Shaping Sustainability: Public Perception Towards Water Consumption

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Abstract

Understanding public perception towards water consumption is crucial for promoting sustainable water management, shaping effective policies, and enhancing the awareness of water conservation in diverse communities. Although previous works have studied water consumption from self-reported data and motivations, the topic has not been analyzed from the perspective of cognition from social media. Given the significance of social media's broad reach, real-time engagement, and the diverse demographic representation it offers, understanding how public perception is reflected in online discussions can provide valuable insights into societal attitudes, concerns, and behavioral trends related to water consumption. In this work, we performed a cognitive analysis, based on Reddit discussions about water consumption. Our approach includes both sentiment analysis, representing conscious attitudes, and concept mapping analysis, which captures subconscious cognitive frameworks. Sentiment analysis shows overall positive polarity on Reddit with key aspects of water consumption, while concept mapping reveals cognitive frameworks shaping perceptions. Together, these insights inform communication strategies and policy on water conservation.

Introduction

Understanding public perception towards water consumption is essential to foster sustainable practices and ensuring the equitable management of this critical resource. Water is not only fundamental to life but also closely tied to agriculture, industry, and urban development. Public attitudes and cognition significantly influence water conservation efforts, policy acceptance, and the success of initiatives aimed at mitigating water scarcity and environmental degradation.

Studies on water consumption attitudes have explored various factors such as water restrictions, social norms, media coverage, and socioeconomic influences. Research in Sydney and California highlighted the impact of water restrictions and media coverage on water use patterns (Randolph and Troy 2008; Quesnel and Ajami 2017), while qualitative studies examined household behaviors and the role of moral obligation and social influences (Lowe, Lynch, and Lowe 2014).

Social network and geolocated Twitter analyses provided insights into communication dynamics and the relationship between water insecurity and social unrest (Getchell and Sellnow 2016; Koren, Bagozzi, and Benson 2021). However, despite valuable contributions, our understanding of public perception towards water consumption remains limited. Traditional methods focus on self-reported data and motivations, while quantitative approaches, like network and sentiment analysis, offer structural insights but do not address the underlying public attitudes and perceptions that drive water consumption behaviors.

We are motivated to bridge this gap by employing state-of-the-art cognitive analysis tools (Cambria et al. 2024; Mao et al. 2023b) and the latest social media data to uncover public perception towards water consumption. Our cognitive analysis involves sentiment analysis-represented conscious analysis and concept mapping-represented subconscious analysis. The aim is to provide a more nuanced understanding of how individuals cognitively process water consumption-related issues, examining both their explicit attitudes and the implicit factors that influence their behaviors. The following questions are investigated: 1) What are the prevailing sentiment polarities related to water consumption? 2) What sentiments are expressed regarding key aspects of water consumption? 3) What mentions are most commonly associated with positive and negative discussions on water consumption, respectively? 4) What cognitive frameworks underlie positive and negative discussions of water consumption?

To address the above research questions, we collected all posts and comments related to "water consumption" on Reddit[1]. Reddit is our source of data, because it offers authentic discussions on water consumption, capturing diverse opinions and experiences. Its spontaneous content provides naturalistic insights, while detailed narratives enable a deeper understanding of public perceptions. The rich content and vivid discussions on Reddit support longitudinal analysis of trends and responses to events, and its large, publicly available data allow scalable exploration using natural language processing-based, bottom-up research methods. The dataset spans discussions from March 2010 to December 2024.

[1]https://www.reddit.com

The research findings are as follows:
1) Positive sentiment shows a predominance in the posts and comments related to water consumption, accounting for 63.0% of the total. This suggests that public opinion regarding "water consumption" is generally positive on Reddit.
2) Broader aspects ("drink", "food", and "animal") have more positive sentiment, suggesting that discussions about water consumption often emphasize its importance to life and ecosystems. Aspects like "alcohol", "smell", and "capitalism" have a higher proportion of negative sentiment. These are likely tied to specific concerns such as water contamination and the commodification of water resources.
3) Mentions like "hope", "love", "best", "add", "thank" are most commonly associated with positive discussions on water consumption. These mentions reflect active social discussions, highlighting water consumption as a key topic in community well-being and environmental sustainability. Mentions like "kill", "old", and "basic" are most commonly associated with negative discussions on water consumption. These mentions suggest frustration over failures in water conservation efforts, accessibility, or government policies.
4) Positive discussion about water consumption often highlights reliability, and systematic behaviors. This could suggest that discussions emphasize the importance of consistent water use or reliable water resources as a foundation for well-being and sustainability. Negative discussion about water consumption includes several cognitive frameworks. Negativity could arise from misinformation or poor communication about water-related issues. Water can be framed as a resource, with negativity focused on perceived inequities or exploitative practices in water access and consumption. Scarcity or pollution leads to social or environmental disruptions, emphasizing its importance for life and health.

The contribution of this work can be summarized as follows: (1) We conducted an in-depth analysis of public perception regarding water consumption, examining it through the lenses of sentiment analysis, and concept mapping-based cognitive frameworks. (2) Based on social media data, we present findings that offer insightful and practical recommendations for policymakers aimed at improving public awareness of water consumption issues.

Related Work

The analysis of attitudes toward water consumption has garnered significant attention in social science. A study conducted in Sydney between 2004 and 2005 employed a random quota telephone survey targeting 2,179 addresses across diverse dwelling types (Randolph and Troy 2008). The survey revealed that water restrictions significantly influenced usage patterns, with compliance varying by dwelling type. Awareness of actual water consumption levels was low, yet respondents commonly believed their usage was average or below average. Research on water consumption during the California drought has examined the influence of media coverage and socioeconomic factors (Quesnel and Ajami 2017). Using k-means clustering, the study grouped service areas based on water demand characteristics and employed ANOVA to evaluate models with and without media coverage and unemployment as covariates.

The findings revealed a significant correlation between increased media coverage and reduced water consumption, demonstrating the impact of public awareness on water use behaviors. Qualitative research has examined household water consumption behaviors, focusing on motivations, barriers, and the impact of social influences (Lowe, Lynch, and Lowe 2014). Participants reported adopting various water-saving behaviors, such as reducing shower times and fixing leaks, driven by a sense of moral obligation and trust in water management institutions. Social norms strongly influenced conservation efforts, with participants voicing concerns about non-compliant "free riders".

Social network analysis has been utilized to examine opinion during crises, such as the West Virginia water crisis (Getchell and Sellnow 2016). A study analyzed the "follow" relationships and retweet interactions among 41 official Twitter accounts, including those of government officials and organizations like FEMA, the CDC, and the EPA. Using NodeXL and UCInet, the research revealed a low network density, indicating underutilized connections for information sharing. The findings emphasized the importance of collaboration and robust communication networks to improve public information dissemination during emergencies. Research leveraging geolocated Twitter data has examined the relationship between food and water insecurity and its link to social unrest in urban Kenya (Koren, Bagozzi, and Benson 2021).

Using interactive models, the study revealed a statistically significant relationship between the co-occurrence of these insecurities and increased social unrest, highlighting their mutually reinforcing effects (Cambria 2024). A quantitative textual analysis of tweets from the "Water-Use It Wisely" campaign demonstrated the effectiveness of social media in promoting water conservation (Boyer et al. 2021). Analyzing 3,500 tweets and data from 15,204 related accounts, the study identified key terms and themes in the campaign's messaging. It also examined the demographics and geographical distribution of the audience, highlighting social media's role in engaging diverse groups.

However, traditional survey and qualitative methods primarily rely on self-reported data and motivations, offering limited insight into the cognitive processes that drive water consumption behaviors. On the other hand, the quantitative approaches surveyed, such as social network and geolocated Twitter analyses, provide valuable structural insights but fail to address public sentiment and perceptions regarding water consumption and its related factors.

Data

We collected data from Reddit by searching for posts containing the keyword "water consumption". This process included retrieving not only the original posts but also all comments associated with each post, along with their respective publication timestamps. To ensure the dataset reflected historical discussions, we limited the collection period to content published before 20 December 2024. Text data were cleaned by removing URLs, and special characters, e.g., "&", "#", ";", "{", "}". After data cleansing, we obtained 38,096 posts and comments.

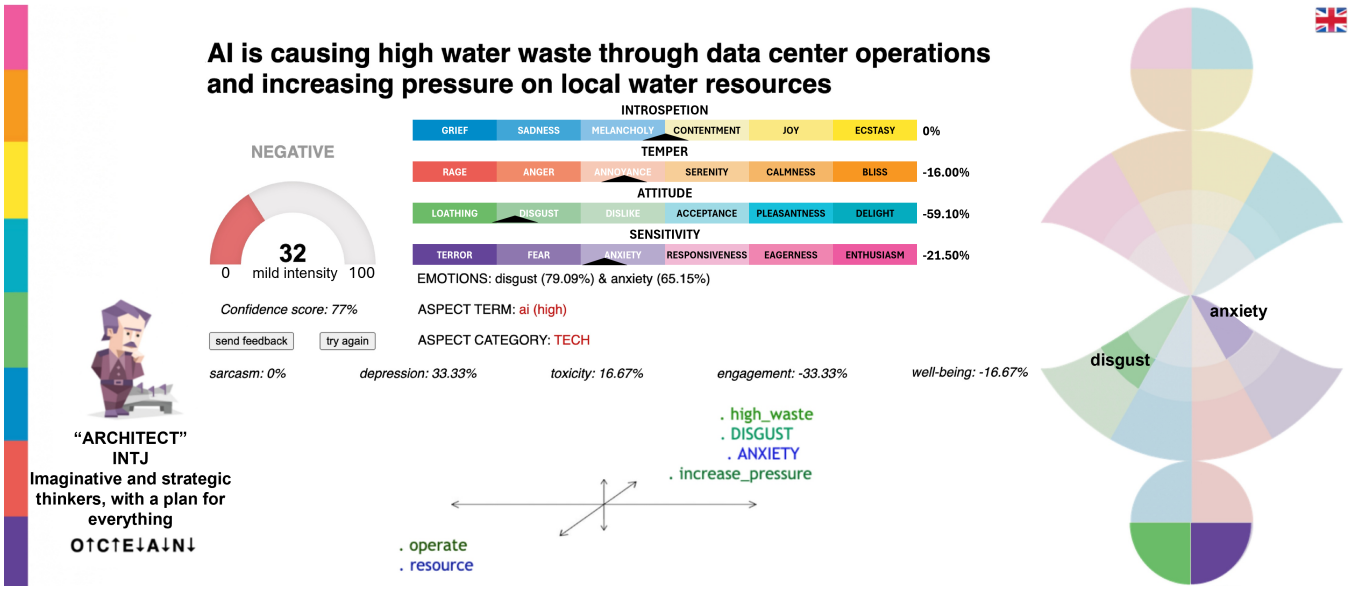

Figure 1: Example outputs of Sentic APIs.

These posts and comments yield 38,060 sentiment polarity labels, 77,970 aspects[2], 519,409 explicit mentions[3], 5,763 target concepts[4], 5,763 source concepts[5], and 5,763 concept mappings[6]. There are 2,032 unique concept mappings, showing the diversity of the cognitive patterns will be analyzed in the following section.

Methodology

Preliminary

Public perception is a multifaceted phenomenon that reflects how individuals or groups interpret, react to, and internalize events, ideas, or issues. This perception manifests itself in two major aspects: sentiment and concept mappings, representing explicit and implicit opinions, respectively. Sentiment analysis aims to identify and quantify the emotional tone embedded in textual data.

[2]An aspect refers to a specific attribute, feature, or component of an entity that is being discussed or evaluated in the text. It represents the focus or topic of a sentiment expression within a sentence or document. In this work, we aim to analyze the aspects related to the topic of "water consumption".

[3]These are direct mentions in the text where the concept is explicitly stated. The reference is literal and corresponds directly to entities, objects, or phenomena.

[4]These are the abstract concepts or ideas that we are trying to understand or describe through metaphorical means.

[5]These are the concrete or familiar concepts from which we draw metaphorical structure to better understand or explain the target concepts.

[6]These are systematic correspondences or mappings between the source domain and the target domain that define the metaphor. They represent how elements, relations, and structures in the source domain are projected onto the target domain. In this work, a concept mapping is represented in the form of "a target concept is a source concept", e.g., "LOVE IS JOURNEY.

Sentiment analysis has been widely applied in cognitive analysis across domains such as politics (Khatua, Khatua, and Cambria 2020), climate change (Duong et al. 2024), finance (Ma et al. 2024), healthcare (Cambria et al. 2010) and art (Luwei et al. 2024). Sentiment serves as an important indicator of public perception because sentiment often drives behaviors and decision-making processes (Wang, Ho, and Cambria 2020). For example, heightened negative sentiment in response to increasing water consumption restrictions may signal widespread frustration or concern over resource scarcity, guiding policymakers to adopt targeted communication strategies that address public anxieties and promote sustainable water use practices. Moreover, tracking sentiment over time provides insights into how public opinion evolves in response to interventions or external events (Grassi et al. 2011).

Public perception is shaped by cognitive frameworks, mental models guiding how people understand and engage with issues like water consumption. A traditional method for uncovering these cognitive frameworks is the use of interview-based word association tests[7] (Bahar, Johnstone, and Sutcliffe 1999; Dhelim et al. 2022; Pranoto and Afrilita 2019). However, this approach is challenging to implement effectively in large-scale analyses due to logistical and resource constraints. Alternatively, conceptual metaphor theory (Lakoff and Johnson 1980) provides a robust framework for exploring cognition through the lens of conceptual mappings. Metaphors, such as "war on climate change", structure understanding by framing environmental challenges as battles that demand urgent and decisive action, thereby shaping public attitudes and policy preferences.

[7]A word-association test evaluates personality and mental function by prompting individuals to respond to a series of words with the first word that comes to mind or a word from a specified category.

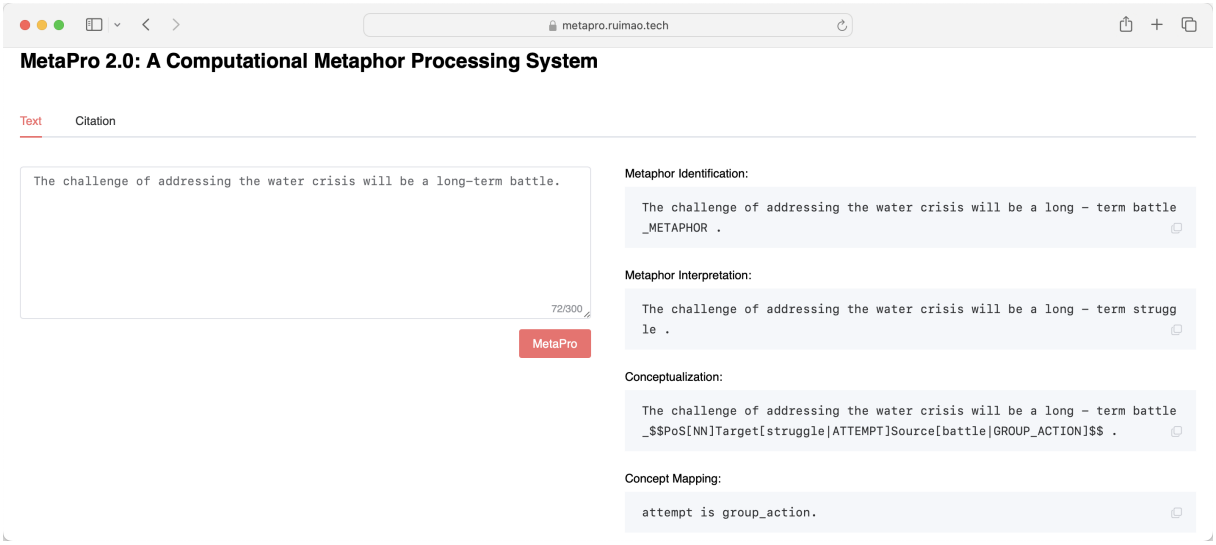

Figure 2: Example outputs of MetaPro.

Studies showed that metaphors triggered brain responses different from literal language (Mao, Wang, and Cambria 2025). This metaphorical approach has been successfully applied to the analysis of public discourse across various domains, including finance (Mao et al. 2023a), weather disasters (Mao et al. 2024b), politics (Mao et al. 2024c), technology (Mao et al. 2025a), and social biases (Ge, Mao, and Cambria 2025), offering a scalable and insightful means of cognitive analysis.

Sentiment Analysis

We utilize Sentic APIs[8] (see Figure 1) for sentiment analysis and explicit mention detection. These APIs are built upon the Sentic computing framework, integrating symbolic AI (SenticNet) with subsymbolic AI (deep learning). For sentiment analysis, SenticNet 8 (Cambria et al. 2024) addresses challenges in affective computing by resolving the symbol grounding problem, creating meaningful connections between abstract symbols and real-world entities to enhance explainable AI. It employs neurosymbolic AI by combining commonsense knowledge representation with hierarchical attention networks to accurately extract sentiment polarity, emotion labels, and opinion targets from text. Notably, SenticNet 8 outperforms models like ChatGPT and RoBERTa, offering interpretability and trustworthiness critical for sensitive domains such as healthcare and education.

For explicit mention detection, we use Sentic Parser (Cambria et al. 2022), a tool designed to efficiently identify affective concepts in free text without requiring detailed phrase structure analysis. The parser uses a graph-based approach to extract "semantic atoms", such as go_bananas, pain_killer, or get_along_with, preserving their contextual meanings and polarity. Results demonstrate that the Sentic Parser improves polarity detection accuracy by 8.55% compared to non-parsed methods and achieves a 5.52% performance improvement over the SpaCy Parser. These gains stem from its effective handling of negation, microtext normalization, and compound word processing.

Concept Mapping Analysis

MetaPro[9] (Mao et al. 2023b) is used in this work for concept mapping analysis as it is the only tool capable of end-to-end concept mapping parsing (Ge, Mao, and Cambria 2023). It consists of metaphor identification (Mao and Li 2021), metaphor interpretation (Mao et al. 2022), and concept mapping generation (Ge, Mao, and Cambria 2022) modules, leveraging a metaphor processing tailored pre-trained language model (Mao et al. 2024a) as a foundation. Given an input sentence, "the challenge of addressing the water crisis will be a long-term battle", the metaphor identification module first identifies "battle" as a metaphor. Then, the "battle" is paraphrased as "struggle" via the metaphor interpretation module. Next, the concept mapping generation module will conceptualize the target concept "ATTEMPT" from the paraphrase, "struggle", and conceptualize the source concept "GROUP_ACTION" from "battle". Finally, the concept mapping "ATTEMPT IS GROUP_ACTION" is yielded by MetaPro in the form of "a target concept is a source concept" (see Figure 2). MetaPro demonstrates state-of-the-art performance across its individual sub-modules, and their integration empowers the system to effectively manage complex cognitive analyses across a wide range of domains (Mao et al. 2025b).

Findings

Sentiment Analysis

Figure 3 shows the distribution of three sentiment polarity labels: Positive, Negative, and Neutral. The largest portion corresponds to positive sentiment, taking 63.0% of the total. The negative sentiment makes up 36.9%. Meanwhile, the neutral sentiment accounts for 0.1%.

[8]https://sentic.net/api

[9]https://metapro.ruimao.tech/

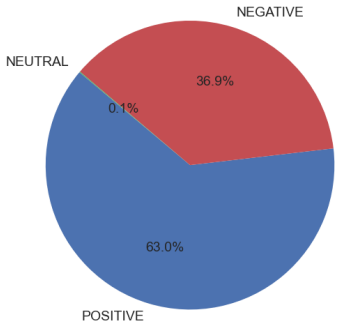

Figure 3: The percentages of sentiment polarity labels.

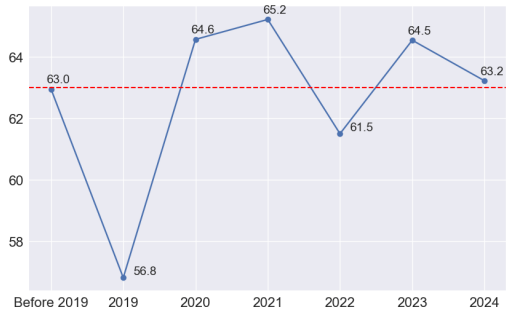

Figure 4: The percentages of positive sentiment for sentences in each year. The red line shows the percentage of positive sentiment in the whole dataset.

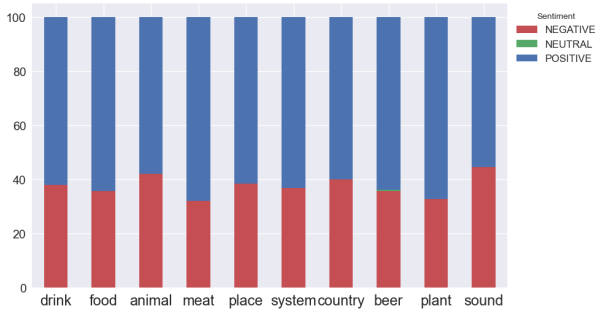

Figure 5: Aspect-based sentiment analysis of top 10 frequent positive aspects. The y-axis indicates the percentages of the aspects with positive and negative sentiment.

It highlights the predominance of positive sentiment on Reddit. Figure 4 shows a trend of the percentages of positive sentiment for sentences over time, with data points ranging from "Before 2019" to 2024. Due to the small number of posts from 2010 to 2018, we merged them into one category "Before 2019". The red dashed line indicates a reference point around 63, which is the positive percentage in the whole dataset. In each time period, more than half sentences are with positive sentiment. The positive percentages in 2019 and 2022 are lower than the positive percentage in the whole dataset. The positive percentage reaches its lowest point in 2019 at 56.8% and attains its peak in 2021 at 65.2%.

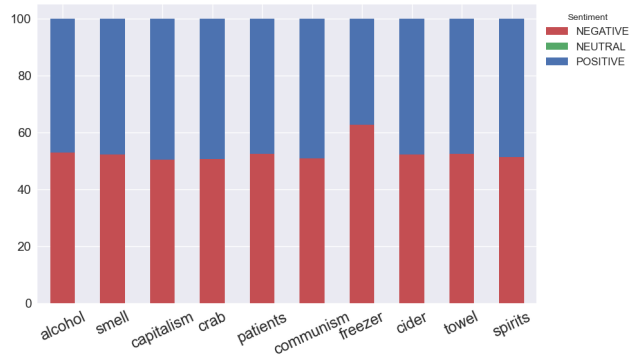

Figure 6: Aspect-based sentiment analysis of top 10 frequent negative aspects. The y-axis indicates the percentages of the aspects with positive and negative sentiment.

Figure 7: Top 25 explicit mentions by frequency ratio in positive vs. negative sentences (from the 100 most frequent overall). Word size reflects this ratio.

Figure 8: Bottom 25 explicit mentions by frequency ratio in positive vs. negative sentences (from the top 100 overall), excluding two offensive words. Word size reflects this ratio.

Figures 5 and 6 visualize the percentage distribution of aspect-based sentiment across frequent positive and negative aspects. Neutral sentiment is minimal, appearing only in a few aspects, such as "beer". This indicates a general dominance of strongly polarized opinions (positive or negative) over neutral perspectives in the frequent aspects. We selected the top 100 frequent explicit mentions in the whole dataset and calculated their ratio of frequency in sentences with positive and negative sentiment. Among the most frequent 100 mentions, 25 explicit mentions with the largest frequency ratio are shown in Figure 7; 25 explicit mentions with the lowest frequency ratio are shown in Figure 8.

Target Concept	Source Concept	Concept Mapping
ACT	ACT	DIRECTION IS POSITION
ACTIVITY	ACTION	ACT IS MOTION
POSSESSION	MOTION	IMPLEMENTAT. IS ACT
ACTION	ACTIVITY	COLLECTION IS LIQ
CHANGE_OF_STATE	POSITION	HIGH_STATUS IS DEGREE
COMMUNICATION	PERSON	POSSESSION IS ACTION
DIRECTION	UOM	MAGNITUDE IS STATUS
MOTION	STATE	POSSESSION IS ACT
COLLECTION	PRODUCTION	CONSISTENCY IS CONCEPT
PERCEPTION	COMMUNICAT.	CONCERN IS STATE

Table 1: Top 10 frequent target concepts, source concepts, and concept mappings in sentences identified with MetaPro. UOM denotes UNIT_OF_MEASUREMENT. LIQ denotes LARGE_INDEFINITE_QUANTITY.

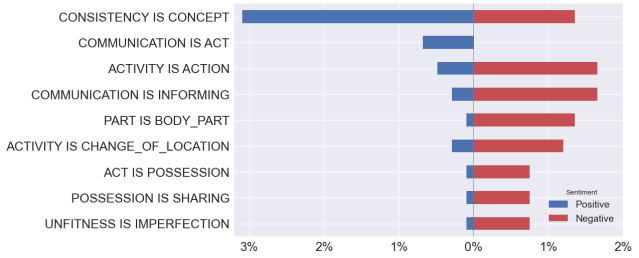

Figure 9: Concept mappings with significantly different counts (p value < 0.05) in sentences with positive or negative sentiment. The blue bars show the frequencies in sentences with positive sentiment. The orange bars show the frequencies in sentences with negative sentiment.

Concept Mapping Analysis

Table 1 lists the top 10 frequent target concepts, source concepts, and concept mappings in sentences, respectively, identified with MetaPro. Half of the concepts (ACT, ACTIVITY, ACTION, COMMUNICATION, MOTION) are top frequent in both target and source concepts. Concepts in frequent concept mappings (HIGH_STATUS IS DEGREE, MAGNITUDE IS STATUS, CONSISTENCY IS CONCEPT) are not top frequent in target or source concepts, implying close connections between these specific target and source concepts.

We did Chi-Square Tests on concept mappings about their counts in sentences with positive or negative sentiment. When the minimal of counts in sentences with positive or negative sentiment is smaller than 5, we use Fisher's exact test instead. Figure 9 visualizes the sentiment label distribution of concept mappings with significantly different counts (p value < 0.05) in sentences with positive or negative sentiment. Most of these concept mappings have higher frequencies in sentences with negative sentiment. Only CONSISTENCY IS CONCEPT and COMMUNICATION IS ACT have higher frequencies in sentences with positive sentiment.

Discussion

The majority of the sentiments are positive, which could indicate satisfaction about water infrastructure, strong awareness in promoting healthy water consumption habits, and growing trends around sustainability on Reddit. A significant portion of the comments being negative suggests underlying concerns. These could be related to water quality issues, newly released policies, and the cost of water. The low level of neutral sentiment suggests that water consumption is highly emotive for the audience. People tend to have strong opinions about it, mainly due to its fundamental importance to life and environmental issues.

The notable decrease in positive sentiment in 2019 might indicate events that caused public concern about water consumption during that year (Xiong, Hswen, and Naslund 2020). The sentiment percentages from 2020 onward show only minor fluctuations, revealing a relatively stable perception of water consumption. This recovery suggests that the public's attitude rebounded, possibly due to improved water management and solved previous concerns (Rajesh et al. 2021). Despite periodic declines, the positive sentiment has consistently remained above 56%, reflecting that most discussions about water consumption remain favorable.

Aspect-based sentiment analysis can provide us with more fine-grained information and thoughts about specific aspects. The strong positive sentiment for "drink" and "food" underscores water's essential role in hydration and its use in preparing meals. The positive discussions of "animal" and "plant" highlight the public's recognition of water's importance to ecosystems and biodiversity (Dudgeon et al. 2006). Discussions about "beer" indicate appreciation and satisfaction with its role in leisure, and social activities (Murray and O'Neill 2015).

Issues like "smell" highlight public concerns about the cleanliness and preservation of water (e.g., unpleasant smell from contaminated water) (Karlsson et al. 2013). This indicates a need for improved infrastructure and water treatment facilities. The negative sentiment of "crab" could refer to issues such as overfishing or the impact of water pollution on marine life. Negative mentions of "patient" might highlight healthcare challenges related to water consumption issues. "Capitalism" and "communism" discussions reflect perspectives about the privatization of water resources and equitable access, emphasizing the ideological and socio-economic dimensions of water consumption (Joy et al. 2014).

The contrasting sentiment around "alcohol", "cider", and "spirits" (more negative counts) versus "beer" (more positive counts) is interesting. These beverages may evoke negative sentiment because alcohol is often associated with health concerns, and the production of alcoholic beverages such as cider and spirits requires significant water resources, raising concerns about sustainability (Turshatov et al. 2023). "Beer" stands out with more positive sentiment, potentially because beer is usually viewed as a social drink, linked to celebrations and relaxation, which might overshadow concerns about water consumption in its production. The frequent explicit mentions with higher counts in positive sentences convey satisfaction and expectations about water consumption.

The explicit mentions like "hope", "love", and "best" imply growing awareness and optimistic attitudes towards sustainable water usage, community efforts, and technological innovations in water conservation (Willis et al. 2011). "Add" could indicate conversations around adding more water sources, improving infrastructure, or encouraging water-saving practices. "Thank" may relate to gratitude for clean water access, successful campaigns or policy addressing water scarcity. Negative explicit mentions are often more emotionally charged, reflecting frustration, dissatisfaction, or concerns (Nandwani and Verma 2021). The explicit mentions like "wrong" and "bad" reflect strong emotional responses, possibly due to severe challenges such as water shortages, pollution, or poor management. "Kill" may represent the harmful effects of water-related issues (e.g., water scarcity "killing" agriculture or livelihoods). The explicit mentions such as "old" and "basic" might signify dissatisfaction with outdated infrastructure, lack of modernization, or insufficient basic amenities.

The conceptual metaphors identified from social media posts and comments about water consumption reveal key insights into how people conceptualize water consumption-related issues. By analyzing the target and source concepts, along with their mappings, we can gain a deeper understanding of public perceptions, concerns, and values related to water consumption. Water consumption can be framed as an ACT or ACTIVITY, emphasizing purposeful human actions like drinking, cooking, or cleaning. The mapping of POSSESSION IS ACT suggests a metaphorical understanding of water as a managed resource. This indicates that access to water is not guaranteed and requires effort, highlighting the importance of its availability and sustainability (McCarthy 2008). The framing of water-related issues in terms of CHANGE_OF_STATE and MOTION suggests that people often perceive water consumption as dynamic and transformative (Fan et al. 2014). The concept mapping DIRECTION IS POSITION reflects concerns about water flow and distribution. Discussions about water conservation may involve metaphors related to guiding water usage in the right direction or maintaining steady motion in its supply. The concept mapping between COLLECTION and LARGE_INDEFINITE_QUANTITY suggests that people view water as something to be gathered and stored. This reflects concerns about water scarcity and the need for sufficient reserves (Kummu et al. 2016). The source concept UNIT_OF_MEASUREMENT indicates a quantifiable aspect of water, such as measuring consumption, which aligns with perceptions of water as a finite resource that needs careful monitoring. Water can be seen as both a responsibility and a privilege. The concept mapping HIGH_STATUS IS DEGREE suggests that access to clean and abundant water is perceived as a marker of societal or individual well-being (Hargrove 2020). This highlights inequality in water distribution and the aspiration for better access in underserved communities.

CONSISTENCY IS CONCEPT suggests that people often view consistency in water-related behaviors (e.g., regular consumption, sustainable practices) as highly desirable and positively impactful (Willis et al. 2011). Consistency might symbolize trust, reliability, and responsibility in the context of water usage. COMMUNICATION IS ACT implies that discussions about water might involve spreading awareness or advocating for responsible consumption. Public discourse and community communication around water issues seem to foster positive engagement. COMMUNICATION IS INFORMING has a higher negative sentiment frequency than the positive. Information shared about water consumption might provoke negative reactions, possibly due to controversial topics like water shortages, poor management, or misinformation (Kummu et al. 2016). ACTIVITY IS CHANGE_OF_LOCATION might refer to concerns about water being misused, displaced, or unevenly distributed. The metaphors used to discuss water consumption influence public sentiment. Positive framing around consistency and collective communication encourages support, while negative framing around harmful actions or unsettling information draws criticism.

Recommendation

Water consumption is vital, and social media discussions about it reflect underlying values, challenges, and behaviors. Analyzing frequent target concepts reveals public attitudes and offers insights for further study. The generally positive sentiment around water consumption indicates a strong baseline of public appreciation for water consumption-related issues. Campaigns can emphasize success stories and innovations to encourage sustainable practices and engage communities in conservation efforts. Using prevalent terms like "hope", and "thank" in outreach materials can connect with public sentiment. Tailoring campaigns to reflect regional concerns, such as water scarcity, pollution, or pricing issues can resonate with specific communities.

Considering several concept mappings with higher negative sentiment, such as COMMUNICATION IS INFORMING, strengthening positive communications is essential. Online activities include utilizing social media to share engaging content about water issues, partnering with local influencers to spread positive messages about water-saving practices, and creating apps or challenges to encourage water-saving behaviors (e.g., tracking water use and offering rewards for conservation efforts). Offline activities, such as collaborative communication, can be promoted by organizing community forums and workshops where citizens can share ideas and solutions related to water conservation.

Furthermore, policies should target key issues driving negative sentiment, such as water quality, equitable access, and affordability through public initiatives and policy reforms. Discussions around polarizing topics like "alcohol" and "capitalism" highlight the need for transparent communication about water management and sustainable water use in industries. Organizations can focus on regions with the highest levels of dissatisfaction to resolve issues causing negative sentiment.

Regular assessment on public attitudes toward water-related issues can measure the effectiveness of campaigns, identify emerging concerns, and refine policies. Possible methods include using sentiment analysis tools and conducting annual surveys and public consultations.

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