are distributed across categories. It measures whether all categories have roughly the same number of observations or whether some categories dominate while others are rare. High evenness means that observations are spread relatively equally across all categories. Low evenness indicates that one or a few categories contain most of the data, while others are underrepresented. The categorical data, in most cases is either very evenly or very unevenly distributed, this is specifically important for the sustainability indicators categories. As a result, the group feature, which demonstrates the natural emergence of subjects that mirror the sustainability indicators, has an evenness value of ~0.5.

Table 10 shows the summary statistics for the temporal data.

Table 20: Statistical summary for the textual data temporal features

Features	Mode	Cardinality	Evenness
Hour of day	16	24	0.986

Day of week	1	7	0.996
Months since Jan 2024	10	92	0.579
Month	11	12	0.994
Week of year	48	53	0.988
Is weekend	FALSE	2	0.792
Part of day	night	4	0.988

Notice that in this case the evenness is very high for all features except for the is weekend feature, which is inherently non even seeing that there are 5 days in the work week and only 2 in the weekend, and months since Jan 2024 feature, which is uneven mostly because of a small amount of posts collected from Instagram, where the query can't specify a timeframe and as a results we had retrieved posts not only from 2024, but this is a small number of posts from one platform.

Table 11 shows the summary statistics for the numeric data.

Table 31: Statistical summary for the textual data numeric features

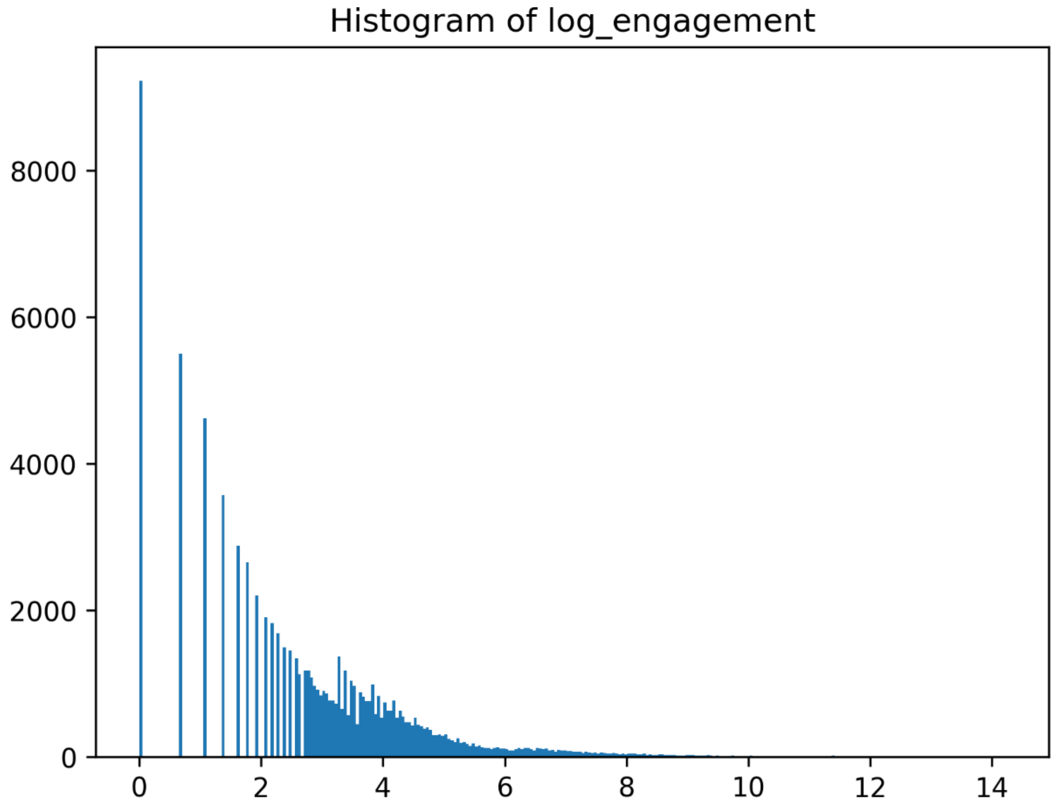
	Min	25%	50%	75%	Max	Mean	STD	Skewness
# emojis	0	0	0	2	104	1.39	3.41	7.03
# hashtags	0	2	6	11	373	8.63	12.52	8.42
# words	1	15	32	56	719	49.67	58.15	3.05
Sentiment compound	-0.99	0	0.42	0.8176	0.99	0.35	0.50	-0.53
Log engagement	0	1.39	2.64	3.78	14.22	2.70	1.87	0.81

We can see that Hashtags are not very common and emojis are not common at all, less than half of the posts include them, but there are cases of significant use, which leads to skewed distribution. The sentiment compound has positive mean and median and negative skewness, which means that the posts tent to have a more positive sentiment with a significant left tail.

4.1.2 Log engagement analysis

We want to check if any of the features in our data set have a significant difference in engagement between post. For this purpose, we first look at the histogram of the log engagement, shown in Figure 4.

Figure 4: Histogram of log engagement values



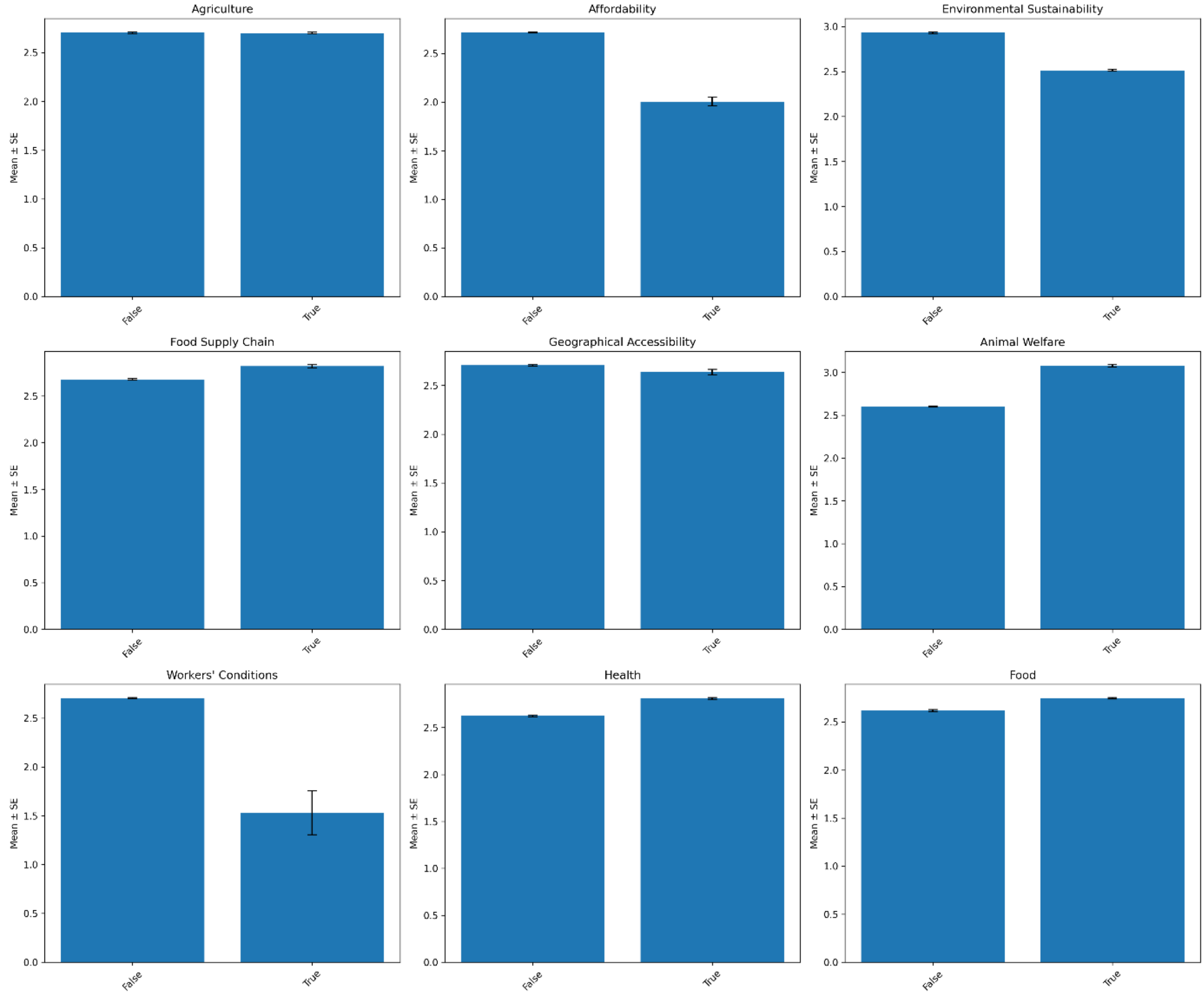
We can see that even after log-transforming the overall engagement, the distribution is not normal. For this reason, when evaluating the significance of the difference between the different categorical and temporal data, we use a Mann-Whitney U test. For features with multiple categories, we use Kruskal–Wallis H test, and if it is significant, we use the Mann-Whitney U test on each pair of categories.

When researching social media engagement around a specific topic, such as food sustainability, focusing on total engagement is important because it reflects the overall attention and reach the topic receives. While most posts may have low engagement, a few highly viral posts can drive substantial discussion and visibility, making the mean a meaningful measure of aggregate impact. With a very large dataset, the mean is stable even in the presence of skewed engagement, as individual outliers have a minimal proportional effect. Using the mean and standard deviation in this context is appropriate because they capture the full distribution of engagement and allow for quantitative comparisons across groups, while the median alone would fail to reveal differences driven by high-engagement posts. For this reason, we will continue using mean values to analyse the log engagement data. Results regarding smaller groups, such as workers conditions, might be less reliable.

Figure 5 shows bar plots of log engagement for sustainability indicators found to have a significant difference in log engagement.

Figure 5: Bar plots for sustainability indicators with statistically significant difference in log engagement

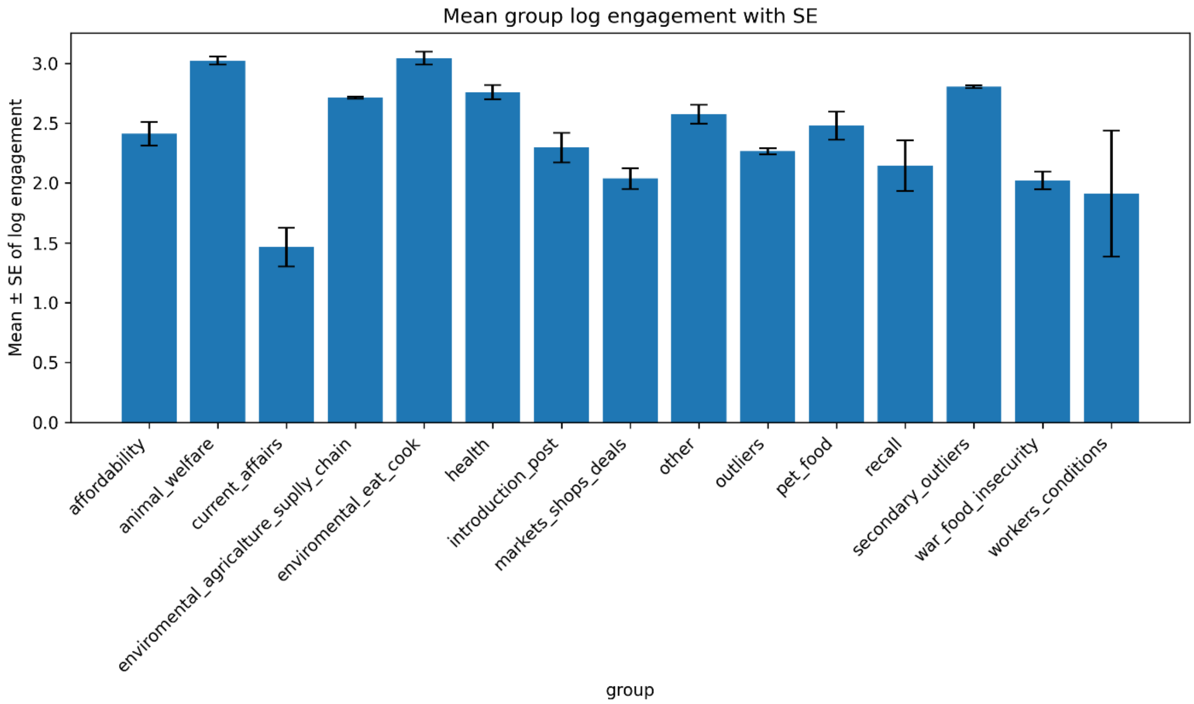
SE shown in error bars.



We can see that the biggest difference is in the case of workers' conditions, posts that discuss workers' conditions receive significantly less engagement, though because of the small sample size this might not be reliable, similarly posts discussing affordability receive less engagement. The biggest positive significant difference is for posts discussing animal welfare. Other subjects show a significant but smaller difference.

Figure 6: Bar plot of log engagement for the different topic groups

Most of the pairs have a significant difference, SE shown in error bars.

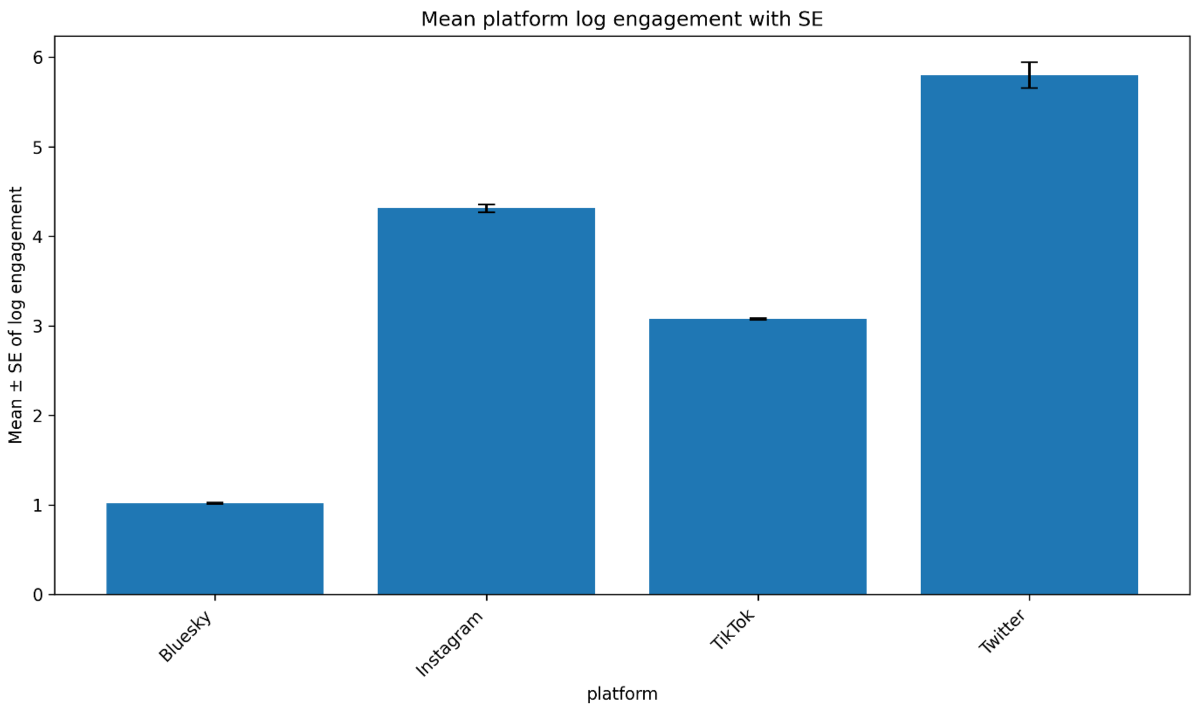


We can see that posts that discuss current affairs receive the least engagement, and posts that discuss animal welfare and the environmental aspects of eating and cooking food get the most engagement.

Figure 7 shows a bar plot of the log engagement for the different platforms. All platform pairs were found to have a significant difference in log engagement.

Figure 7: Bar plot of log engagement for the different platforms

All pairs have a significant difference, SE shown in error bars.

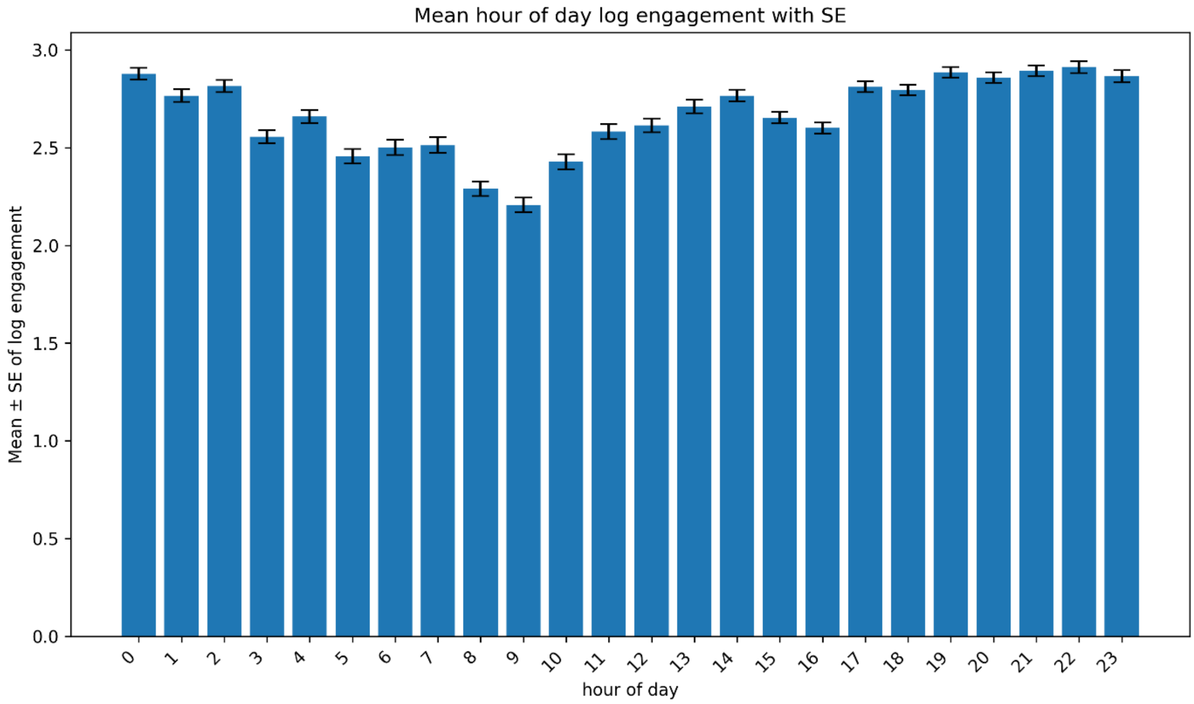


Interestingly, Twitter has the highest engagement, though because of the smaller sample size the result might not be reliable, and Bluesky has the lowest engagement.

Looking at the temporal data, all features had some pairs with significant difference in log engagement, but they are generally small and/or expected. For example, Figure 8 shows a bar graph of the log engagement for the different hours of the day.

Figure 8: Bar plot of log engagement for the different hours of day

Some of the pairs have a significant difference, SE shown in error bars.



We can see that content posted around 08-09, gets the lowest engagement, and content posted around 20-22 gets the highest engagement. We can speculate this is due to the time at which people are at home or at work, and the platform's algorithm that highlights content the more engagement it receives, and so there is an exponential negative effect to posting content at hours when people are at work and use social media less.

Figure 9 shows a bar graph of the log engagement for the different emojis. Looking at the difference in the log engagement between different emojis, we can see a few interesting trends. Firstly, there is a big variance between the engagement with posts that have different emojis of the check mark symbol (✔), most interesting is that the V symbol with the highest engagement, which is also the emoji with the highest engagement overall, is distinctive to the affordability topic group. This topic group is not one of the topic groups with a particularly high engagement (see Figure 6). On the other hand, the Earth emoji is one of the emojis with the lowest average engagement, though it is distinctive to secondary outliers and environmental agriculture supply chain topic groups, 2 of the 5 topic groups with the highest average engagement (See Figure 6). These point to a possibly more complex connection between the engagement, the topic groups, and visual, non-verbal communication.

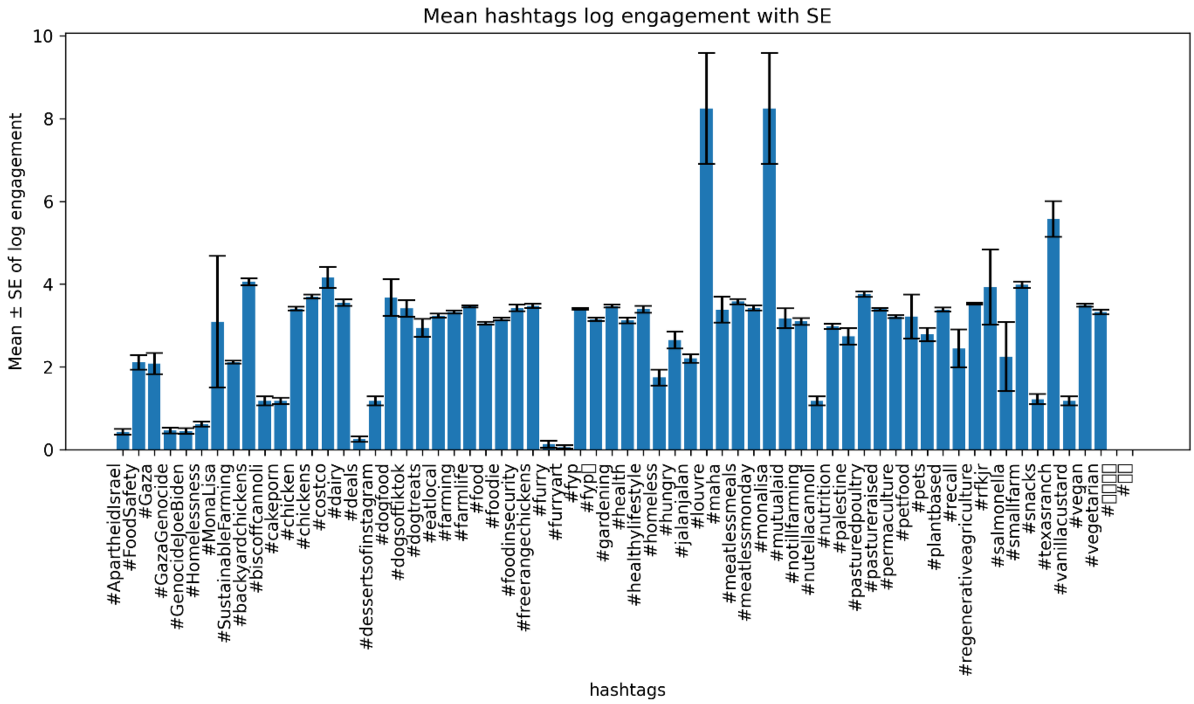
Figure 9: Bar plot of log engagement for the different emojis

Some of the pairs have a significant difference, SE shown in error bars.

Figure 10 shows a bar graph of the log engagement for the different hashtags.

Figure 10: Bar plot of log engagement for the different hashtags

Some of the pairs have a significant difference, SE shown in error bars.



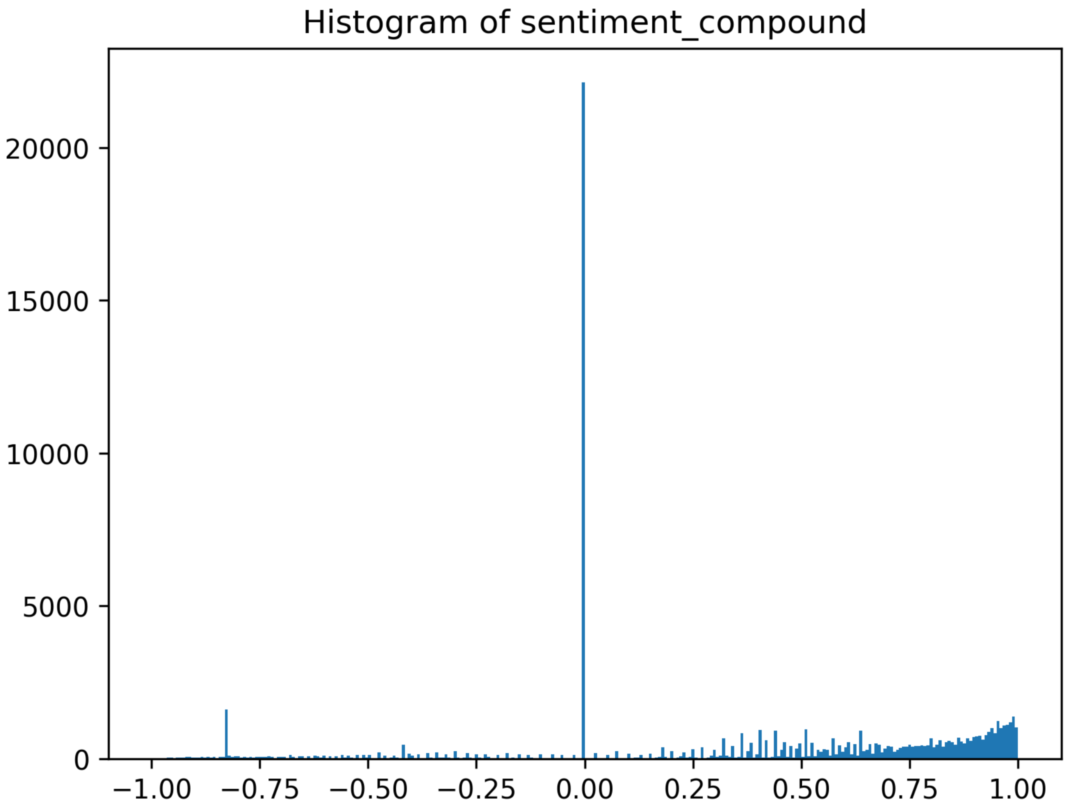
Interestingly the hashtags #louvre and #monalisa have a very high average engagement, even though they are distinctive to the current affairs topic group This might be a result of the high variance of engagement with different sub-topics within this topic group, which can be very different from one another.

In exploring the numerical data, no correlation was found between high engagement and number of words, number of emojis, number of hashtags or sentiment compound.

4.1.3 Sentiment analysis

As in the previous section when exploring the log engagement, we will first look at the histogram of the sentiment compound shown in Figure 11.

Figure 11: Histogram of sentiment compound

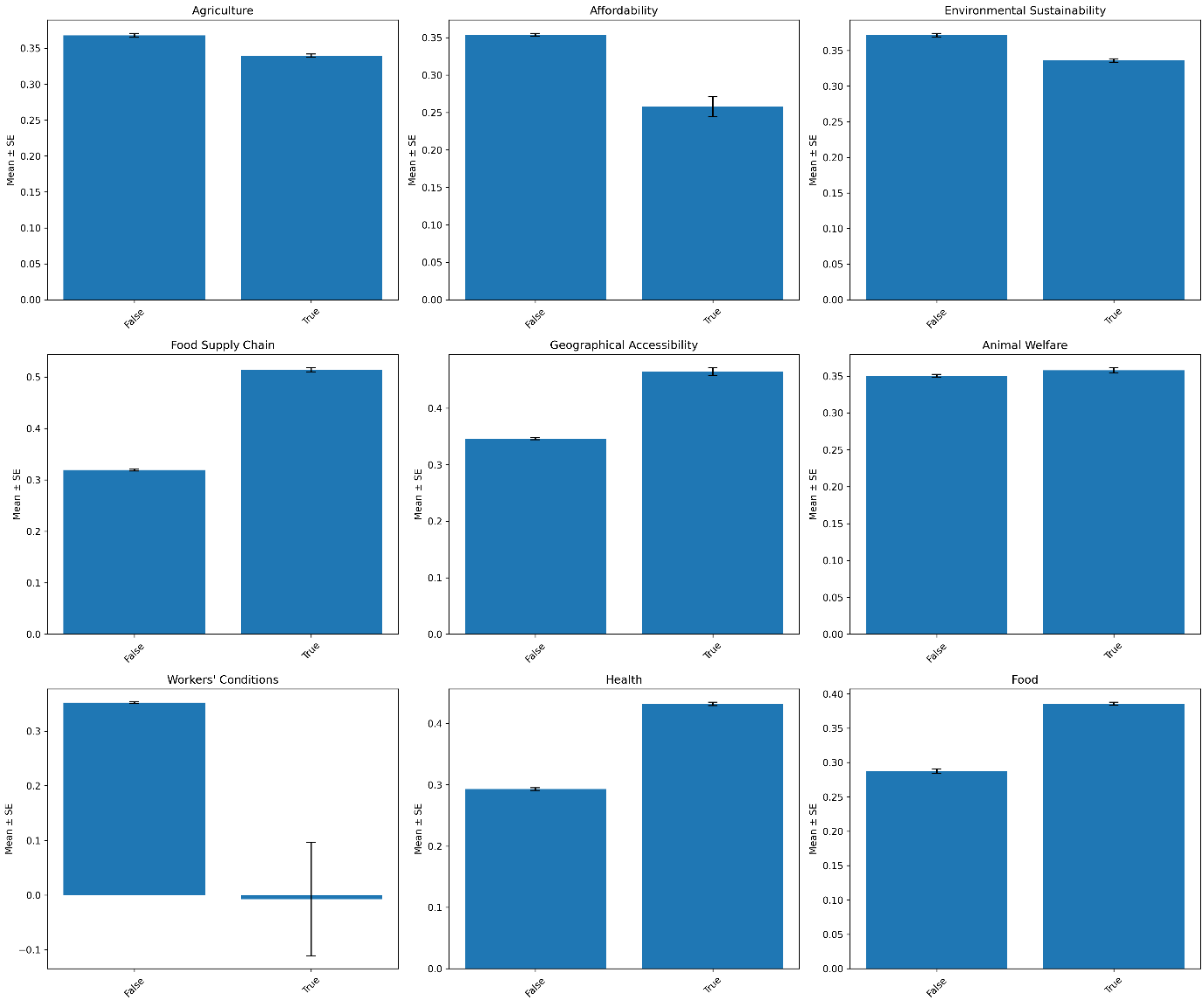


The distribution does not appear to be normal, with most posts showing neutral sentiment. Therefore, we also use the Kruskal–Wallis H test and Mann-Whitney U test to assess whether there are statistically significant differences in sentiment compound across the different categorical features.

Figure 12 shows bar plots of the average sentiment compound for sustainability indicators found to have a significant difference in sentiment compound.

Figure 12: Bar plots for sustainability indicators with statistically significant difference in sentiment compound

SE shown in error bars.

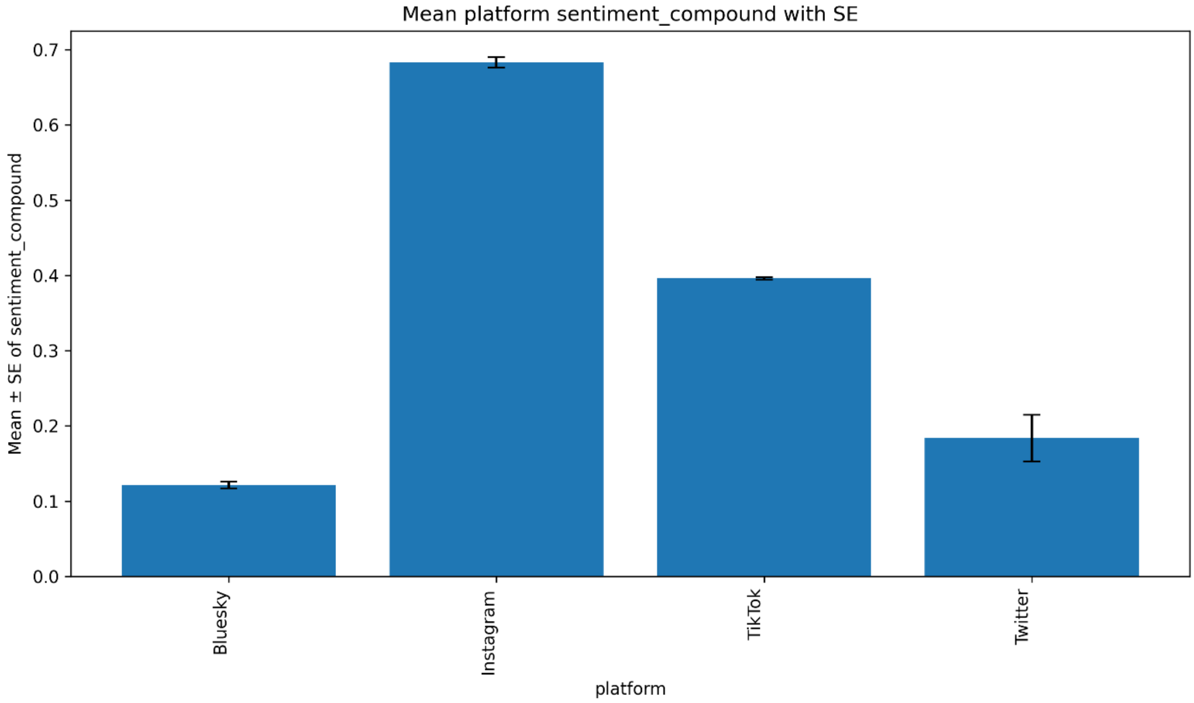


Posts discussing workers’ conditions show notably lower sentiment scores, Note the small sample size makes this analysis less reliable, and posts about affordability also tend to have lower sentiment. In contrast, posts related to the food supply chain, food, and health tend to have higher sentiment scores. Overall, sentiment appears more positive for topics related to health and more negative for topics related to affordability and workers’ conditions.

Figure 13 shows the average sentiment compound on the different platforms. All platform pairs were found to have a significant difference in the sentiment compound.

Figure 13: Bar plot of sentiment compound for the different platforms

All pairs have a significant difference, SE shown in error bars.

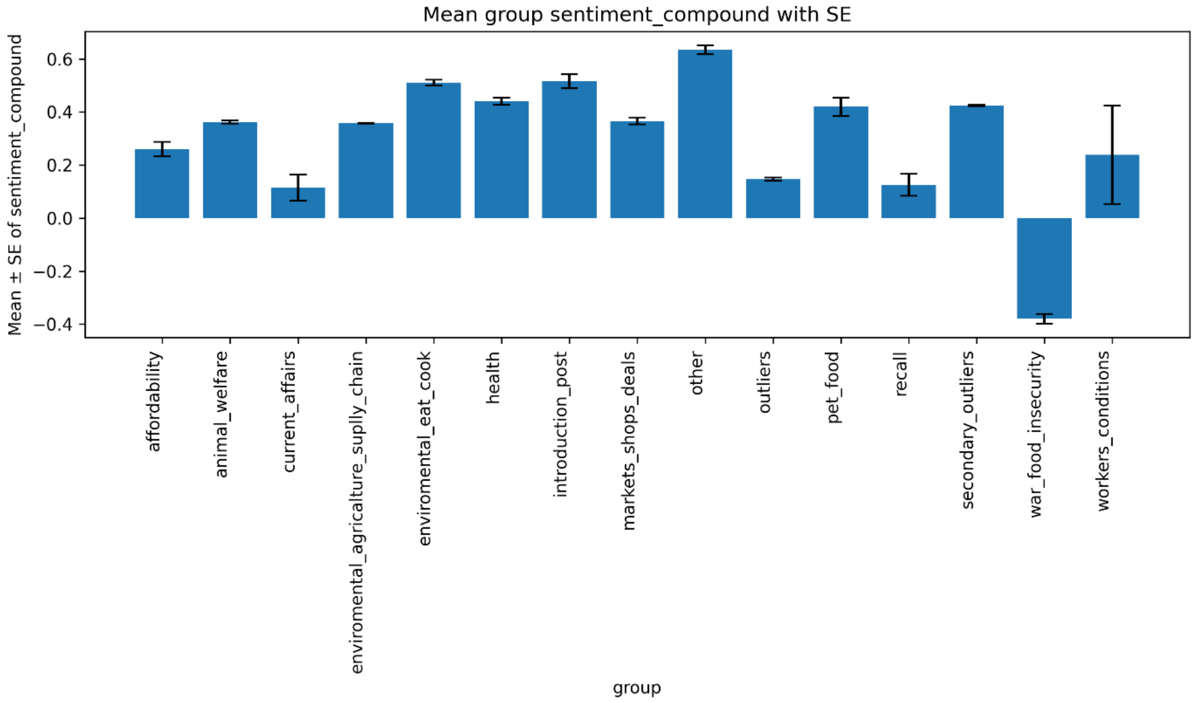


We can see that Instagram is the most positive platform, while Bluesky and X are the most negative platforms.

Figure 14 shows the average sentiment compound when discussing different topic groups.

Figure 14: Bar plot of sentiment compound for the different topic groups

Some of the pairs have a significant difference, SE shown in error bars.



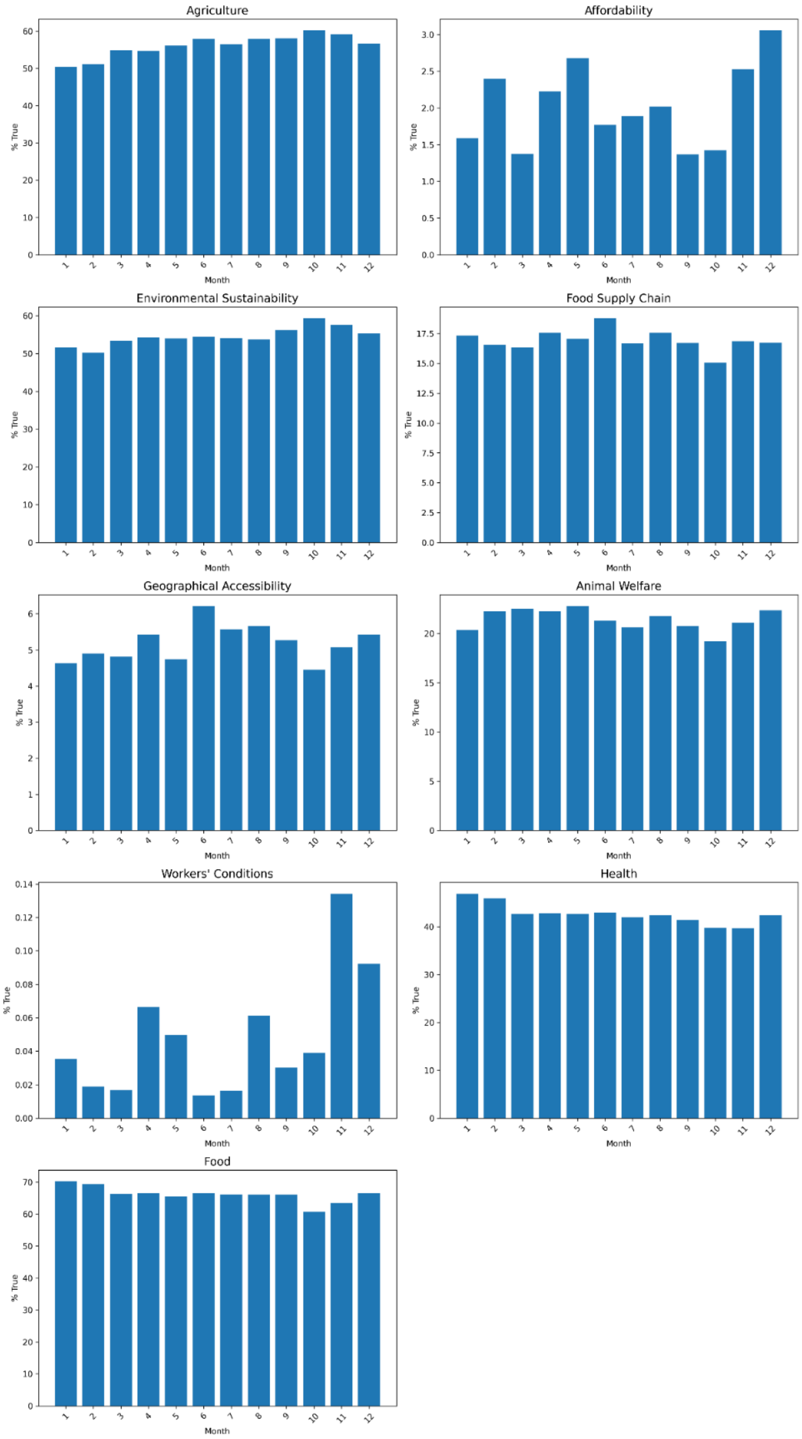
As one might expect, people discuss war and food insecurity with a negative sentiment. Interestingly, all other topic groups are discussed with a positive sentiment on average.

Temporal trends for sentiment though significant, didn't show a noteworthy difference.

4.1.4 Temporal trends in discussions about sustainability indicators

We wanted to know whether discussions around specific sustainability indicators change with time. To do so we looked only at posts that were created in 2024, and we calculated the percent of posts discussing each of the sustainability indicators per month. The results are presented in Figure 15.

Figure 15: Percent of posts discussing each of the sustainability indicators for each month of 2024



Most indicators don't have strong trends. Specifically, we can see that the affordability indicator seems to have a large variance between month and had the highest percent of posts discussing it in November and December. The workers conditions indicator can also seem to be very volatile, but this is most likely a result of the very low number of posts discussing this indicator.

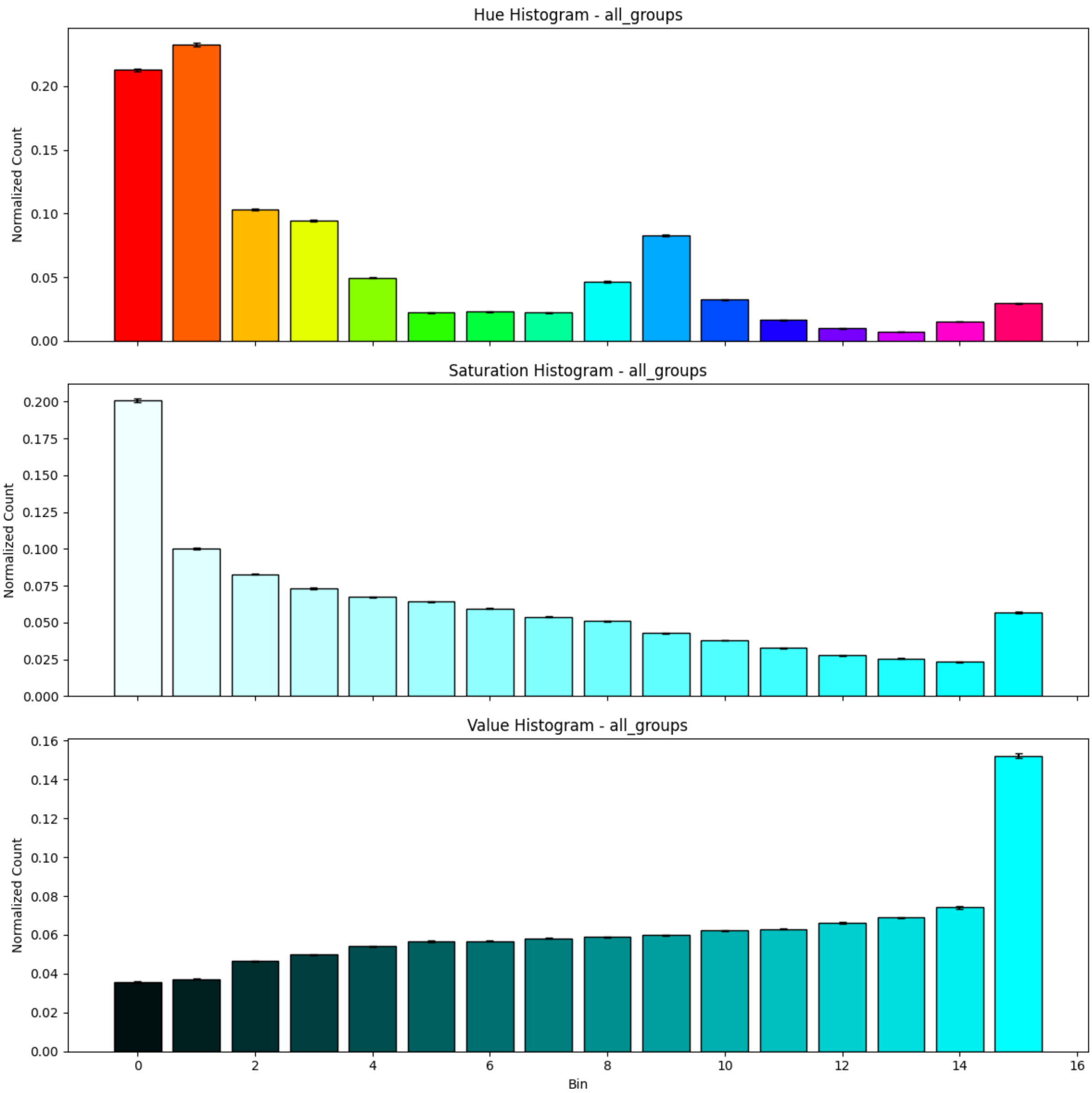
4.2 Visual Data Analysis

4.2.1 Image level color analysis

Figure 16 shows the general distribution of colors, color bins are defined in 3.2.1.

Figure 16: Colour distribution averaged over all images

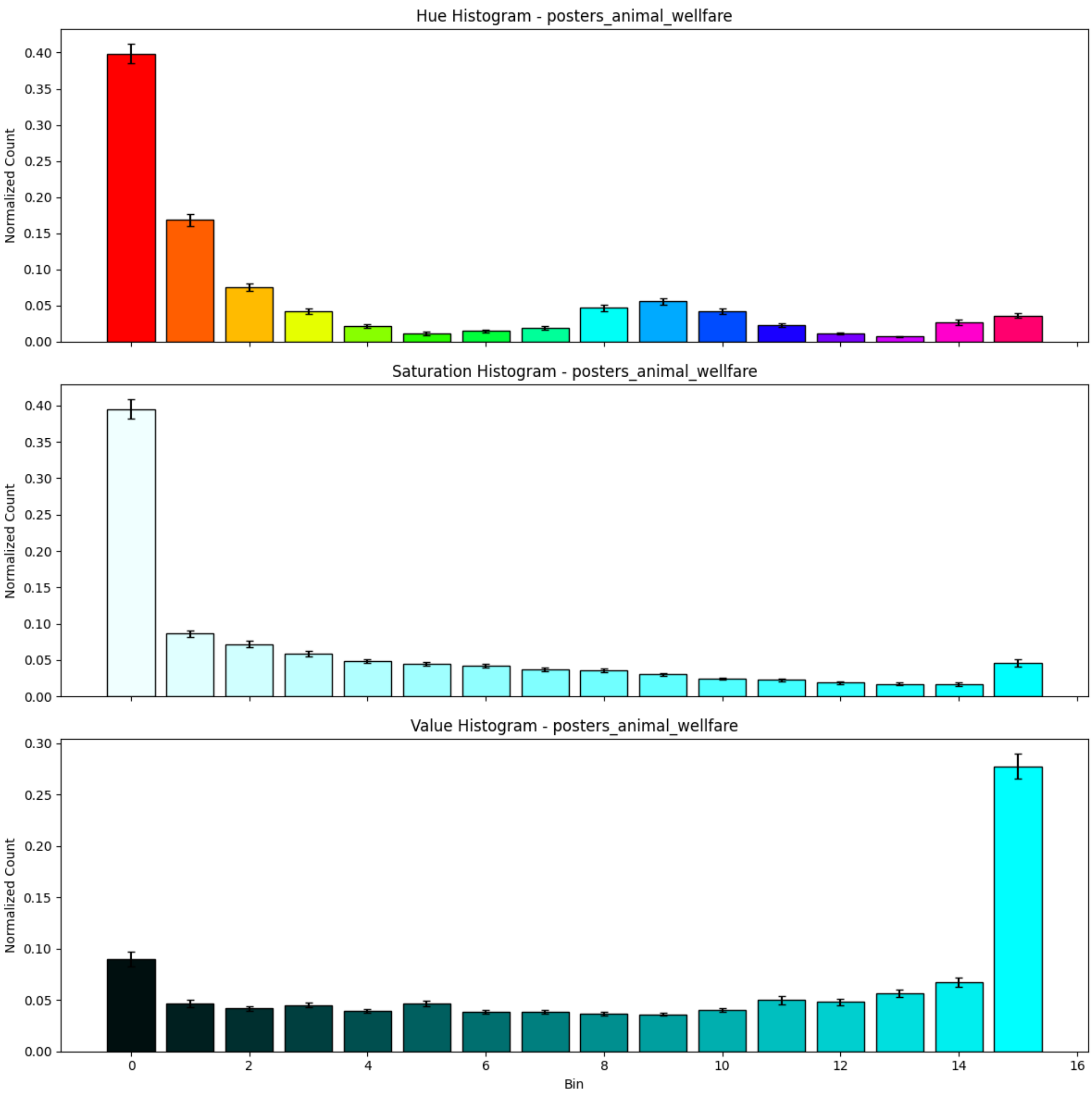
SE shown in error bars.



We can see the reds and oranges dominate the colours in the images, with another peak at blue-teal colours. Also, the images are generally low in saturation, with a very small peak at full saturation, and very bright. The high saturation and the brightness might be a result of the high number of posters we have in our dataset, unlike real photos, which capture real objects that tend to have more natural colors, posters can use high saturation and brightness to get more attention, which might also somewhat explain the red and orange dominance. An example histogram of the topic group posters animal welfare showing similar stronger trends is found in Figure 17.

Figure 17: Colour distribution averaged over all images in the poster's animal welfare topic category

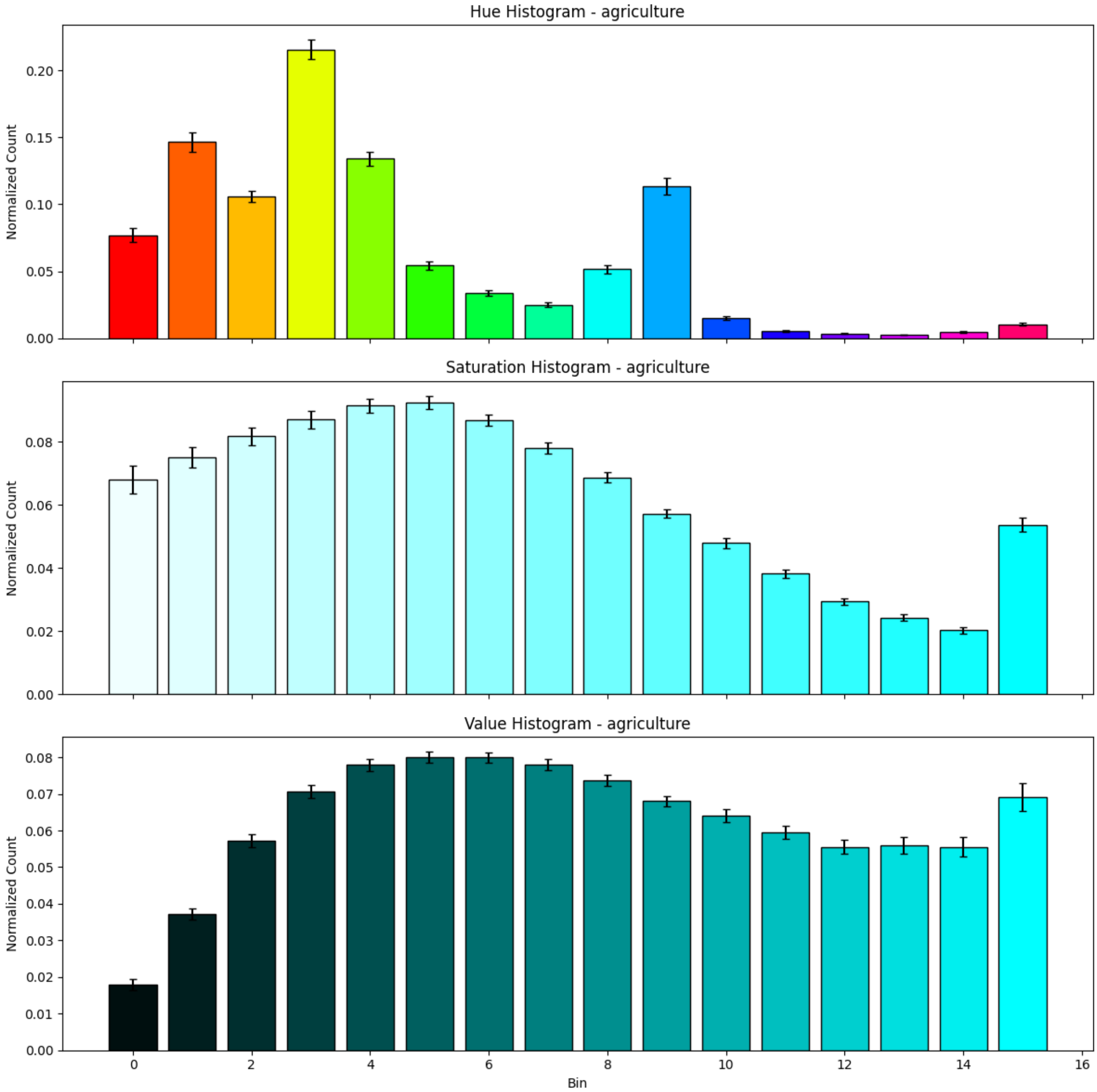
SE shown in error bars.



On the other hand, topic groups with images that are most commonly taken outside, such as nature, agriculture, people farm work, and tech agriculture, have a higher ratio of blues and greens and yellows (reds and oranges are still strong but not always dominant), are somewhat more saturated, and have more non-bright colours. An example histogram of the topic group agriculture showing these trends is found in Figure 18.

Figure 18: Colour distribution averaged over all images in the agriculture topic category

SE shown in error bars.



4.2.2 Aggregate post level log engagement analysis

First, we will look at the general distribution of the log engagement in Figure 19.

We can see that the number of posts goes down with the log engagement, with a secondary peak at log engagement of about 7, which means an overall engagement of about 1k.

We didn't find any correlations for the log engagement with any of the visual features. We explored the secondary peak further by splitting the data into high (log engagement >=7), and low (log engagement <7) engagement. We used the Mann-Whitney U test to check for significance, and only significant results are shown.

Figure 19: Histogram of log engagement for visual data.

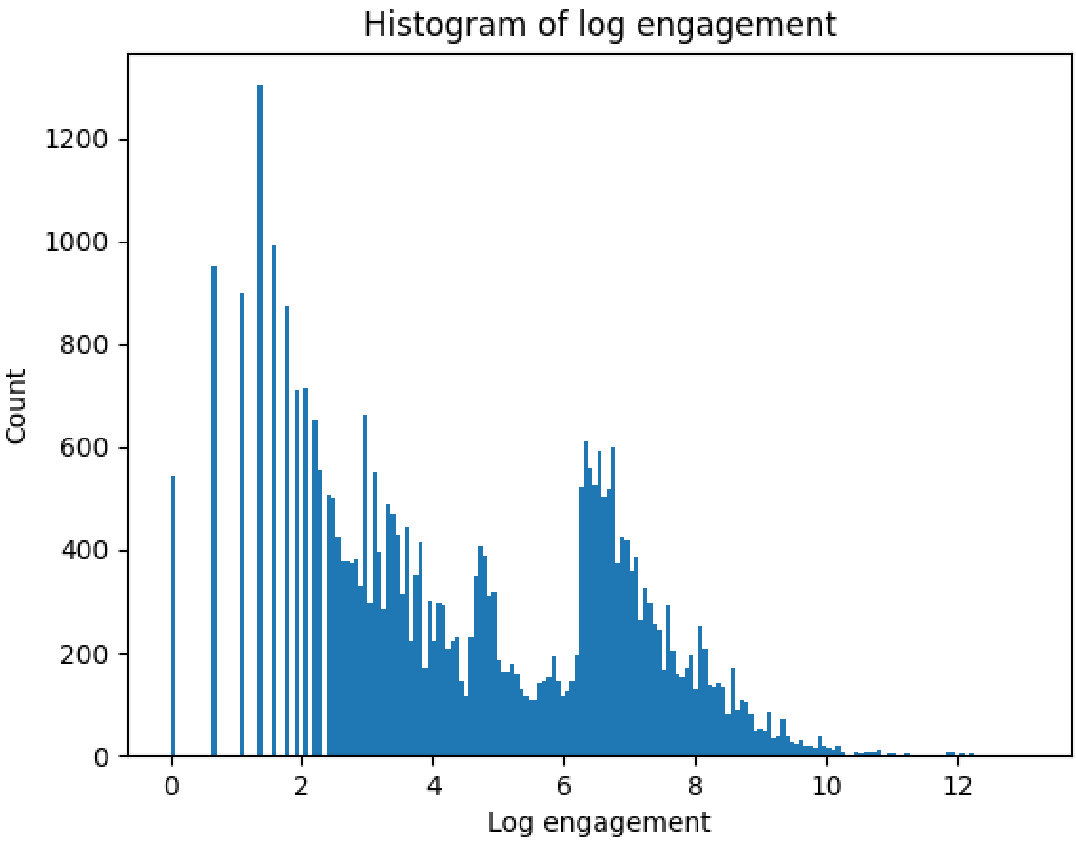


Figure 20 shows differences in log engagement across topic groups. Subjects such as alcohol, nature, and people food work are associated with lower engagement, whereas topics like food, posters animal welfare, and posters other subjects are associated with higher engagement.

Figure 20: Bar graphs for average ratio of images in post with each topic group for high and low engagement

SE shown in error bars.

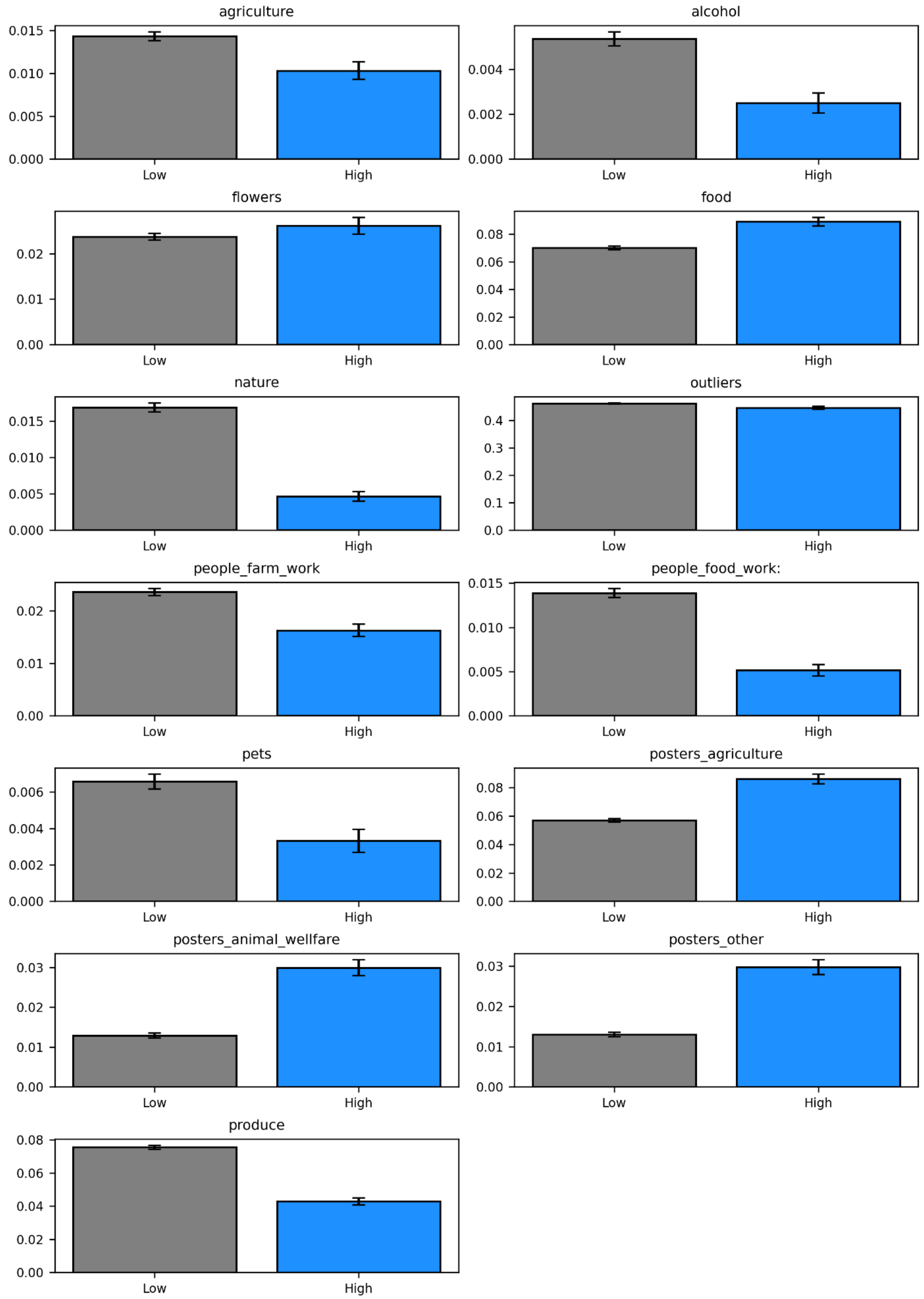


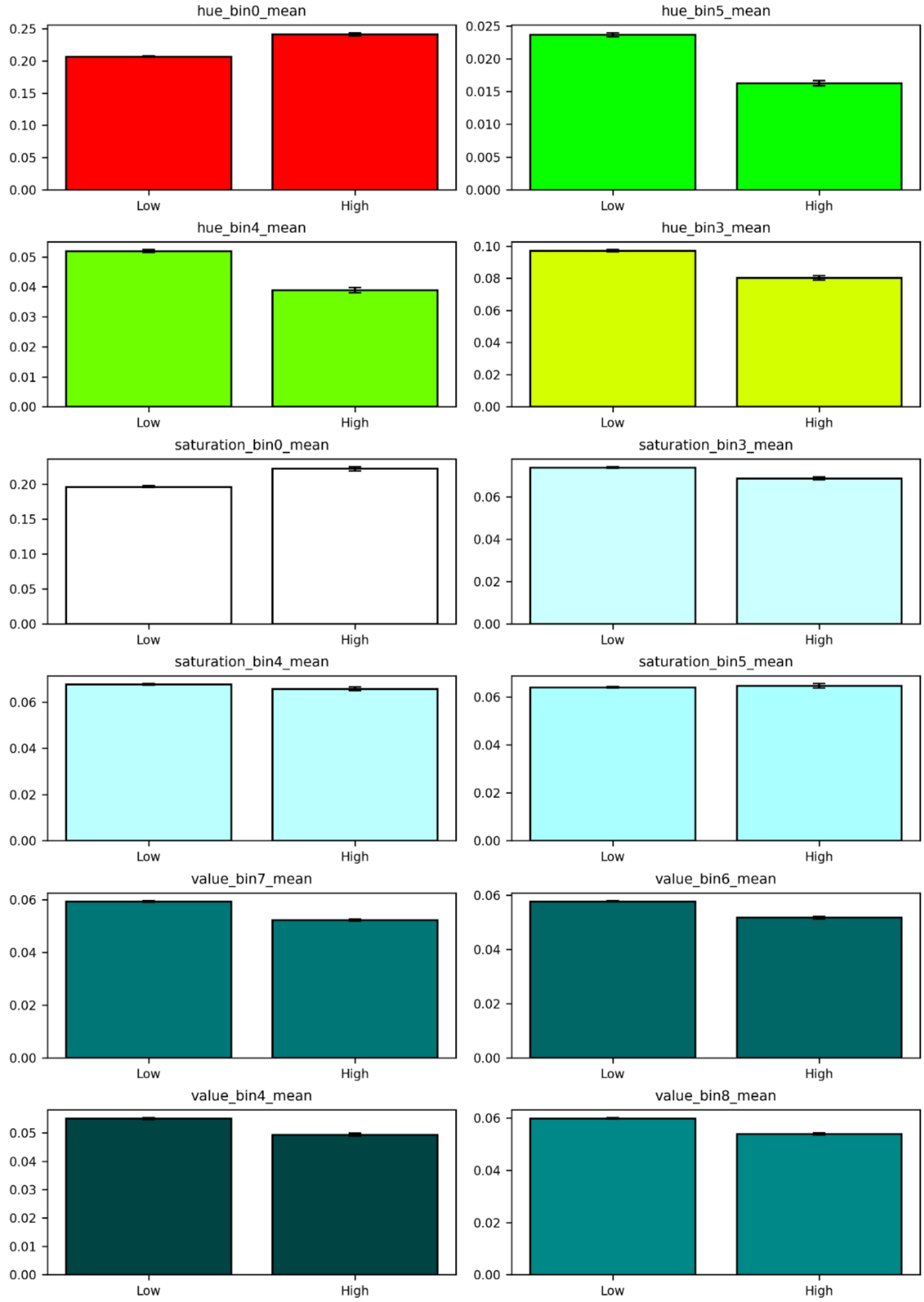
Figure 21 shows the significant colour features with the biggest effect size on high vs. low engagement.

We compared the proportion of each color bin within each color feature of the HSV system. For hue, saturation, and value, Figure 21 highlights only the four color bins that showed the largest effect on log engagement within each feature.

We see that posts with images containing a higher proportion of red tend to receive higher engagement, whereas images with more green or yellow tend to receive lower engagement. Images with very low saturation are associated with higher engagement, while darker images with low value generally show lower engagement.

Figure 21: Bar graphs for average ratio of colour features with the highest effect size on high vs. low engagement

SE shown in error bars.



Examining specific dominant topics, we observe differences in the association between color and engagement. For each dominant topic, we highlight the colors with the most significant differences between high- and low-engagement posts. In several cases, the same colors appear across different topics but with varying patterns. For example, turquoise blue (Figure 22) is associated with higher engagement in posts about animal welfare and posters other topics, but lower engagement in posts about agriculture; green (Figure 23) shows lower engagement for pets and higher engagement for people farm work; blue (Figure 24) is linked to higher engagement for the topic group other and lower engagement for people children; and pink red (Figure 25) is associated with higher engagement for posters food topics and lower engagement for alcohol.

Figure 22: Association of turquoise blue colour with engagement in dominant topics for which turquoise blue has the highest significant effect

SE shown in error bars.

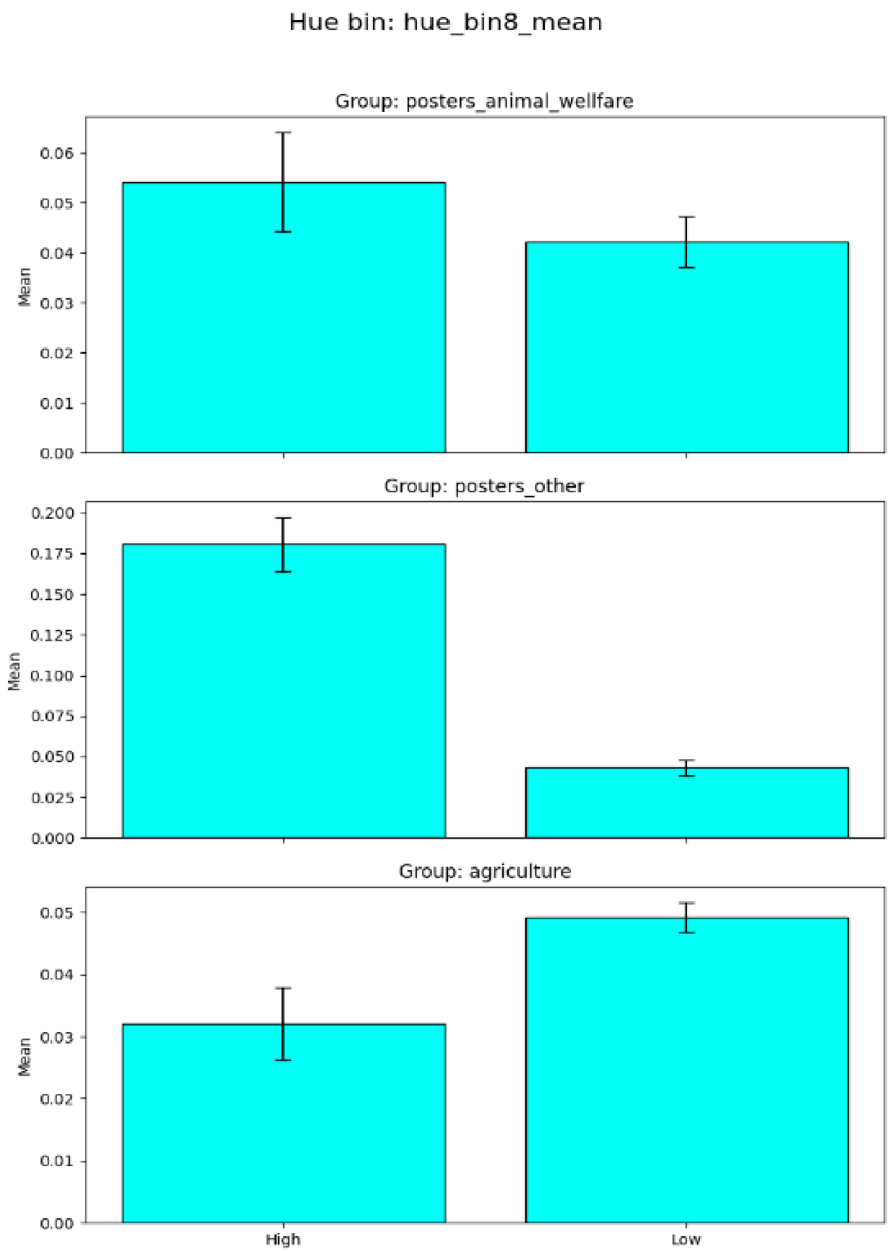


Figure 23: Association of green colour with engagement in dominant topics for which green has the highest significant effect

SE shown in error bars.

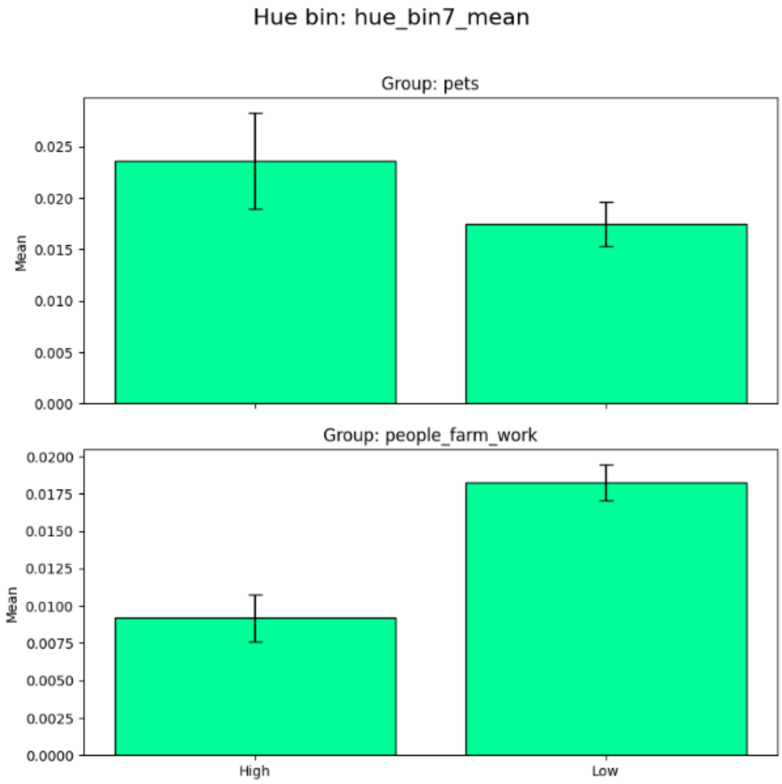


Figure 24: Association of blue colour with engagement in dominant topics for which blue has the highest significant effect

SE shown in error bars.

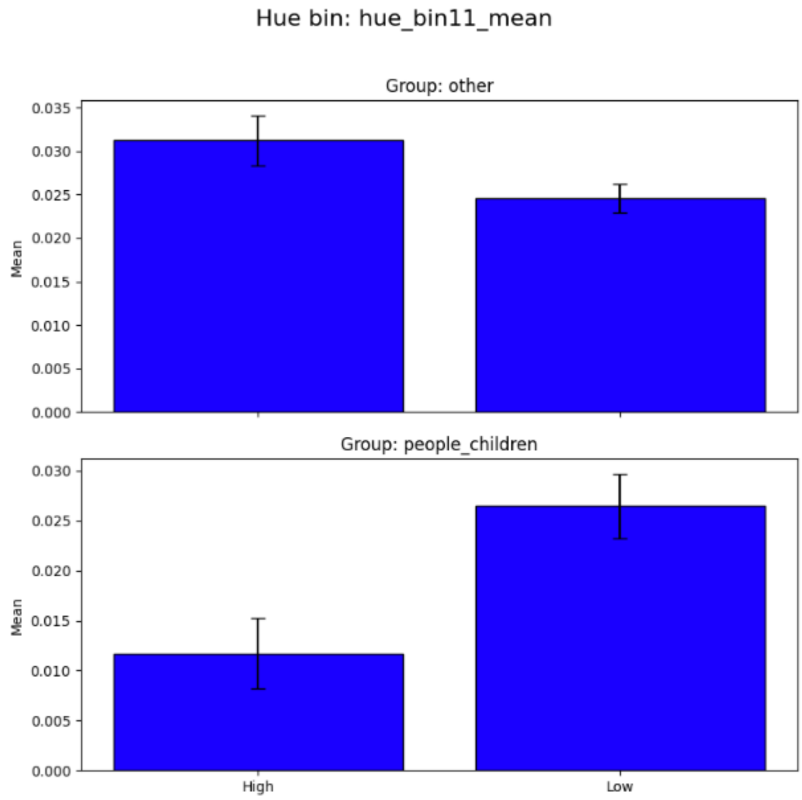
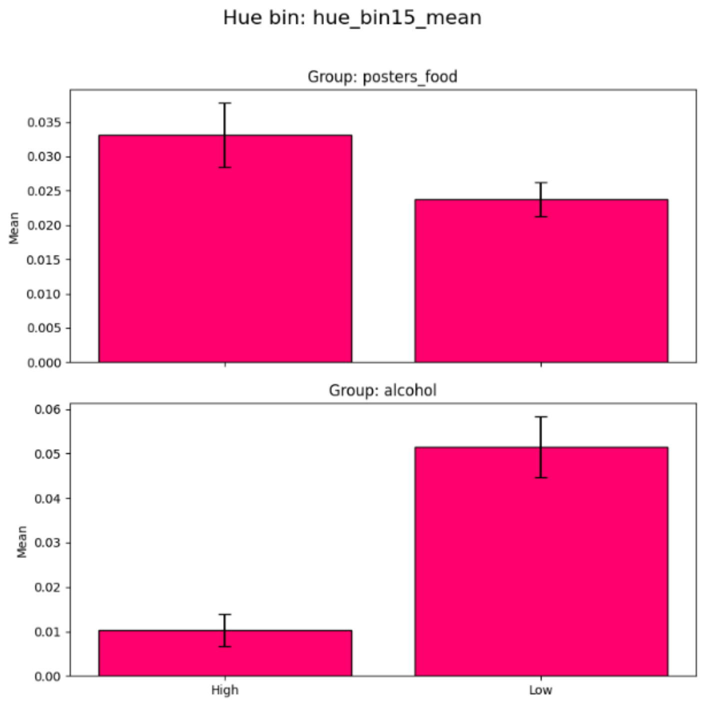


Figure 25: Association of pink red colour with engagement in dominant topics for which pink red has the highest significant effect

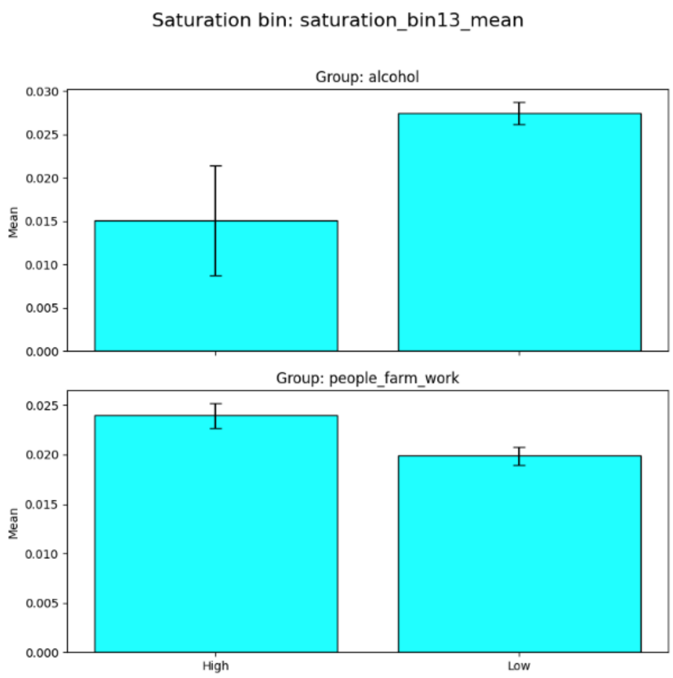
SE shown in error bars.



We can also see that highly saturated images (Figure 26) have a positive effect on engagement for the people farm work topic group and a negative effect for the alcohol topic group.

Figure 26 Association of high saturation with engagement in dominant topics for which high saturation has the highest significant effect

SE shown in error bars.



5. Discussion

The analysis conducted in Task 2.4, derived from the collected data across four prominent online media environments, provides empirical insights into the behavioural aspects of sustainability discussions related to food and agriculture. The interpretation of these findings must be viewed through the lens of the robust recursive search-term expansion and sophisticated classification methodologies employed.

The key KPI for this task is achieving the highest possible F1 score. This KPI was achieved with a reported F1 score is 0.906.

5.1 Methodological Considerations in Data Acquisition

The data collection strategy prioritized topical breadth and temporal relevance, focusing primarily on content uploaded in 2024, when platform constraints allowed. The iterative, recursive methodology, which generated over 100 search terms for Bluesky and X and over 300 for Tik-Tok/Instagram, ensured a comprehensive capture of relevant search terms. Several limitations are posed to the analysis using multiple platforms. First the ranking of the posts, used in the data collection, utilizes a different algorithm within each platform. Second, the number of posts collected from each platform is substantially different which might lead to a bias towards behaviours on the larger platforms. Lastly, for Instagram and TikTok the main modality of the platform is not textual, this might affect the results of the textual analysis.

Post-collection, a rigorous filtering process was necessary. The textual dataset was refined using Support Vector Classification (SVC) models, which were trained using zero-shot classification results generated by GPT-3.5-turbo. The high F1-scores achieved by these SVC models (ranging from 0.84 to 0.97 across categories such as Workers' Conditions and Animal Welfare) justify the subsequent filtering, which retained only those English posts (64.41% of the English corpus, over 50k posts) that discussed both a Food/Agriculture subject and sustainability indicator. This systematic filtering step ensured that the subsequent engagement and sentiment analyses were conducted on content highly relevant to the TealHelix objectives.

Engagement metrics were standardized using the log transform, which was essential for mitigating the extreme skewness observed in raw engagement counts (Likes, Shares, Replies), thereby producing more statistically tractable and understandable results. Given the non-normal distribution of both Log Engagement and Sentiment Compound, the statistical evaluation of categorical differences utilized non-parametric tests, specifically the Mann-Whitney U test and Kruskal–Wallis H test to reliably assess differences across categorical groups without assuming normality.

5.2 Interpretation of Textual Analysis

The analysis reveals a significant disparity in online resonance among different sustainability dimensions. Discussions concerning workers' conditions and affordability receive the lowest average log engagement, while topics related to animal welfare and the environmental aspects of eating and cooking food exhibit the highest average engagement. This suggests that socioeconomic sustainability aspects struggle to achieve the same level of visibility or virality as animal or environmental themes. The high engagement for both animal welfare and environmental eating can be attributed to the frequent overlap in online discourse, particularly regarding discussions of vegan and vegetarian diets.

Platform behaviour further illuminates other dynamics. Bluesky displayed the lowest average engagement. This is likely a result of it being a newer platform that has a smaller user base, leading to lower overall content exposure compared to established platforms.

Temporal analysis identified that content posted between 20:00 and 22:00 received the highest engagement, while posts around 08:00–09:00 received the lowest. This aligns with expected user activity patterns, where evening hours represent peak engagement, strengthened by platform algorithms that may amplify this effect.

The sentiment analysis, utilizing the VADER compound score, provides insight into the emotional valence associated with different topic areas. The strongest negative sentiment was associated with posts discussing workers' conditions and affordability. Discussions concerning food supply chain, food, and health showed a positive effect on sentiment. These topics likely elicit more constructive, prescriptive, or celebratory content, such as health advice or culinary descriptions.

Regarding platform disposition, Instagram emerged as the most positive platform, whereas Bluesky and X exhibited the most negative mean sentiment. This divergence points towards platform-specific community norms and content curation, where visual-centric platforms like Instagram may favour positive or aspirational framing.

5.3 Interpretation of Visual Analysis (Instagram)

The visual data analysis was conducted exclusively on Instagram posts, often containing multiple images (carousels). Significant findings relate to the image characteristics. The general colour distribution was dominated by reds and oranges, exhibiting low saturation but high brightness. This distribution is likely linked to the high proportion of images classified into "Posters" topic groups. Posters, unlike organic photographs, frequently utilize high brightness and primary, attention-grabbing colours (reds and oranges) for maximal visual impact. Regarding engagement, posts featuring images with a higher ratio of red trended toward higher engagement. This suggests that visually attention-grabbing or salient elements, often found in advocacy or dramatic posters (e.g., "posters animal welfare"), are highly effective in securing interaction on Instagram. Conversely, a higher ratio of greens and yellows trended toward lower engagement.

The analysis revealed that the effect of specific hues on engagement is highly topic contingent. For instance, turquoise blue had a positive effect on engagement for 'posters animal welfare' and 'posters other', but a negative effect when the dominant topic was 'agriculture'. This highlights that visual effectiveness is not universal but must be contextualized by the specific thematic group being discussed.

The data analysis conducted on online media environments suggests several possible consequences and considerations for the development of sustainable food product labelling, particularly concerning which sustainability indicators are likely to gain resonance and how they might be perceived or visually communicated.

Consideration Related to Online Visibility and Consumer Engagement for Sustainable Food Label Development

Based on the analysis of social media engagement, sentiment, and visual features, several patterns emerge that can inform the design and communication of sustainability labels. The following recommendations are derived from observed trends, while noting interpretive points and limitations of the analysis.

Observations:

1. Posts discussing animal welfare and environmental aspects of eating and cooking food received the highest average log engagement.

2. Posts discussing workers' conditions and affordability received significantly lower engagement.
3. Discussions on workers' conditions and affordability were associated with negative sentiment, while posts about food, health, and the food supply chain showed positive sentiment.
4. Visual analysis indicates that images with a higher ratio of red trended toward higher engagement, while images with more green or yellow trended toward lower engagement.
5. The effect of specific colors on engagement is topic-dependent; for example, turquoise blue had a positive effect for some topics but a negative effect for agriculture.

Recommendations:

1. Highlighting topics such as animal welfare and environmentally relevant aspects of food may increase visibility and engagement.
2. When addressing workers' conditions or affordability, labels should be aware that these topics may attract critical discussion or negative sentiment; framing strategies could be adjusted accordingly.
3. Emphasizing food quality, health, and supply chain transparency may position labels within a generally positive emotional frame, potentially enhancing consumer acceptance.
4. For visual design, using high-salience colors (reds, oranges) may increase engagement, whereas green-dominated visuals may attract less attention.
5. Color choices should consider the topic-specific context of the label, as a color effective for one topic may be counterproductive for another.

Limitations:

1. Engagement patterns are correlational, higher engagement does not imply causation.
2. Social media data may be biased toward certain demographics or content styles.
3. The observed patterns are based on specific social media platforms and may differ on other digital platforms or in physical product contexts, applying these insights elsewhere may require context-specific adjustments.
4. Sentiment analysis is limited by lexical and contextual nuances, which may not capture all subtleties of user reactions.

6. Appendix A – Search terms

6.1 Initial search terms list

List of the search terms used to start the recursive search-term expansion process, collected from researchers input and ChatGPT suggestions:

Sustainable food, Food sustainability, Fairtrade food, Animal welfare, Sustainable agriculture, Zero waste cooking, Ethical Eating, Food Justice, Nutritional Sustainability, Organic food, Eco score, Nutri score, Sustainable Diet, Greenhouse gases food production, Ozone layer damage agriculture, Radiation exposure food production, Smog pollution from agriculture, Airborne particles food production, Toxic chemicals in agriculture health, Acid rain food production impact, Agricultural runoff dead zones, Nutrient buildup soil agriculture, Water pollution toxic agricultural chemicals, Deforestation food production, Water use in agriculture, Natural resource depletion food production, Biodiversity loss from farming, Salt content in food health, Saturated fat food health risk, Added sugar health effects, Dietary fiber benefits, Protein in food nutrition, Essential minerals in diet, Vitamins nutrition sources, Food industry labor standards, Fair wages food production, Animal social interaction farming, Free-range farming practices, Animal space and welfare, Humane animal slaughter, Animal healthcare farming, Antibiotics in livestock farming, Short-distance animal transport, Food affordability and access.

6.2 Bluesky and X (twitter) collected search terms list

List of search terms collected using the recursive search-term expansion process from Bluesky and X:

sustainable food system, ecological food system, food security, sustainable agriculture, food waste, healthy sustainable food, healthy sustainable meal, grow food sustainable, ecological food supply, eat meat sustainable, eat meat ecological, food social justice, eat less meat sustainable, eat less meat ecological, sustainable whole food, ecological whole food, sustainable global food, ecological global food, sustainable farm, sustainable farming, sustainable local food, ecological local food, waste food, reduce food waste, Farming Sustainable, food insecurity, ATTRA Sustainable Agriculture, agriculture more sustainable, organic farming, sustainable farming practices, sustainable agricultural practices, acute food shortage, acute food insecurity, soil health, National Sustainable Agriculture, Sustainable Agriculture Coalition, Soil Health in Agricultural, regenerative agriculture, factory farming, environmentally sustainable farming, environmentally sustain-able agriculture, environmentally sustainable food, agroecology, permaculture, sustainable food production, food forest, ensure food security, agroecological practices, permaculture garden, food sovereignty, food loss and waste, regenerative farming, feed the world, Permaculture Farm, soil fertility, soil health, Regenerative Agriculture, local organic, food security and sustainable, Integrated Food Security, levels of food insecurity, permaculture foodforest, fight food insecurity, resilient food, agriculture regenerative, food systems sustainability, practices, Sustainable Farming Scheme, resilient food systems, gardening permaculture, urban farm, address food insecurity, permaculture principles, free range, food deserts, Permaculture Design, food carbon footprint, organic free range, organic free range eggs, organic free range chickens, free range eggs, free range chickens, live in food deserts, urban agriculture, free range organic, organic eggs, eggs are free range, grass fed, cage free, pasture raised, grass fed beef, free from the cage, pasture raised eggs, Organic Pasture, Organic Pasture Raised, industrial farmingchickens free range, housing food insecurity, access to food, access to food, food and housing insecurity, access to food water.

6.3 TikTok collected search terms list

List of search terms collected using the recursive search-term expansion process from Tiktok:

regenerativeagriculture, sustainablefarming, regenerativefarming, sustainableagriculture, foodforest, farmtotable, foodwaste, pastureraised, grassfed, foodinsecurity, reducefoodwaste, sustainablefood, pastureraisedeggs, freerangeeggs, aquaponicsrevolution, localfood, urbanfarm, sustainableeating, freerangechickens, farmtofork, fooddesert, nofoodwaste, foodaccess, zerohunger, verticalfarming, aquaponicsbreeding, aquaponics, foodwastesolution, eatlocal, foodwaste, soilhealth, foodsecurity, grassfedbeef, foodsovereignty, fooddeserts, hydroponics, supportlocalfarmers, covercrops, foodforestinthemaking, permacultura, growfoodnotlawns, freerange, cagefreeeggs, foodsecurity, foodjustice, hydroponics, holisticaquaponics, foodsovereignty, foodinsecurityawareness, hungerrelief, urbanfarmer, sustainablefoodsystems, bronxfoodinsecurity, nutritioninsecurity, agroforestry, aquaponicstrout, silverperchaquaponics, foodwasteprevention, foodwastedisposer, aeroponics, sustainablefoods, urbanagriculture, regenerativeag, foodscarcity, pastureraisedpork, soilhealthmatters, hydroponic, zerofoodwaste, foodforestinthemaking, upcycledfood, fooddisparity, aquaculture, agricultura, organicfarming, healthysoil, ecofriendlyfarming, eatlocal, soilhealth, fooddeserts, foodpoverty, pasturedpoultry, rotationalgrazing, mealinsecurity, agroforestry, aquaponicstrout, pastureraisedchicken, nofoodwasted, ecofriendlyfarming, regenerativeag, foodwastereduction, soilhealthmatters, urbanfarming, eatlessforearth, foodjustice, healthysoil, stopfoodwaste, foodwastetip, foodwastewarriors, foodwastetips, grassfedmeat, foodequality, regenerativeranching, foodrescue, urbanfarming, healthysoil, foodpoverty, pasturedpoultry, knowwhereyourfoodcomesfrom, backtonaturefarms, urbanfarmers, mealinsecurity, foodwastewarriors, agroecologia, ecofriendlyfarming, foodwastesolutions, notillfarming, freerangepork, foodwastemanagement, foodforestabundance, soilfoodweb, biodynamicfarming, sustainablefoodsystem, regenerativegrazing, syntropicagroforestry, foodsecurityforall, adaptivegrazing, foodrecovery, foodaccessibility, fightfoodwaste, lessmeat, freerangechicken, heritagebreeds, ecofriendlyfarming, cagefree, supportlocalfarmers, soillessagriculture, zerowastekitchen, urbanfarming, troutaquaponics, hydroponicfarming, stopfoodwaste, foodwastetip, nofoodwasted, foodwastesolutions, ethicalfarming, freerangeducks, regenerativeranching, foodapartheid, pasturedpork, foodequality, foodaccessibility, fightfoodwaste, areoponica, rotationalgrazing, troutaquaponics, freerangeducks, farm2fork, hydroponicfarming, syntropi-cagriculture, rescuedfood, agriculturaregenerativa, greenfarming, soillessagriculture, fastforearth, ecofarming, freerangechickenfarming, urbanhomesteading, eatlocalgrown, sustainableag, greenagriculture, regenag, climatesmartagriculture, grazingpubliclands, dontwastefood, foodapartheid, pasturedpork, lovefoodhatewaste, foodwastedisposal, permacultureprinciples, hydroponicgreenhouse, foodsustainability, troutaquaponics, precisionfarming, ecofarmingpupukorganiksuperaktif, surplusfood, horitculture, urbanfarmersoftiktok, agriculturaregenerativa, localfarming, regenerativeagriculturemovement, ethicalfarming, zerowastecooking, hydroponicsystem, precisionagriculture, foodwastetips, knowyourfarmerknowyourfood, pastureraisedchickens, sustainablekitchen, righttofood, ecofarmingfotosintesa, ecofarming, foodapartheid, agricolturaecosostenibile, notillfarmer, hydroponiclettuce, agrofloresta, veticalfarming, sustainableag, permaculturefarm, freerangeturkeys, freerangegoats, endfoodwaste, hydroponicfarm, hydroponicvegetables, freerangegeese, soilconservation, sustainablecooking, notill, freerangefarming, soil-lessagriculture, greenfarm, agroforestrysystems, pasturedeggs, cattlerotation, pastureraisedchick-en, healthysoilhealthyplants, urbanfarmerlife, intercropping, soilregeneration, endfoodwaste, ecofarmingpremium, sustainablecooking, ecofriendlykitchen, agroforestrysystems, hydroponicfarm, freerangefarming, conservationagriculture, stopfoodwasteday, cofarmingsinergi, slowfoodmovement, communitysupportedagriculture, humanelyraised, surplusfoodrescue, sus-tentable, holisticfarming, greeneating, savethefood, foodwastereduction, grassfedmeat, nfthydro-ponics, ecofarmingsawit, ecofarmingpremium, hydroponicsystems, hydroponicvegetables, eco-friendlycooking, hydroponicsfarming, endfactoryfarming, ecofarmingsawit, hidroponia, hydro-ponicvegetable, hydroponicfarmer, endfactoryfarming, growfoodnotlawns, agroflorestal, hidro-ponia, conservationagriculture, precisionag, hidroponia, surplusfoodrescue, endfactoryfarming, freerangechickensoftiktok, stopfoodwasteday, ecofriendlycooking, hydroponicsfarming, fre-erangegeese, surplusfoodrescue, hydroponicsystems, ecokitchen, friendsnotfood, peacebe-ginsonyourplate, shutdownslaughterhouses, youcantloveanimalsandeatthem, diyhydroponics, hydroponicsfarm, veganfortheanimals, dairyisscary, selectivecompassion, meatlessmonday, meatismurder, dairyindustryisthemeatindustry, ecofriendlyfood, nfthydroponicsystem, meat-lessmeals, notyourmomnotyourmilk, goveganfortheplanet, donteatanimals, animalsarenotfood, cowspiracy, dairyiscruel, veganfortheplanet, meatlessmondays, meatfree, seaspiracy, meateater-sarehypocrites, meatisviolence, meatfreemonday, animalliberationnow, notyourmumnotyour-milk, meatfreemondays, keepanimalsoffyourplate, ecofriendlyeating, sentientbeings

6.4 Initial hashtags search term list for Instagram

List of the hashtags search terms used to start the recursive search-term expansion process for Instagram. The "#" sign was removed for ease of reading:

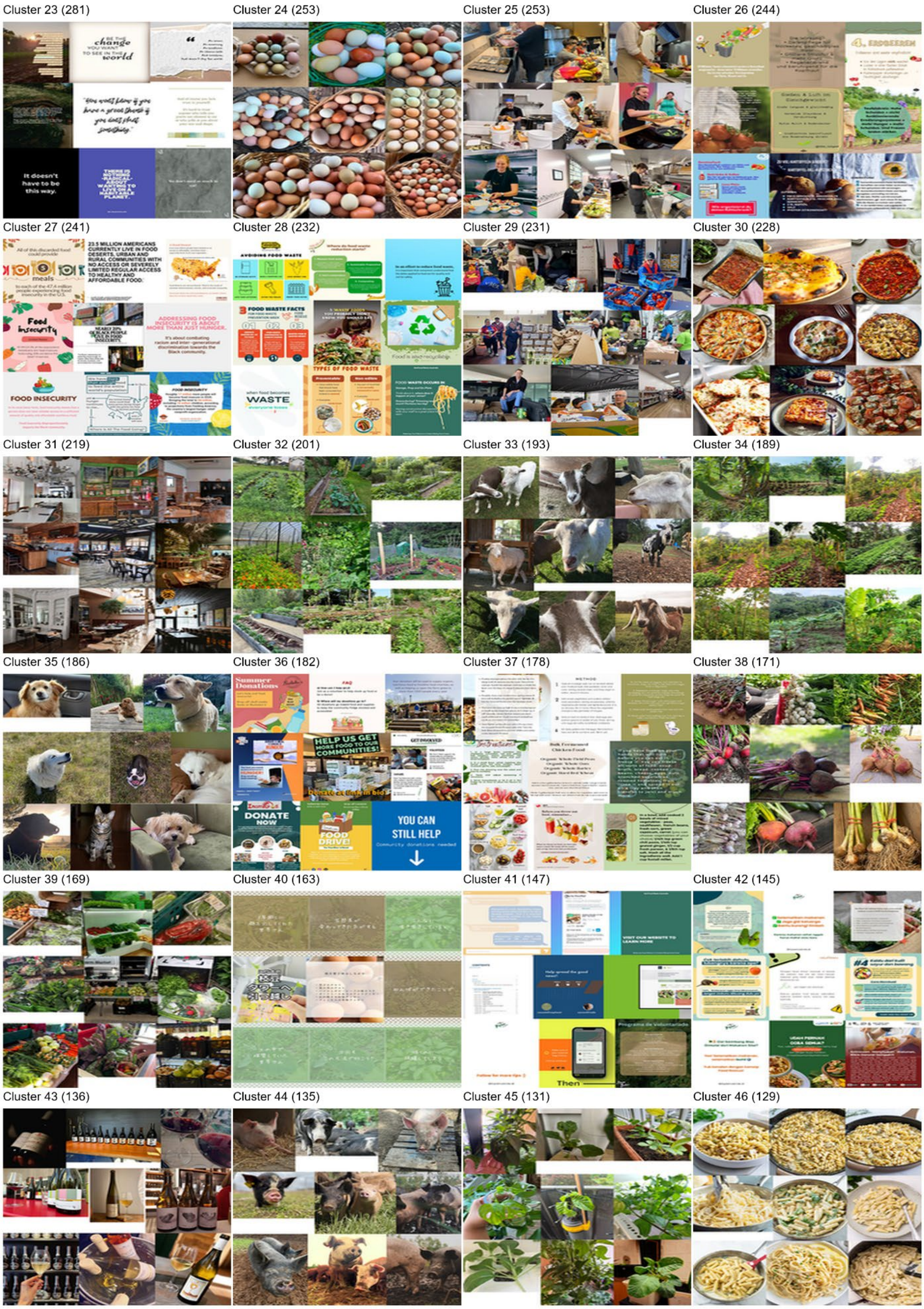
regenerativeagriculture, sustainablefarming, regenerativefarming, sustainableagriculture, food-forest, farmtotable, foodwaste, pastureraised, grassfed, foodinsecurity, reducefoodwaste, sus-tainablefood, pastureraisedeggs, freerangeeggs, aquaponicsrevolution, localfood, urbanfarm, sustainableeating, freerangechickens, farmtofork, fooddesert, nofoodwaste, foodaccess, zero-hunger, verticalfarming, aquaponicsbreeding, aquaponics, foodwastesolution, eatlocal, food-waste, soilhealth, foodsecurity, grassfedbeef, foodsovereignty, fooddeserts, hydroponics, sup-portlocalfarmers, covercrops, foodforestinthemaking, permacultura, growfoodnotlawns, fre-erange, cagefreeeggs, foodsecurity, foodjustice, hydroponics, holisticaquaponics, foodsovereign-ty, foodinsecurityawareness, hungerrelief, urbanfarmer, sustainablefoodsystems, bronxfoodinse-curity, nutritioninsecurity, agroforestry, aquaponicstrout, silverperchaquaponics, foodwastepre-vention, foodwastedisposer, aeroponics, sustainablefoods, urbanagriculture, regenerativeag, foodscarcity, pastureraisedpork, soilhealthmatters, hydroponic, zerofoodwaste, foodforestinthe-making, upcycledfood, fooddisparity, aquaculture, agricultura, organicfarming, healthysoil, eco-friendlyfarming, eatlocal, soilhealth, fooddeserts, foodpoverty, pasturedpoultry, rotationalgraz-ing, mealinsecurity, agroforestry, aquaponicstrout, pastureraisedchicken, nofoodwasted, eco-friendlyfarming, regenerativeag, foodwastereduction, soilhealthmatters, urbanfarming, eatless-forearth, foodjustice, healthysoil, stopfoodwaste, foodwastetip, foodwastewarriors, food-wastetips, grassfedmeat, foodequality, regenerativeranching, foodrescue, urbanfarming, healthy-soil, foodpoverty, pasturedpoultry, knowwhereyourfoodcomesfrom, backtonaturefarms, urban-farmers, mealinsecurity, foodwastewarriors, agroecologia, ecofriendlyfarming, foodwastesolu-tions, notillfarming, freerangepork, foodwastemanagement, foodforestabundance, soilfoodweb, biodynamicfarming, sustainablefoodsystem, regenerativegrazing, syntropicagroforestry, food-securityforall, adaptivegrazing, foodrecovery, foodaccessibility, fightfoodwaste, lessmeat, fre-erangechicken, heritagebreeds, ecofriendlyfarming, cagefree, supportlocalfarmers, soillessagricul-ture, zerowastekitchen, urbanfarming, troutaquaponics, hydroponicfarming, stopfoodwaste, foodwastetip, nofoodwasted, foodwastesolutions, ethicalfarming, freerangeducks, regenerativer-anching, foodapartheid, pasturedpork, foodequality, foodaccessibility, fightfoodwaste, areoponi-ca, rotationalgrazing, troutaquaponics, freerangeducks, farm2fork, hydroponicfarming, syntropi-cagriculture, rescuedfood, agriculturaregenerativa, greenfarming, soillessagriculture, fastforearth, ecofarming, freerangechickenfarming, urbanhomesteading, eatlocalgrown, sustainableag, greenagriculture, regenag, climatesmartagriculture, grazingpubliclands, dontwastefood, foodapart-heid, pasturedpork, lovefoodhatewaste, foodwastedisposal, permacultureprinciples, hydroponicgreenhouse, foodsustainability, troutaquaponics, precisionfarming, ecofarmingpupukorganiksuperaktif, surplusfood, horitculture, urbanfarmersoftiktok, agriculturaregenerativa, localfarm-ing, regenerativeagriculturemovement, ethicalfarming, zerowastecooking, hydroponicsystem, precisionagriculture, foodwastetips, knowyourfarmerknowyourfood, pastureraisedchickens, sustainablekitchen, righttofood, ecofarmingfotosintesa, ecofarming, foodapartheid, agricolturaecosostenibile, notillfarmer, hydroponiclettuce, agrofloresta, veticalfarming, sustainableag, permaculturefarm, freerangeturkeys, freerangegoats, endfoodwaste, hydroponicfarm, hydroponicvegetables, freerangegeese, soilconservation, sustainablecooking, notill, freerangefarming, soillessagriculture, greenfarm, agroforestrysystems, pasturedeggs, cattlerotation, pastureraisedchicken, healthysoilhealthyplants, urbanfarmerlife, intercropping, soilregeneration, endfoodwaste, ecofarmingpremium, sustainablecooking, ecofriendlykitchen, agroforestrysystems, hydropon-icfarm, freerangefarming, conservationagriculture, stopfoodwasteday, cofarmingsinergi, slowfoodmovement, communitysupportedagriculture, humanelyraised, surplusfoodrescue, sustentable, holisticfarming, greeneating, savethefood, foodwastereduction, grassfedmeat, nfthydroponics, ecofarmingsawit, ecofarmingpremium, hydroponicsystems, hydroponicvegetables, ecofriendlycooking, hydroponicsfarming, endfactoryfarming, ecofarmingsawit, hidroponia, hydroponicvegetable, hydroponicfarmer, endfactoryfarming, growfoodnotlawns, agroflorestal, hidro-ponia, conservationagriculture, precisionag, hidroponia, surplusfoodrescue, endfactoryfarming, freerangechickensoftiktok, stopfoodwasteday, ecofriendlycooking, hydroponicsfarming, freerangegeese, surplusfoodrescue, hydroponicsystems, ecokitchen, friendsnotfood, peacebeginsonyourplate, shutdownslaughterhouses, youcantloveanimalsandeatthem, diyhydroponics, hydroponicsfarm, veganfortheanimals, dairyisscary, selectivecompassion, meatlessmonday, meatismurder, dairyindustryisthemeatindustry, ecofriendlyfood, nfthydroponicsystem, meatlessmeals, notyourmomnotyourmilk, goveganfortheplanet, donteatanimals, animalsarenotfood, cowspiracy, dairyiscruel, veganfortheplanet, meatlessmondays, meatfree, seaspiracy, meateatersarehypocrites, meatisviolence, meatfreemonday, animalliberationnow, notyourmumnotyour-milk, meatfreemondays, keepanimalsoffyourplate, ecofriendlyeating, sentientbeings.

6.5 Instagram collected search terms list

List of Hashtags search terms collected using the recursive search-term expansion process from Instagram:

foodrescue, conservationagriculture, nofoodwasted, urbanfarmer, communitysupportedagricul-ture, sustainableag, ecofriendlyfood, foodsecurityforall, foodwastesolutions, sustainablefoods, cagefreeeggs, animalsarenotfood, urbanfarmerlife, meatlessmeals, grazingpubliclands, endfactoryfarming, cofarmingsinergi, seaspiracy, urbanfarmersoftiktok, pasturedpork, grassfedbeef, pasturedeggs, foodjustice, soilregeneration, foodwaste, selectivecompassion, regenag, biodynamicfarming, freerangefarming, grassfed, farm2fork, eatlessforearth, fooddeserts, syntropicagricul-ture, agroforestry, permaculturefarm, soillessagriculture, mealinsecurity, silverperchaquaponics, grassfedmeat, dairyiscruel, agriculturaregenerativa, ethicalfarming, growfoodnotlawns, foodequality, fightfoodwaste, regenerativeagriculture, troutaquaponics, hydroponicfarm, food-forest, meatismurder, agroecologia, hydroponic, ecofriendlykitchen, animalliberationnow, surplusfoodrescue, righttofood, goveganfortheplanet, meatisviolence, diyhydroponics, supportlocalfarmers, foodwastetip, ecofarmingpremium, eatlocal, ecofarmingsawit, agricultura, areopon-ica, verticalfarming, soilhealthmatters, zerowastekitchen, soilhealth, holisticfarming, food-wastetips, agricolturaecosostenibile, urbanhomesteading, backtonaturefarms, pastureraisedpork, ecofriendlycooking, holisticaquaponics, foodforestinthemaking, precisionfarming, foodsustainability, regenerativeranching, veticalfarming, ecofarming, friendsnotfood, meatlessmondays, pastureraisedeggs, veganfortheanimals, fooddesert, freerangegeese, fooddisparity, meatfreemon-days, foodrecovery, hydroponicsystems, surplusfood, stopfoodwaste, precisionag, pas-tureraisedchicken, aquaponicsrevolution, lovefoodhatewaste, urbanfarm, pastureraisedchickens, foodforestabundance, localfarming, greenfarm, foodinsecurityawareness, ecofriendlyeating, hi-droponia, permacultureprinciples, reducefoodwaste, foodaccess, shutdownslaughterhouses, re-generativefarming, savethefood, healthysoil, sustainablecooking, freerangechicken, hydropon-icsystem, hydroponiclettuce, freerangepork, freerangechickensoftiktok, regenerativegrazing, hy-droponicfarmer, aquaponics, foodaccessibility, pasturedpoultry, ecofriendlyfarming, food-wastedisposer, freerangegoats, freerangechickens, regenerativeag, aquaponicstrout, bronx-foodinsecurity, foodapartheid, sustainablefarming, hydroponics, permaculture, foodsecurity, knowwhereyourfoodcomesfrom, foodinsecurity, agroecology, sustainablefood, hydroponicgar-den, foodsovereignty, notill, naturalfarming, handsoffmymeat, endhunger, farmtofork, farmtota-ble, pastureraised, hydroponicfarming, agrofloresta, nofoodwaste, zerohunger, meatlessmonday, urbanfarming, syntropicfarming, permacultura, slowfood, freerange, sustainableagriculture, foodforall, farmtotabledinner, indoorfarming.

7. Apendix B – Image topics



Cluster 71 (68)

Cluster 72 (62)

Cluster 73 (61)

Cluster 74 (59)

Cluster 75 (59)

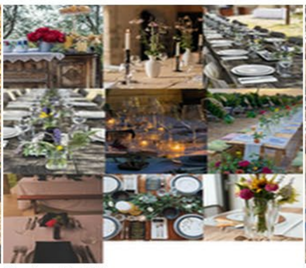
Cluster 76 (59)

Cluster 77 (57)

Cluster 78 (56)

Cluster 79 (55)

Cluster 80 (55)



Cluster 81 (55)

Cluster 82 (55)

Cluster 83 (55)

Cluster 84 (52)

Cluster 85 (52)

Cluster 86 (51)

Cluster 87 (48)

Cluster 88 (47)

Cluster 89 (46)

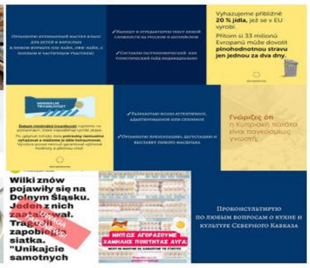
Cluster 90 (46)

Cluster 91 (46)

Cluster 92 (45)

Cluster 93 (45)

Cluster 94 (45)



Cluster 47 (128)

Cluster 48 (126)

Cluster 49 (118)

Cluster 50 (112)

Cluster 51 (110)

Cluster 52 (110)

Cluster 53 (101)

Cluster 54 (94)

Cluster 55 (94)

Cluster 56 (88)

Cluster 57 (85)

Cluster 58 (81)

Cluster 59 (80)

Cluster 60 (79)

Cluster 61 (78)

Cluster 62 (78)

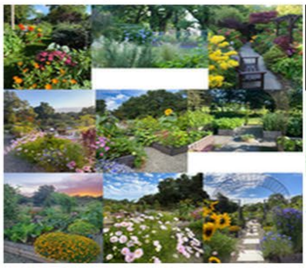
Cluster 63 (78)

Cluster 64 (76)

Cluster 65 (74)

Cluster 66 (74)

Cluster 67 (72)



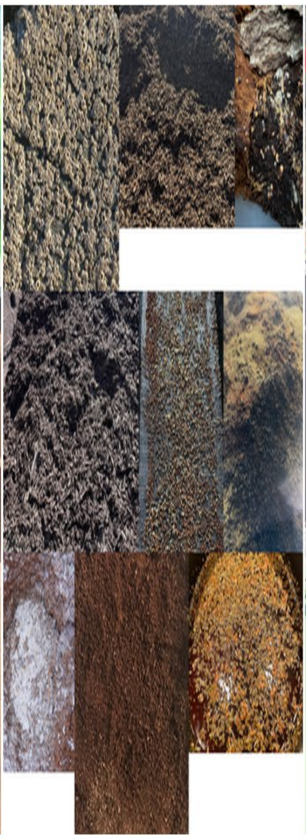
Cluster 68 (71)

Cluster 69 (71)

Cluster 70 (70)

Cluster 95 (44)

Cluster 96 (44)



Cluster 97 (44)

Cluster 98 (42)

Cluster 99 (41)