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Crisis communication and media influence during Nokia water contamination event☆

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ABSTRACT

This study analyzes public narratives, stakeholder communication, and media framing during the Nokia water contamination crisis (2007–2008), Finland's largest waterborne epidemic. Especially, using data from online forum (Suomi24), news reports, and official audits, we apply a new aspect-based sentiment analysis combined with thematic clustering over a 3-month crisis timeline period to trace the evolution of public perception in response to crisis events and stakeholder actions. The findings reveal that *positive sentiment clusters* were driven by visible mitigation efforts and hygiene-related practices, while *negative sentiments* were centered around contaminated water, institutional mistrust, and health fears. Media analysis showed minimal bias, with most coverage remaining factual, though occasional sensationalism could have amplified public anxiety. Compared to previous institutional communication research, our findings provide a data-driven perspective on citizen discourse-based analysis, offering new insights into how digital platforms can serve as real-time indicators of public trust and emotional response. The study underscores the importance of timely, transparent, and coordinated communication and highlights the potential of aspect-based sentiment analysis as a tool for adaptive crisis management and comprehending stakeholder actions.

1. Introduction

"Water Crisis" is one of the 30 known overall risks in the Global Risks Interconnection Map with substantial impacts on global health and economic activities [1], threatening the sustainability of urban water supply and treatment systems. This partly explains why it is directly associated with one of the key United Nations Sustainable Development Goals (Clean Water and Sanitation). Water contamination, as one of the "water crises" manifestations, can escalate into national emergencies, exposing populations to health risks and triggering widespread public anxiety. Effective and transparent communication between government agencies and affected communities is essential to mitigate harm and maintain public trust, as discussed by Kumalasari et al. [2] in their study about influence of digital communication transparency and public trust on crisis communication effectiveness in local governments in the Middle East and North Africa (MENA) region, with public engagement as a mediator. In the absence of a coordinated communication strategy, misinformation can spread rapidly, exacerbating confusion, distrust and discomfort with respect to application of national policy in this matter.

Consequently, building, maintaining and sustaining efficient communication channels with various stakeholder groups, including general public is essential. For this purpose, public participation has emerged as a valuable decision-making approach by incorporating diverse stakeholder perspectives into environmental governance and sustainability [3]. Social media became central for information sharing and discussions, playing an important role in understanding social phenomena, including water contamination [4]. Intuitively, understanding the information ecosystem related to water contamination on social media has the potential to provide insights in identifying opportunities and challenges related to the effectiveness of local and national policies, as well as comprehending the extent of public support. This can reduce the disaster impact and cultivate community resilience, which transforms extreme events into growth opportunities [5]. However, the complexity of the emergency communication framework and the

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inherent quality issues of social media content raise further challenges to the data processing pipeline, which calls for further research in this field.

This study investigates data from social media data and news corpus to uncover prevalent patterns emerging from public interaction, media outlets, and stakeholder reporting concerning a water contamination event occurred in Nokia city of Finland, in 2007, the largest reported water contamination in Finland [6]. The study aims to achieve two key objectives. First, it tracks the evolution of public perception in response to crisis events and stakeholder actions, identifying key aspects that can explain user perception. Second, it investigates the extent to which the news content is biased during the contamination event. More specifically, the study is guided by the following two research questions:

- RQ1: How does the general public respond to the crisis and, to what extent the public get influenced by actions taken by stakeholders?
- RQ2: To what extent is media bias present in the news reporting of water contamination crises? How does it shape public perception and stakeholder accountability?

To address these research questions, we advocate an empirical and theoretically grounded approach in text mining and natural language processing (NLP) methods to uncover relevant patterns from news outlets and social media datasets, identify relevant stakeholder groups, and evaluate the amount of support and argumentation. This expects to provide useful insights on the dynamics of public perception during water contamination events, focusing on the roles of government agencies, media, and other stakeholders in shaping crisis communication. Through the use of NLP techniques and Large Language Models (LLMs), we study both public and stakeholder discourse, distinguishing various phases of crisis development to capture temporal shifts in narratives. The findings aim to support policymakers in refining crisis communication strategies and improving public health responses in future water-related emergencies.

2. Related works

Several notable studies have been conducted in this area. Yamashita [7] explored how disaster-related information influences risk perceptions and migration decisions in Japan, particularly in areas threatened by the Nankai megathrust earthquake. The study found that younger people, low-income earners, and individuals with prior earthquake experiences were more likely to consider relocation, though government-issued disaster information had limited influence on such decisions, pointing to the need for more effective disaster prevention policies. Complementing this, Fakhruddin et al. [8] stressed that risk communication must be integrated into all stages of disaster planning rather than treated as an afterthought. Their study highlighted the necessity of timely, trusted, and accessible messages tailored to vulnerable groups, though challenges remain in reaching diverse populations meaningfully. Similarly, Chatterjee et al. [9], through the use of India's COVID-19 Risk Assessment Tool, demonstrated that effective communication strategies can positively influence individual behavior and foster trust in authorities, though their study was constrained by sample size and uneven spatial representation.

Shifting to the European context, Ommer et al. [10] revealed that flood risk governance in Germany remains largely top-down, with citizens perceiving limited clarity regarding their roles and responsibilities. The study underscored the importance of co-defining responsibilities with citizens and enhancing collaboration with local authorities to strengthen governance structures. Governance failures were also evident in Bangladesh management of COVID-19 crisis. For instance, Prodhan et al. [11] reported widespread job and income losses among lower-income workers during COVID-19, coupled with gender disparities in aid distribution and weaknesses in social safety nets. Finally, Prasetyo et al. [12] highlighted the significance of community participation during Indonesia's natural disasters and identified twelve critical communication elements for disaster preparedness, calling for comprehensive communication strategies despite limitations in data and time. In the same spirit, Diviani et al. [13] examined government communication effectiveness during COVID-19 from the Swiss public perspective using a cross-sectional online survey. Their results revealed moderate public satisfaction of governmental communication policy with a clear discrepancy among various demographic groups.

Recent studies further advance this discussion by integrating emerging technologies and updated crisis frameworks. For instance, Akbar et al. [14] emphasized the importance of effective crisis communication supported by technology, proactive education, and community training to build resilience. Upadhyay et al. [15] highlighted how organizations can enhance crisis management through digital collaboration, social media, and AI-driven tools. Godinho [16] discussed the challenges of analyzing social media data during disasters, emphasizing sentiment analysis as a key tool for understanding public response. Similarly, Jiang [17] explored how large language models (LLMs) like GPT-3.5 can transform emergency management by improving information processing, risk assessment, and real-time communication.

Noor et al. [18] provided an overview of crisis communication during disasters, focusing on social media engagement. Heath et al. [19] explored risk management complexity and advocated ethical, cooperative crisis communication. Specific to water contamination, Bixler et al. [20] emphasized drinking water emergency countermeasures and their economic, environmental, and health tradeoffs, while Miettinen et al. [21] detailed the 2007 Nokia contamination event. Public discourse studies include Logan [22] who analyzed Flint's water crisis public relation discourse. Wahid et al. [23] reviewed AI techniques in crisis social media analysis, limited to English Twitter data and lack of ethical/platform diversity discussion. Similarly, Chaudhary et al. [24] applied Aspect-Based Sentiment Analysis (ABSA) to African American tweets during COVID-19, revealing concerns like food insecurity and vaccine hesitancy, although limited to 2020 dataset.

Shaik and Oussalah [25] used ABSA and customized ontology to analyze Nordic emergency apps, and comprehend positive and negative sentiment reviews in a way that provides insights into identifying communication gaps and user behavior. Xiong et al. [26] analyzed tweets from the 2019 Chennai water crisis, revealing public emotions and media influence. Areia et al. [27] examined climate change media framing in the Iberian Peninsula, highlighting the gap between expert and public understanding. Ezell and Chase [28] surveyed Flint residents' attitudes on health impacts and revealed consistent discrepancy among residents according to their cultural norms and health experience. The findings have motivated the development of Critical Race Theory of Environmental Disaster. Tevapitak and Helmsing [29] stressed the importance of stakeholder interaction in environmental management of industrial water pollution in Thailand. However, the generalization of the result is also limited to nature of local government policies. Safford et al. [30] examined public perceptions of responses to the 2010 BP Deepwater Horizon spill, highlighting the importance of compensation schemes and media trust in shaping citizens' opinions. Panahi and Moayerian [2] explored social capital's role in Shiraz flood community resilience, emphasizing institutional support. More relevant technical studies on modeling frameworks include Pyo and Chiang [31]'s proposal on improved record linkage by fine-tuning PLMs with LLMs; Pecher et al. [32]'s study on small language models, indicating the possibility of small labeled sample to match large language model performances at scale. From Finnish language perspective, Lehti et al. [33] explored forest perceptions on Suomi24 using topic modeling and clustering techniques, though many relevant documents were classified as 'noise' by HDBSCAN. Ertiö et al. [34] analyzed Finnish social media landscape, revealing the dominance of commenting-like activity, which raises the importance of Suomi24 like platform. It also reveals that most users consider themselves more like occasional commentators

Table 1
Key studies.

Author(s)	Methods	Findings	Limitations
Logan	A new theoretical framework named Fully Functioning Society Theory (FFST) to investigate corporate responsibility and community interests during the crisis.	Corporate responsibility emerged as a key theme in analyzing the crisis, Trust restoration is challenging after Public officials fail to protect community health	Analysis is largely qualitative and interpretive
Ezell and Chase	A cross-sectional survey method to gather data from Flint residents about their experiences during the water crisis	Institutional and community mechanisms shape residents' understanding of the crisis and its health impacts	The sample was not randomly selected
Diviani et al.	Systematically reviewed COVID-19 communication strategies, using trust metrics and regression analyses to assess their impact on public health behaviors.	Moderate satisfaction with COVID-19 communication in Switzerland, with trust and public health attitudes varying across demographic groups	The cross-sectional design limits causal inferences regarding the relationships studied, also exploratory approach may not fully capture the complexities of public health communication
Wahid et al.	Examines ML, DL, and topic modeling strategies for crisis text analysis, emphasizing transformer models, LSTM/SVM methodologies, and the significance of pre-trained models for low-resource languages.	Deep Learning transformer models, such as BERT and Roberta, enhance sentiment analysis by improving contextual knowledge. Topic modeling combined with neural embeddings boosts situational awareness analysis	Exclusive focus on English-language Twitter data and lacks discussion on other platforms and ethical considerations in crisis analysis.
Shaik and Oussalah	Employs Natural Language Processing (NLP) & text mining techniques for analyzing user reviews of mobile emergency apps, Key methods include data collection, aspect term extraction, sentiment classification, and ontology construction	Negative sentiments dominate user reviews, particularly regarding battery usage & location accuracy, Positive aspects include effective communication of traffic announcements & emergency updates	Limited by a small, negativity-biased sample and the dominance of the 112-Suomi app, reducing the diversity of emergency app reviews analyzed
Chaudhary et al.	The research utilized Twitter data from 2020 to analyze pandemic-related experiences of African Americans using aspect-based sentiment analysis	Indicate a predominance of negative sentiment in tweets, correlating with major pandemic-related events	only includes 2020, which limits the ability to understand how opinions change over time.
Tevapitak and Helmsing	It employs stakeholder analysis as the primary analytical tool to understand the interactions between local governments, entrepreneurs, and the local community regarding environmental management.	Stakeholder interaction is crucial for effective environmental management by local governments (LGs) and communities.	Constrained by time and budget, as it was part of a thesis
Safford et al.	Data was gathered from 2023 residents in coastal parishes and counties of Louisiana and Florida impacted by the Deepwater Horizon oil leak using a random-digit telephone survey approach.	Evaluations of the responding organizations were greatly impacted by direct personal consequences and compensation. Opinions of the response efforts are shaped by trust in BP and television news as information providers.	Relies on a telephone survey; focus on specific areas may introduce geographic bias
Panahi and Moayerian	Investigating the effects of social capital during and after Shiraz's flood catastrophe using a qualitative study approach	Social capital surged during the Shiraz flood response, enhancing community resilience despite centralized governance challenges, Informal networks facilitated transparency and trust, compensating for ineffective government planning	Generalizability is limited due to specific conditions of the studied region

instead of active crisis discourse participants. Table 1 summarizes key studies underpinning this research alongside their limitations.

In summary, despite extensive research on crises such as floods and COVID-19, limited work has analyzed water contamination through public discourse. This study addresses this gap by exploring Nokia's water contamination crisis, focusing on public perception and stakeholder communication, and examining how biased journalism can shape public perception regarding the crisis. At the same time, the study integrates modern LLMs with traditional NLP methods, a relatively underexplored area in crisis analysis.

3. Materials and methods

3.1. Research design

Fig. 1 presents an overview of our research methodology, outlining how RQ1 and RQ2 are addressed. As illustrated in the graph, the process begins with data collection, which is divided into three categories: (1) User-Generated content (public opinions and comments) from Suomi24, a Finnish discussion board platform, (2) the official report of the 2007 Nokia water contamination crisis [6], and (3) online news articles related to the Nokia water crisis. This is followed by appropriate preprocessing and sisambiguation task to ensure high quality data and filter out noisy data, utilizing the power of LLMs as will be explained later on.

We use Aspect-Based Sentiment Analysis (ABSA), a natural language processing method that determines sentiment polarity (positive, negative, or neutral) toward particular aspects mentioned in the text, to address our first research question about public response (for more information, see Section 3.3). To maximize the performance of our ABSA model and tailor it to our domain, we fine-tune it by generating ground truth data. Specifically, inspired by Pyo and Chiang [31], who leveraged LLMs for generating training data and fine-tuning pre-trained language models(PLMs), and achieved over 45% improvement in F1 score compared to traditional methods, we prompt an LLM on a sample(20%) of the preprocessed Suomi24 data to identify aspects and their associated sentiments. The fine-tuned ABSA model is then applied to the entire dataset to extract aspect-level sentiments.

Study done by Pecher et al. [32], which observed that specialized models can often outperform general models with only a relatively

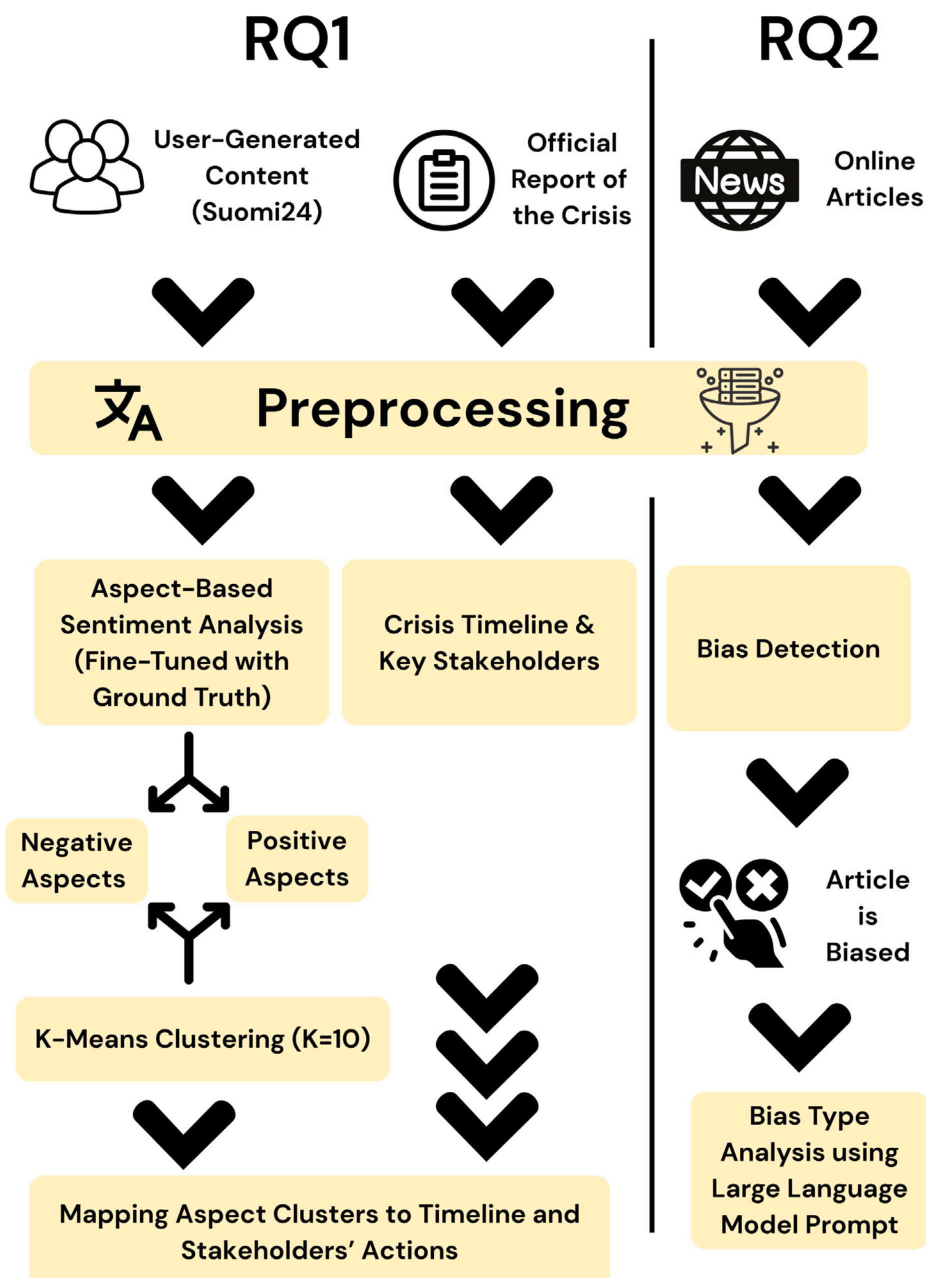


Fig. 1. Research design.

small number of labeled samples (10 – 1000), inspired us to decide sample requirements for fine-tuning the model. The detailed information about fine-tuning parameters and LLM prompts used is provided in Appendix A. Our study focuses on extreme sentiments: positive and negative polarities. As such, aspects are categorized by sentiment and grouped into 10 clusters. Since each comment in the Suomi24 dataset can contain multiple aspects, the resulting aspect set is large. Therefore, clustering was used to reduce this complexity and enhances interpretability. The number of clusters was set to 10 after experimenting with different values and evaluating both interpretability and visualization clarity. A higher number of clusters (e.g., 15 or 20) led to excessive fragmentation, making it difficult to identify themes and visualize trends over time. Fewer than 10 clusters, on the other hand, merged distinct aspects into overly broad categories.

In this study, we prioritize visualizing clusters to extract meaningful insights rather than focusing on achieving high evaluation scores, as the latter were relatively low but did not hinder the interpretability of results. The clustered aspects are then visualized weekly to analyze the evolution of public discourse. These weekly discussions are mapped onto the crisis timeline, alongside stakeholder actions derived from the official report [6]. This mapping provides valuable insights for answering our first research question. To address the second research question, the preprocessed news articles are passed through a bias detection model to compute bias scores and find out if an article is biased, and then the biased article is passed through an LLM prompt to classify the type of bias. This enables analysis of media framing and its potential influence on public perception as will be detailed later on.

3.2. Dataset description

Our research deals with the Nokia Water Contamination event, which happened on November 27–28, 2007, in Nokia, Finland [21]. According to Miettinen et al. [21], the city(population $\approx$ 30,000) experienced a severe drinking water contamination outbreak. A cross-connection between the wastewater system and the drinking water pipeline led to extensive fecal contamination of the distribution network. Early warning signs, such as customer complaints about unusual color, taste, and odor were initially ignored. The outbreak was only recognized after the first illness cases emerged. Tests showed that the drinking water had incredibly high levels of indicator bacteria. Subsequent analyses confirmed the presence of Campylobacter, Giardia, noroviruses, Salmonella enteritidis, as well as rota-, entero-, astro-, and adenoviruses in the samples. For public opinions about the contamination event, we collected threads and comments posted around that time on the Suomi24 website. Suomi24 is one of the Finland's most prominent disucssion forum for public self-expression, also discussed in this article by Lehti et al. [33]. Over 1 million comments and discussion threads from the Suomi24 platform were collected for this case from publicly available data spanning from 2001 to 2017 [35]. The data includes thread text, title, date, etc. Filtering by the timeline of the crisis (from November 27, 2007, to February 27, 2008) and by keywords such as "Nokia" or "vesi" (water) reduced the data set to approximately 25,000 rows. All of this data is in the Finnish language.

The Finnish language lacks the training data necessary to build accurate, state-of-the-art NLP systems, which is why it can be considered a low-resource language. A language is deemed low-resource if it does not have extensive parallel or monolingual corpora and/or manually constructed linguistic resources adequate for developing statistical NLP applications [36]. Therefore, the Finnish language data we have is being translated into English. For translation, we have utilized the Argos Translator GitHub Repository [37]. Following this, another filtering was performed for keywords related to the crisis, which were "sick","ill","disease","children","death","water","stomach","drinking", "vomit", and "pipes". This reduced the data to 15,000 entries, and to narrow the focus even closer to posts directly relevant to the Nokia crisis (since Suomi24 hosts national discussions). Imitating Rusee et al. [38], who suggested a precision prompt format for targeted responses, we used a Zero-Shot large language model (LLM) prompt(more details in Section 3.4), to classify the topic of every entry. Zero-shot prompting involves instructing the model to perform a task without using examples to guide it. We just kept the topics which were relevant to the crisis and combined them into 6 broad categories for better understanding(water, health, energy & heating, childbirth, infrastructure, politics), resulting in 4461 records. These average about 48 comments per day, with an average length of approximately 101 tokens per comment, ranging from 1 to 1870 tokens, and a vocabulary size of 19,951 unique words.

Additionally, we collected 206 Finnish news articles from various Finnish news websites using the Python library from the GitHub repository Finnish Media Scrapers [39] using keywords "vesi" and "Nokia", and the resultant articles includes the title, article text, URL, published date, author name, etc. These articles were then disambiguated to include only Nokia-specific content using the Facebook/BART-large-MNLI model, which can be effectively utilized for ambiguity disambiguation through its zero-shot classification capabilities [40], resulting in 89 relevant news items. These average about 1.13 articles per day, with an average length of roughly 247 tokens per article, ranging from 22 to 767 tokens, and a vocabulary size of 1205.

Complementing this, we analyzed an official investigation report [6] with a vocabulary size of 4418, that outlined the timeline, technical causes, and stakeholder actions during the crisis. A brief overview of both the dataset attributes and example entries is presented in Tables 2 and 3.

3.3. Aspect-based sentiment analysis(ABSA)

For Aspect-Based Sentiment Analysis (ABSA), we utilized Instruct ABSA [41]. InstructABSA is a framework for Aspect-Based Sentiment Analysis (ABSA) that, through instruction tuning, reinterprets the traditional tasks in sentiment analysis. Rather than having narrowly defined subtasks, such as aspect extraction, opinion term identification, or sentiment classification, where the tasks are all trained in isolation, InstructABSA considers these tasks as instruction-following problems, thus introducing a human-interpretable and flexible approach to ABSA. The approach leverages the capabilities of instruction-tuned large language models (LLMs) such as Flan-T5, OPT-IML, and InstructGPT. These models are pretrained to comprehend general natural language patterns and human-written instructions. InstructABSA leverages this strength by utilizing customized prompts that specify what the model should extract.

A significant advantage of InstructABSA is its zero-shot and few-shot nature. Indeed, since the model is instructed to perform a task, it generalizes across datasets and domains with little or no additional training. Hence, such flexibility makes the system highly adaptable and scalable to real-world scenarios, where annotated data is generally scarce or domain-specific fine-tuning is not possible. The instruction-based interface also enhances the transparency of the output and facilitates customization, as users can modify instructions according to their specific needs for analysis. Empirical results show that InstructABSA achieves state-of-the-art performance on the three ABSA subtasks (Aspect Term Extraction (ATE), Aspect Term Sentiment Classification (ATSC), and Joint Task) on several benchmark datasets(SemEval 2014, 15, and 16), often outperforming dedicated ABSA models [41]. Remarkably, these results were obtained with less training data, highlighting the model's efficiency and strong generalization ability. This evidence reinforces our decision to employ InstructABSA, as its instruction-based learning paradigm not only enhances interpretability but also maintains competitive accuracy with significantly smaller data requirements.

To illustrate ABSA, consider this anonymized public comment from the Nokia crisis – *"The government failed to stop contaminated water, and the quality still seems bad, but the water trucks and Red Cross help have been great"*. Negative aspects are Water contamination, Government, and Quality, while positive aspects are Red Cross and Water trucks.

3.4. Large language models

In this study, two different Large Language Models (LLMs) have been used: Meta Llama 3 and Google's Gemma 3. The Meta Llama 3 model, specifically the meta-llama/Meta-Llama-3-8B-Instruct variant [42]. It has been trained on a large text corpus and contains four times more code than its predecessor, Llama 2 [43]. Due to the large volume of data processed during topic classification, running such tasks on a lightweight local model would have taken days or weeks. For faster turnaround, we used a premium Hugging Face service to run Meta Llama 3 in the cloud. For the ground truth generation task, which involves smaller datasets, we used Google's Gemma 3. Gemma is a lightweight, state-of-the-art open model, designed for efficient deployment without the need for large-scale compute [44]. We deployed Gemma 3 locally using Ollama, a supported deployment tool compatible with our existing GPU(Graphics Processing Unit) and RAM (Random Access Memory) configuration [45]. To generate high-quality ground truth labels, we designed a few-shot prompt for Gemma 3, including clear task instructions, example inputs, and output formatting guidelines.

3.5. Ground truth

Ground truth data is essential for fine-tuning any NLP model, as it provides accurate, domain-specific annotations that enable the model to learn the contextual nuances. We decided to use a Few-Shot LLM prompt to label a sample(20%) of the data(using the Google Gemma 3 model), inspired by Pecher et al. [32]. Then, for this portion of the dataset, we labeled the public comments of every case for aspect-sentiment pairs. Few-Shot Prompting enables the model to be provided

Table 2
Snapshot of Suomi24 dataset.

Attribute	Description	Example value
thread_id	Unique discussion thread ID	5431380
datetime	Date and time of post/comment	2008-02-26 23:05:02
title	Thread title	"Wegenerin Granulomatoosi"
thread_text	Post/Comment text	"No , tislattu ja suodatettu vesi..." Translation: "Well, distilled and filtered water..."

Table 3
Snapshot of News dataset.

Attribute	Description	Example value
id	Unique news article ID	3-5813156
url	Article URL	"http:yle.fiuutiset....."
date_modified	Date/time of article	2007-12-09T22:37:19Z
title	Article title	"Nokia palailee arkeen - juomavesi...." Translation: "Nokia Returns to everyday life – Drinking...."
article_text	Full article	"Nokian terveyskeskuksen..." Translation: "Nokia's health centre's..."

with input–output examples included within the prompt, which allows the model to better adapt to tasks [38]. This allows the model to tailor its response based on the provided instructional examples. The prompt structure is designed to guide the task in the particular context of a water contamination event. Even though LLMs prompt exceptionally well in understanding the text context, the answers still demand our careful attention and consideration. Therefore, we carefully evaluated and rechecked some of the prompt answers to make sure that the answers were not misleading or incorrect. We used an LLM prompt instead of manual labeling because of cost-effectiveness and subjectivity. Additionally, LLMs have already demonstrated the potential to act as a judge to assist in manual labeling operations, as previously discussed in the study by Pyo and Chiang [31].

To ensure data reliability and domain relevance, human evaluators were involved in validating and refining the LLM-labeled dataset. Two independent researchers from the DiGeMERGE project manually reviewed and annotated a representative subset of the data using the Covidence platform. Approximately 20% (1000+) samples from LLM-labeled samples were cross-checked to evaluate the accuracy of the labels and guide the fine-tuning process. Specifically, each record was independently reviewed by two independent annotators, and disagreements were resolved through discussion and consensus. In rare cases where consensus could not be reached, a third expert annotator was consulted to make the final determination. While a formal Cohen's Kappa score was not calculated, annotators demonstrated a high level of consistency comparable to strong reliability ranges reported in similar annotation studies. This hybrid approach – LLM-assisted labeling with human verification – ensured that the fine-tuned model was grounded in high-quality, human-validated data while maintaining scalability.

3.6. Fine-tuning

Fine-tuning is essential in domains such as crisis communication, where interpreting public sentiment demands both contextual understanding and model precision. In our study, we fine-tuned the InstructABSA model, a T5-based text-to-text transformer [46], using instruction-driven prompts specifically tailored for aspect-based sentiment analysis. The dataset was sampled and annotated using the ground truth generation process described in Section 3.5, and reformatted into instruction–response pairs compatible with the InstructABSA framework. The base model checkpoint (`allenai/tk-instruct-base-def-pos`) was selected due to its suitability for instruction-based NLP tasks and its prior success in ABSA subtasks.

The fine-tuning workflow followed a structured pipeline to ensure reproducibility and model consistency. The labeled dataset was divided into training (80%) and testing (20%) subsets using a fixed random seed to maintain balanced class representation. Data preprocessing was handled using the `InstructionsHandler` and `DatasetLoader` modules of the InstructABSA framework, which transformed each input into instruction-based text pairs specifying the aspect terms, sentiment polarity, and corresponding context. The model checkpoint (`allenai/tk-instruct-base-def-pos`) was initialized via the `T5Generator` class, and tokenization was performed using the framework's predefined sequence-to-sequence tokenizer. The training process employed the *cosine learning rate scheduling* with standard optimization parameters tuned for stability and generalization. Core hyperparameters such as learning rate, batch size, number of epochs, and weight decay are summarized in Appendix A (Table A.6). This configuration ensured gradual convergence without overfitting, while maintaining a balanced trade-off between efficiency and performance. Validation loss was monitored after each epoch to assess convergence. For inference, the fine-tuned checkpoint was reloaded to generate aspect–sentiment predictions on unseen text data. Predictions were computed and saved in structured CSV format. This process enabled systematic evaluation and ensured that the fine-tuned model could generalize effectively to previously unseen data.

3.7. Clustering aspects

As the outcome of the ABSA can yield several aspects, it becomes difficult to interpret the outcomes; therefore, a clustering-based approach was implemented through the standard k-means algorithm. For clustering, we first separated the positive and negative aspects to analyze them independently. To generate meaningful clusters, we applied word embeddings to both sets of aspects. Specifically, we used GloVe (Global Vectors for Word Representation) [47], an unsupervised learning algorithm that generates vector representations of words based on aggregated global word–word co-occurrence statistics from a corpus. These embeddings capture semantic relationships and linear substructures in the word vector space. The resulting aspect embeddings were then passed to the K-Means clustering algorithm, a widely used unsupervised machine learning method that groups unlabeled data into clusters based on distance [48]. We also chose K-means to avoid losing important text to "noise" like Lehti et al. [33], who chose HDBSCAN. The number of clusters, denoted by K, was set to 10 in our case. This choice was based on our aim to balance granularity and interpretability: fewer clusters would merge distinct themes, while more clusters would result in fragmented, harder-to-visualize groupings, as shown by our initial testing.

3.8. Crisis timeline and key stakeholders

The official report of the crisis [6] describes the crisis as Finland's largest waterborne epidemic, with over 8000 residents suffering from gastrointestinal illnesses. According to the National Public Health Institute, symptoms ranged from mild diarrhea to prolonged intestinal and joint issues, with two deaths under investigation for potential links to contaminated water. A survey found that 5100 of the 9000 residents in the affected area reported symptoms between 28 November 2007 and 20 January 2008, and even residents of Nokia's clean water area and nearby Kangasala showed elevated illness rates. The crisis response began on 30 November 2007, when boil-water advisories were issued, followed by a full water ban after a main pipe burst on 5 December. During the peak days, the Nokia Health Centre was overwhelmed with patients, leading to inter-municipal cooperation and support from the Pirkanmaa Hospital District (PSHP). A special epidemic telephone line was launched on 6 December and operated for nine days, receiving thousands of inquiries.

Key stakeholders involved in managing the crisis included the City of Nokia, Nokia Water Utility, PSHP, the Accident Investigation Board, and the Western Finland Provincial Government. The Finnish Defence Forces were mobilized to manage large-scale water distribution starting 5 December, establishing 18 water points across the city. Simultaneously, voluntary services played a pivotal role: Vapepa and the Finnish Red Cross (Nokia branch) coordinated over 900 person-hours of door-to-door and site-based water and hygiene aid between 5–9 December, while continuing information distribution efforts into mid-December. In total, 5.5 million liters of tanked water and 700,000 liters of bottled water were distributed. The civil assistance operation concluded on 10 December, though support continued into January 2008. By 17 February 2008, most water use restrictions were lifted and treatment of patients had concluded. Following the crisis, authorities recognized the need for better preparedness. Measures taken included improving inter-agency coordination, clarifying crisis communication protocols, and developing structured contingency plans for future municipal water emergencies.

Crisis communication is a central focus of our study and is extensively detailed in the official investigation report. It began on November 29, 2007, when a water utility engineer sent an internal email after a citizen tip-off, and the newspaper Aamulehti contacted the waterworks. The next day, a boil-water advisory was issued along with multiple online bulletins, media outlets were contacted, and the emergency center received its first calls. On December 1, the city appointed the water utility director to manage communications, including announcements via a loudspeaker van. December 2 involved preparing and distributing a press release, conducting media interviews, and planning a press conference with officials such as the environmental health manager, the mayor, and public broadcasters. The first official press conference took place on December 3, with the city responding to public questions online. By December 5, a water ban was announced, Tampere officials assisted with communication, and emergency alerts were sent via fax and teletext. On December 6, Tampere University Hospital (TAYS) launched an epidemic helpline, accompanied by national and regional water status broadcasts. The next day, YLE's Pasila office was questioned by the emergency center regarding bulletin timeliness, prompting updated city communication. Finally, from December 8 to 19, the acute communication phase ended with final bulletins and teletext updates. For a detailed overview of events and stakeholders, see Table 4, where we have divided the crisis into 3 phases (initial phase, active phase (when the crisis was at its peak), and recovery phase) and have explained the role of key stakeholders in each phase.

The report also mentions that Crisis communication was poorly coordinated, with unclear responsibilities, fragmented messaging, and a lack of readiness. The municipality's emergency communication plan was limited in distribution and not available to first-line responders. Authorities relied on emails and phone calls without a centralized system, which led to delays, confusion, and congestion in communication during the early stages of the crisis. The media played a three-stage role: initially reporting routine updates, then investigating failures, and finally assisting the public by relaying crucial information. While media coverage helped increase awareness, inconsistent messaging and the absence of official bulletins early on contributed to public confusion.

3.9. Media bias analysis

To detect bias in a news article, we used a pre-trained model(d4data /bias-detection-model) for bias detection from the Hugging Face platform [49]. It is built on the DistilBERT-base-uncased architecture [50], which is a lighter and faster version of BERT(Bidirectional Encoder Representations from Transformers), making it well-suited for real-time tasks like sentiment classification, thanks to its compact size and efficient architecture. The bias detection model was trained and released as part of a larger research initiative titled "Bias and Fairness in AI" [51] to examine various methods and challenges faced with bias detection in AI systems. This research area is critical as bias in journalism can affect people's perception and decision-making, making this concept very important for fair and balanced information dissemination. However, this model only tells us if a news article is biased or non-biased; it does not give any reason why an article is biased or what kind of bias is present in the article. Therefore, we decided to make the process of bias detection hybrid by introducing an LLM (Gemma 3) prompt to explain what bias is in biased news articles. Gemma 3 is a lightweight, state-of-the-art open source model from Google [44] (See Section 3.4) for more details.

4. Results

4.1. Public response to the crisis

Fig. 2 illustrates the distribution of aspect sentiments during the Nokia water crisis. As expected in a crisis context, positive aspects were the least frequent. Interestingly, neutral aspects were highly prevalent, even surpassing those with negative sentiment. The figure also highlights the most frequent aspect terms associated with each sentiment category. Neutral and negative sentiments exhibit a very similar distribution, which suggests that many users were primarily stating factual information about the crisis rather than expressing opinions. This observation aligns with findings from a previous study [34], which indicates that Finnish people tend to comment only occasionally. Positive sentiment aspect terms reflect appreciation for government and stakeholder actions, whereas negative aspects focus on health concerns and criticisms of the government. For this study, we concentrated on positive and negative sentiments. We also examined aspects appearing in both sentiment categories, revealing the duality of the situation.

The overlapping positive and negative aspects across weeks (see Fig. 3) reveal a duality in public discourse, where certain topics elicited both concern and optimism. The weekly timeline spans from November 27, 2007, to February 27, 2008, with each week running from Tuesday to the following Monday, except for the final week (Week 14), which contains only two days. In earlier weeks, attention was centered on core necessities such as bottled water distribution, water supply, and water quality, highlighting the urgent need for clean and safe water. The mention of the City of Nokia in Week 2 likely reflects mixed public sentiment toward local authorities, encompassing both appreciation and criticism. A similar dynamic is evident in Week 5 with the appearance of the aspect 'government'. As the crisis unfolded, discussions expanded to include broader themes such as health and electricity, although water-related concerns remained persistent throughout. The recurring overlap of aspects week by week suggests ongoing uncertainty and divided public perception toward key elements of the crisis. A detailed

Table 4
Roles of key stakeholders during different phases of the Nokia water contamination crisis.

Stakeholder	Early Phase (28–30 Nov)	Active Phase (1–10 Dec)	Recovery Phase (11 Dec–Feb 2008)
City of Nokia	Limited preparedness and unclear leadership. Delayed official bulletins and weak coordination.	Activated enhanced management group to unify decisions. Issued press conferences, loudspeaker announcements, and collaborated with Tampere officials.	Led post-crisis review. Introduced preparedness reforms and improved communication protocols.
Nokia Water Utility	Detected contamination and sent first internal alerts. Issued initial boil-water advisory.	Supported city communication and coordination. Worked with health agencies and Defence Forces on logistics.	Assisted in restoring water supply and repairing damaged infrastructure.
PIRTEVA (Environmental Health Unit)	Provided early health risk assessments and local inspections.	Took lead in issuing hygiene guidance and medical advisories. Coordinated data reporting between municipalities.	Continued long-term water testing and health monitoring.
PSHP (Pirkanmaa Hospital District)	Not formally involved during initial detection.	Established epidemic helpline and coordinated patient care. Provided risk communication and outbreak information.	Evaluated patient outcomes and improved regional preparedness.
Finnish Defence Forces	Not active in this phase.	Mobilized on 5 Dec to manage logistics. Set up 18 water distribution points across the city.	Withdrew after 10 Dec. Supported contingency planning for future crises.
Vapepa & Finnish Red Cross	No involvement in initial detection phase.	Contributed over 900 volunteer hours. Provided door-to-door water and hygiene aid and distributed bulletins.	Continued outreach for elderly residents and offered psychosocial support.
Media (YLE, Aamulehti, Radio)	Broke the story after citizen tip-off. Relayed early public warnings and updates.	Intensified coverage, investigated accountability, and spread official safety messages.	Focused on recovery progress and lessons learned. Helped reinforce institutional credibility.

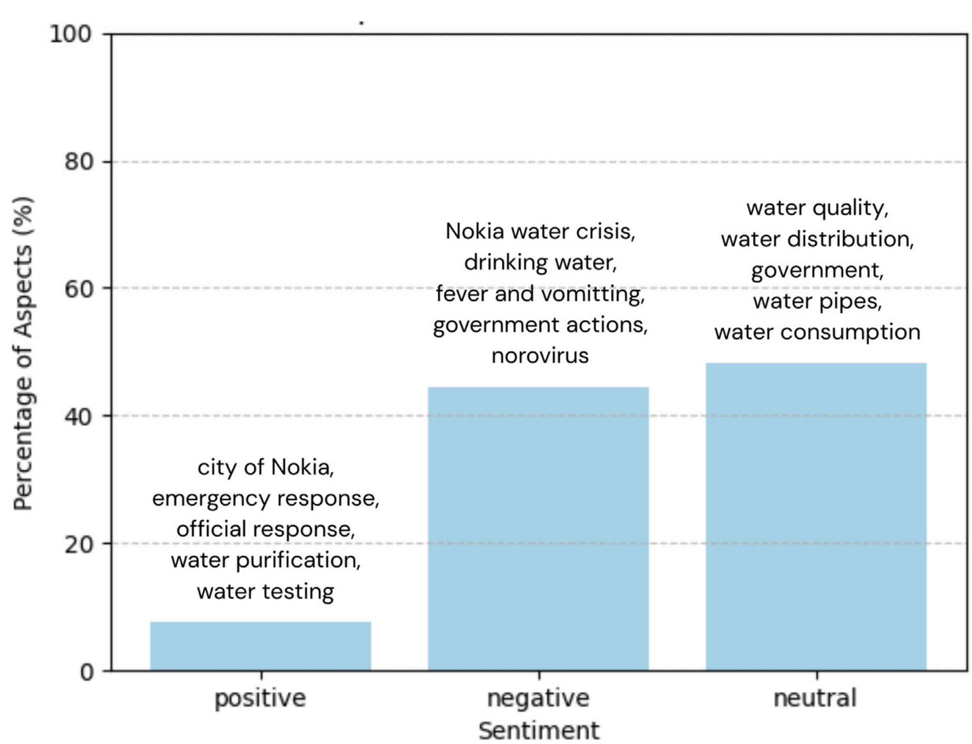


Fig. 2. Distribution(%) of aspects for each sentiment polarity.

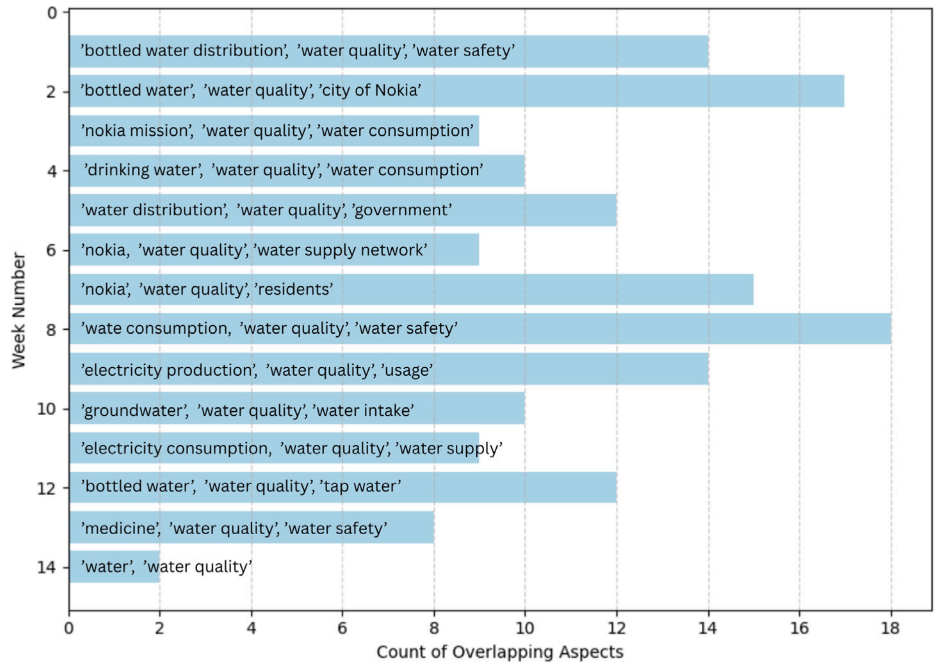


Fig. 3. Overlaping aspects(positive and negative) per week.

summary of overlapping aspects can be found in Table B.7 of Appendix B.

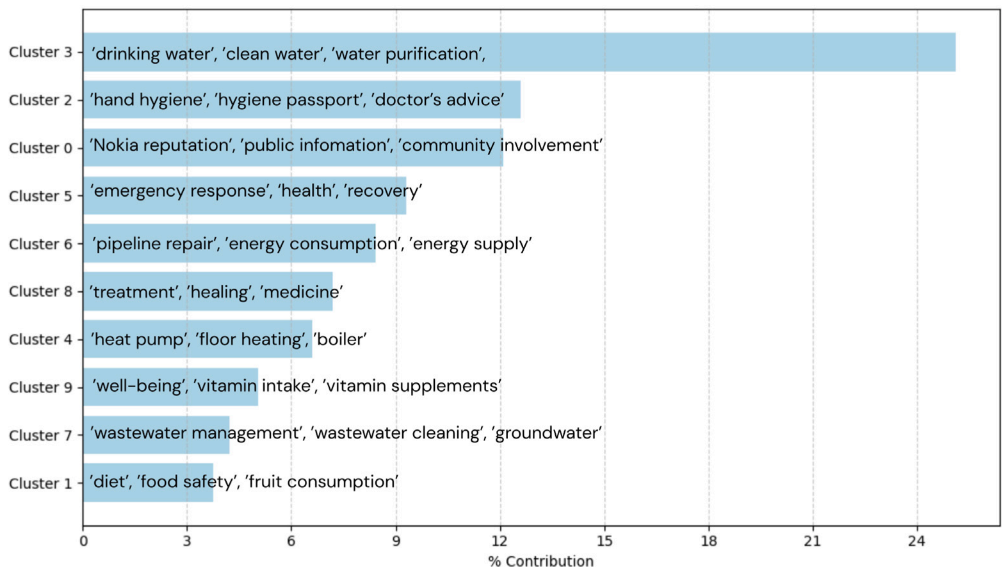
Fig. 4 present the clustering of positive and negative aspects extracted from public comments during the crisis. These clusters offer insight into the dominant themes in public discourse. For each cluster, a set of representative terms was manually selected based on domain knowledge to best capture its underlying theme. The positive clusters (see Fig. 4(a)) reflect a degree of trust and hope placed in institutional responses, with mentions of public information, emergency response, and community involvement. There is also a strong focus on technical and infrastructural solutions, such as pipeline repairs, wastewater management, and energy supply, suggesting public recognition of ongoing recovery efforts. Several clusters also emphasize health, hygiene, and personal well-being, indicating that some individuals coped by focusing on resilience and healthy lifestyles. Notably, terms like “Nokia reputation” suggest efforts to reframe the crisis as an opportunity for long-term recovery.

In contrast, the negative clusters (see Fig. 4(b)) reveal deep concern over systemic failures and public health risks. Water-related anxieties are particularly prominent, with repeated references to contamination. Several clusters express dissatisfaction with local authorities and government bodies, pointing to issues of accountability, poor crisis communication, and political blame. Economic strain is another recurring theme, with concerns over repair costs and broader financial impact on the community. The presence of detailed medical and disease-related terminology further underscores the intensity of public fear regarding health consequences. In one cluster, officials are directly blamed, reflecting the erosion of public trust. Overall, while positive aspects reflect cautious recognition of recovery efforts and limited institutional confidence, negative aspects dominate the discourse, capturing frustration, distrust, and a lingering sense of vulnerability. The detailed tables of both of these clusters can be found in Tables B.8 and B.9 of Appendix B.

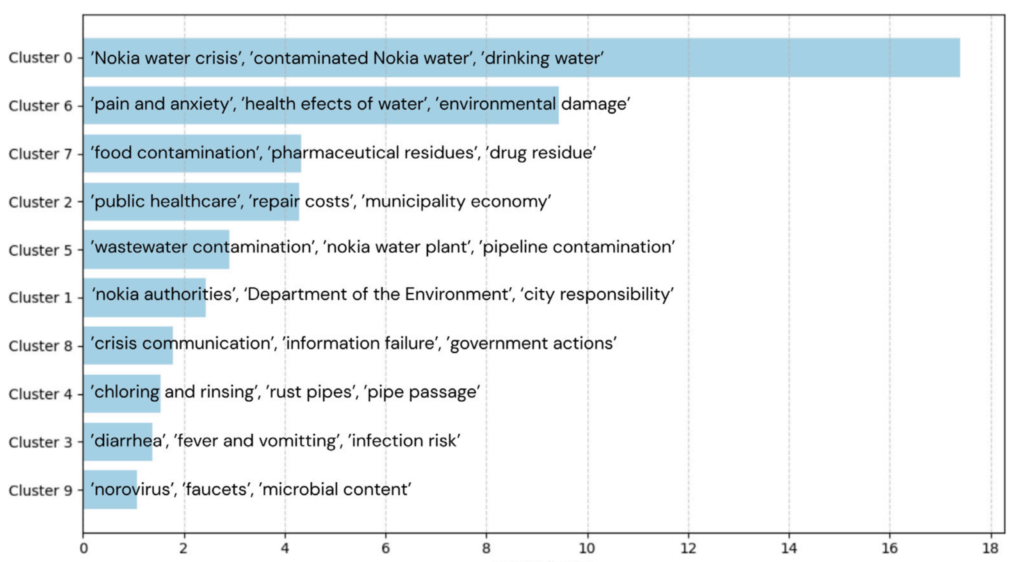
Fig. 5 visualize the temporal distribution of aspect clusters associated with positive and negative sentiments throughout the 14-week duration of the Nokia water crisis. In the positive sentiment heatmap (see Fig. 5(a)), Cluster 3, focused on water-related aspects, consistently stands out, highlighting sustained public attention to the recovery efforts, such as “water purification”. This also suggests that communication around visible improvements in the water system played a key role in fostering positive sentiment. Cluster 0, which includes terms related to public information, community reassurance, and the city’s reputation, is prominent in the early weeks and resurges around Week 9. This pattern indicates renewed efforts by municipal authorities to rebuild trust after the most acute phase of the crisis. Cluster 2, centered on hygiene practices and personal health, shows a sharp increase in Week 5, likely reflecting intensified individual precautions or responses to public health advisories. Most other clusters remain relatively stable, except Cluster 6, which mostly seemed to be related to energy and pipeline repair, spiked in Week 12. This late peak may be incidental and not directly connected to the water crisis.

In the negative sentiment heatmap (see Fig. 5(b)), Cluster 0, dominated by concerns around drinking water and contamination, prevails throughout nearly every week, especially during the initial onset of the crisis. This reflects widespread fear over water safety and lack of access, reinforcing the pivotal role that uncertainty and perceived risk played in shaping public discourse. Cluster 1, which captures discussions about Nokia authorities and city responsibility, peaks in the final week, suggesting a delayed but significant demand for accountability. This may have been triggered by new revelations or retrospective blame as the crisis was being resolved. Cluster 3, which includes health-related concerns, becomes more prominent in Week 5, potentially due to growing illness reports or intensified media coverage on health risks. Interestingly, this aligns with the positive hygiene-related Cluster 2 from the other heatmap, indicating a dual public response, fear and frustration on one hand, and proactive personal adaptation on the other. Cluster 5, dealing with discussions about wastewater, maintains a low but steady presence, hinting at persistent environmental concerns that may have been secondary to immediate health concerns. Other clusters remained minor and did not appear to significantly shape the overall public response.

Together, these heatmaps and aspect clusters illustrate how public sentiment closely tracked the timeline of events and the actions taken by key stakeholders during the Nokia water contamination crisis. Finally, we have also investigated how various stakeholders shape public perception by comprehending how specific aspects are associated with stakeholder groups according to timely crisis evolution. For this purpose, Fig. 6 shows the frequency of positive and negative aspects and how the spike or fall in aspect frequency of certain sentiment can be

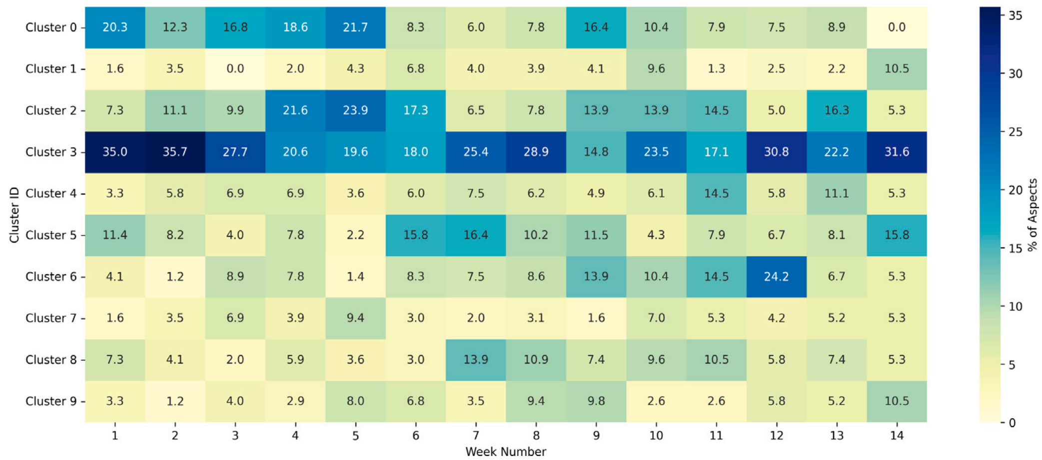


(a) Summary of Positive Aspects Clusters

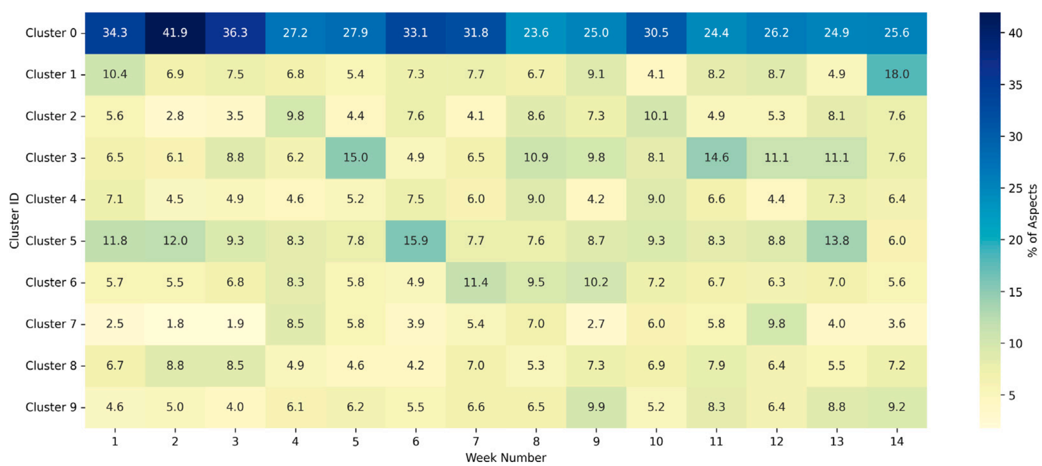


(b) Summary of Negative Aspects Clusters

Fig. 4. Summary of aspects clusters: (a) Positive aspects, (b) Negative aspects.



(a) Positive Aspect Cluster Weekly Distribution



(b) Negative Aspect Cluster Weekly Distribution

Fig. 5. Weekly distribution of aspect clusters: (a) Positive clusters, (b) Negative clusters.

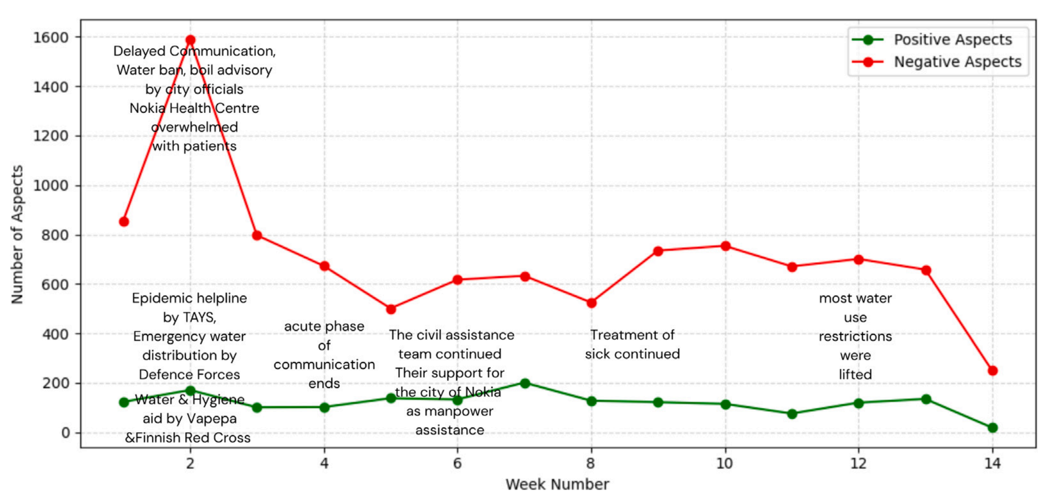


Fig. 6. Aspect frequency mapped with stakeholder actions.

triggered by stakeholder actions. In the initial phase (Week 1–2), negative sentiment surged as the public grappled with contaminated water, health risks, and institutional failures, and anxiety was exacerbated by fragmented and delayed crisis communication. As the crisis intensified in Week 2 with a citywide water ban and overwhelmed health services, illness-related fears deepened. However, limited positive sentiment began to emerge with the launch of the epidemic helpline and the commencement of emergency water distribution. Notably, the visible involvement of the Finnish Defence Forces and the Red Cross sparked trust and appreciation, reflected in positive clusters focused on hygiene and clean water access.

During the mid-crisis phase (Weeks 3–8), public sentiment gradually stabilized as the support from various stakeholder groups, such as the Finnish Defence Forces and other authorities, continued, and people were getting treated, though underlying negativity persisted due to continued health issues and inconsistent messaging. After Week 8, a very small increase in negativity could be related to some revelation in public discussions, because no stakeholder action was taken during this period, so it could not be a response to some action. The final weeks showed a slight return to optimism, driven by the lifting of water use restrictions and institutional reforms, though lingering resentment remained. Overall, the public reaction followed a three-phase emotional trajectory: initial panic and outrage, followed by cautious adaptation (with steady positive and negative sentiment), and concluding with post-crisis reflection. Key insights include the critical importance of timely and coordinated communication, the positive impact of visible stakeholder action and inter-organizational support, and the lasting reputational damage caused by early communication breakdowns and governance failures.

4.2. Media's role in crisis

The Nokia water crisis received relatively balanced media coverage, with only 21% (17 out of 89) of the articles showing apparent signs of bias. One of the most prominent bias types identified was sensationalism, evident in the use of dramatic phrases such as "Tampere is paralyzing" and "Homeland... in Fear of Water Disaster". While these were likely intended to convey urgency, they may have overstated the actual threat. Additionally, some articles used emotionally loaded language from interviewees, particularly references to "children", which can strongly influence readers by evoking protective instincts and heightened concern. Confirmation bias was another notable category, particularly visible in statements like: "An employee of a wastewater treatment plant who performed maintenance work at a water plant had inadvertently opened a valve that distinguishes wastewater and clean water". This framing may reflect an attempt to simplify the crisis by attributing blame to a single individual, rather than exploring broader systemic or infrastructural failures. Other forms of bias detected by the language model appeared less frequently and did not significantly shape the overall narrative. In conclusion, media reporting on the Nokia water crisis was largely neutral and responsible, with a strong focus on factual information and minimal use of emotional or political rhetoric. The limited presence of biased articles suggests that public perception was likely not heavily distorted and reflects a commendable level of journalistic integrity during the crisis. A detailed overview of the detected bias types is presented in Table 5.

A comparative analysis of different communication channels during the Nokia water crisis revealed that while online news media occasionally amplified risk perception through sensational or blame-oriented narratives, traditional media such as radio, television, and printed newspapers largely maintained an informative and corrective function. According to the official report [6], the first public announcements were made through radio and TV on 30 November 2007, followed by televised interviews and newspaper updates that increasingly focused on disseminating practical instructions. These outlets, though initially slow to react due to delayed official communication, gradually became critical in relaying verified information and supporting the authorities' public guidance efforts. In contrast, online community forums and local discussion spaces played a more spontaneous and emotional role by enabling peer-to-peer information exchange and public expression of concern.

5. Discussions

5.1. Answering research questions RQ1 and RQ2

The evolving communication efforts of different stakeholders had a visible influence on public perception throughout the crisis. In the early phase, delayed and fragmented communication from the municipality and the water utility contributed to confusion and distrust, reflected in heightened negative sentiment in public discussions. As coordinated communication began – through regular press briefings, epidemic helplines, and clear updates from the Defence Forces and the Red Cross – public anxiety gradually subsided, giving way to cautious optimism and expressions of trust. By the recovery phase, consistent and transparent messaging from health agencies and voluntary organizations helped restore a sense of credibility, even though residual skepticism toward municipal authorities persisted. Overall, this pattern demonstrates that credibility, timing, and empathy in communication were central to shaping the trajectory of public sentiment.

This study aimed to understand how public responses to the Nokia water contamination crisis evolved and how these responses may have been influenced by stakeholder actions and media coverage. The results show that during the early weeks of the crisis, public discourse was dominated by negative sentiment, particularly concerning water safety, health risks, and the lack of timely information. This aligns with the findings of Fakhruddin et al. [8], who emphasized the necessity of timely, trusted, and accessible communication in disaster management. These reactions intensified in the second week, when water bans and public health concerns peaked, supporting the study by Chatterjee et al. [9], who demonstrated that timely and tailored communication strategies can foster behavioral change and trust in authorities. Over time, as authorities began implementing recovery measures, such as launching an epidemic helpline, mobilizing the Finnish Defence Forces, and organizing emergency water distribution, some positive sentiment started to emerge. The shift from panic and distrust to cautious optimism parallels findings by Ezell and Chase [28], who observed that institutional mechanisms strongly shape public understanding and health-related anxieties during crises. Similarly, our findings reinforce Logan [22], who emphasized that once public officials fail to safeguard community health, trust restoration becomes extremely difficult—something reflected in the persistent negative sentiment even after stakeholder action began.

Additionally, the results align with Tevapitak and Helmsing [29], who argued that no single stakeholder can manage environmental crises alone, and that collaboration is crucial. In Nokia, improved sentiment was only noticed when multiple actors (municipality, health agencies, military) coordinated their responses. However, the continued presence of negative aspects, even during later phases, highlights a discrepancy between stakeholder action and public perception, echoing Safford et al. [30], who found dissatisfaction with both government and industry responses during the Deepwater Horizon oil spill. Overall, this study supports RQ1 by demonstrating that public sentiment was temporally dynamic and shaped by the visibility, transparency, and perceived effectiveness of stakeholder responses. The insights of Prasetyo et al. [12], who identified community participation and critical communication elements as central to effective disaster preparedness, highlight a missed opportunity in Nokia: had local authorities engaged citizens more actively in co-defining responsibilities, the process of restoring trust might have been faster and more robust.

The media analysis revealed a predominantly factual tone in the coverage, with only 21% of articles exhibiting bias. The identified

Table 5
Media bias in Nokia water crisis.

Bias Type	Text Showing Bias	Why it is Biased
Selection bias	“Shocking chlorine may not help”	Focus on the potential ineffectiveness of chlorine, neglecting potential benefits.
Loaded Language	“Parents of children who fell ill from tap water are outraged by the city of Nokia.”	Used words with strong implications to invoke an emotional response
Sensationalism	“reduces water supply acidity”, “Tampere is paralyzing”, “strong chlorine was counted”, “Homeland... in Fear of Water Disaster”	Exaggerating the severity of the situation emphasizing drama and fear rather than providing calm, factual information,
Confirmation bias	“Authorities say the chlorine was successful.”, “Noroviruses have not been found in studies completed on Friday.”, “An employee of a wastewater treatment plant who performed maintenance work at a water plant had inadvertently opened a valve that distinguishes wastewater and clean water.”, “Thousands of people call for the city’s economic difference.”	They emphasize reassuring information that supports a simple, controlled narrative, like chlorine successfully fixing the issue, no viruses found in limited tests, blaming the crisis on one employee’s mistake, or focusing on economic concerns, while downplaying or ignoring ongoing risks, broader problems, or contradictory evidence in the Nokia water crisis.
Source bias	“I have been harassed and harassed” said by Mayor of Nokia.	Focuses on the Mayor’s personal experience, shifting attention from the public impact.

few biased articles used dramatic headlines and emotionally charged language to drive engagement. Although limited in frequency, such a framing may have contributed to heightened public anxiety and oversimplified narratives about institutional failure. In particular, the disconnect between media tone and public sentiment mirrors findings by Panahi and Moayerian [5], who emphasized that informal networks and lived experiences often shape trust more than formal channels, especially in low-trust crisis contexts. The observation from the official report of the crisis [6], which revealed that people first learned about the incident through neighbors rather than official source also resonates with this. Thus, while media bias was present, it was not the dominant driver of public sentiment. These findings answer RQ2 by showing that peer-to-peer communication and institutional visibility were stronger influences on public perception than traditional media narratives.

Sensational headlines and emotionally charged words likely amplified anxiety during the early phase of the crisis, reinforcing perceptions of institutional incompetence. Confirmation bias, on the other hand, simplified accountability by attributing fault to individual actors rather than systemic or procedural shortcomings, potentially diverting public attention from deeper infrastructural issues. Comparative evidence from the official report further highlights that while online news occasionally magnified emotional responses, traditional broadcast media such as radio and television largely adopted an informative and corrective tone once official communication improved. This contrast shows how emotionally framed online narratives can escalate perceived risk and delay trust restoration, whereas factual and consistent reporting through traditional media supports recovery.

5.2. The role of media and crisis communication through the lens of SCCT

Situational Crisis Communication Theory (SCCT) [52] offers a structured foundation for interpreting how communication failures and subsequent recovery efforts influenced public sentiment during the Nokia water contamination crisis. According to SCCT, effective crisis management involves three stages of communication: *instructing information* (guiding public safety), *adjusting information* (expressing concern and empathy), and *rebuilding* (taking responsibility and restoring trust). The municipality’s initial delay in issuing clear warnings represented a breakdown in the instructing phase, leaving citizens dependent on informal channels. Indeed, the official report [6] indicates that many residents first received information about the crisis three days later, on 30 November 2007, primarily through neighbors rather than official announcements or news outlets. This communication gap influenced general public negativity, consistent with SCCT’s prediction that perceived negligence heightens reputational threat and emotional volatility.

The media seemed to have played a dual role: amplifying anxiety through biased framing of contamination and health risks, and also stabilizing discourse by circulating verified updates and health guidance that corresponded to SCCT’s rebuilding phase, where consistent corrective messaging from health agencies and municipal authorities gradually mitigated negativity.

Linking SCCT with media framing thus reveals how communication timing and tone directly shaped the emotional trajectory observed in our sentiment analysis. The initial absence of authoritative instructing communication produced spikes in negativity, while the emergence of empathetic and accountable messages during the rebuilding phase coincided with more neutral and adaptive expressions. This alignment underscores that crisis communication effectiveness depends not only on message accuracy but also on *when*, *through which channels*, and *in what emotional frame* information reaches the public.

5.3. Interpreting sentiment shifts through psychological frameworks

From, a psychological perspective, the sharp rise of negative sentiment during the acute phase, followed by a drastic decrease and emergence of cautious optimism in the recovery period, reflects the processes described by cognitive appraisal theory [53]. According to this theory, individuals’ emotional responses are guided by two types of cognitive evaluations: primary appraisals, which assess the severity and immediacy of the threat, and secondary appraisals, which evaluate coping resources and perceived control. In the early phase of the Nokia crisis, negative sentiment dominated as people perceived high threat and low control, interpreting the event as a failure of institutional responsibility. As recovery actions and transparent updates were introduced, the public’s appraisal shifted toward increased coping efficacy, resulting in a decline in negativity and gradual restoration of trust.

This shift also aligns with risk perception theory [54], which emphasizes that risk is not evaluated purely on objective hazard but on subjective factors such as trust in authorities, voluntariness, and familiarity. When trust is low, perceived risk and emotional distress intensify; conversely, consistent and credible communication can reduce perceived risk even if the objective threat remains. Thus, the observed sentiment trajectory – from intense negativity to cautious optimism – captures how evolving perceptions of control and institutional credibility shaped public emotion and sentiment during the crisis.

5.4. Advancing previous research

The only comprehensive prior research analyzing the Nokia water crisis from the perspective of public discourse was conducted by the Finnish Institute of Occupational Health in collaboration with the University of Helsinki's Communication Research Centre, as mentioned in the Crisis report [6]. That study focused primarily on official crisis communication, stakeholder coordination, and media coverage. It acknowledged the growing role of digital forums and community platforms as spaces for information exchange and emotional support, but it did not conduct an empirical, time-sensitive analysis of public sentiment or systematically extract themes from citizen-generated content. This current study builds upon and significantly extends the scope of that earlier work. By analyzing sentiment-labeled aspects and clustering thousands of public comments, offering a data-driven understanding of how citizens responded emotionally and cognitively over the course of the crisis. In doing so, it complements the previous institutional focus by centering public voices, mapping how they evolved, what concerns they raised, and how these concerns aligned with or diverged from stakeholder actions. Furthermore, the introduction of heatmaps and aspect overlap analysis provides a novel visual framework to trace emotional shifts and thematic transitions over time, adding a level of granularity not previously present in the literature.

These methods complement recent work by Wahid et al. [23] and Shaik and Oussalah [25], who also employed sentiment analysis and NLP to extract real-time insights during crises, albeit in different contexts (natural disasters, mobile apps). However, unlike their focus on technical implementation, this study places stronger emphasis on temporal dynamics and the sociopolitical implications of public discourse.

5.5. Practical implications

The findings of this study provide various practical insights for improving crisis communication and stakeholder coordination. First, the early spike in negative sentiment highlights the critical importance of timely, clear, and coordinated communication. Second, public comments and online discourse serve as valuable real-time indicators of citizen needs, emotional states, and trust levels tools that authorities can use to adjust communication strategies dynamically. Third, the rise in positive sentiment clusters following the involvement of visible and credible actors like the Finnish Defence Forces and the Red Cross underscores the trust-building power of coordinated stakeholder action. Moreover, the coexistence of both positive and negative sentiment around similar themes, such as water supply and government response, suggests that public perception is complex and emotionally layered. This requires communication strategies that are not only factual but also emotionally nuanced. While the media did not appear to significantly shape public sentiment overall, care should still be taken to avoid sensationalism and emotionally manipulative framing, as even limited bias can have a lasting impact on public trust and political accountability. These findings align with best practices in crisis communication literature while contributing empirically grounded, community-driven insights. For future crisis preparedness, integrating real-time sentiment analysis and aspect-based public discourse monitoring can help build more responsive and resilient communication frameworks.

5.6. Limitations

Although our study provides valuable insights into crisis communication and public perception, certain limitations should be acknowledged to guide future improvements. Firstly, the analysis of Nokia's water crisis faced inherent challenges due to Finnish being a low-resource and morphologically complex language. Most pretrained large language models, including those used in this study, are primarily optimized for English or high-resource languages, which can limit contextual accuracy when applied to Finnish. Automated translation was employed to enhance compatibility with instruction-tuned models, yet this process may introduce semantic drift—especially for idiomatic expressions or crisis-related terminology. To mitigate this, translated

Table A.6
Hyper-parameters used for model fine-tuning InstructABSA.

Parameter	Value
`output_dir`	*model_out_path*
`evaluation_strategy`	`epoch`
`learning_rate`	5×10^{-5}
`lr_scheduler_type`	`cosine`
`per_device_train_batch_size`	8
`per_device_eval_batch_size`	16
`num_train_epochs`	4
`weight_decay`	0.01
`warmup_ratio`	0.10
`save_strategy`	`no`
`load_best_model_at_end`	`False`
`push_to_hub`	`False`
`eval_accumulation_steps`	1
`predict_with_generate`	`True`
`use_mps_device`	*use_mps*

Table B.7
Overlapping positive and negative aspects each week.

Week	Overlapping Aspects (Positive and Negative)
1	'bottled water distribution', 'electricity consumption', 'hair', 'nokia', 'oxygen', 'water', 'water cleanliness', 'water plant', 'water quality', 'water safety', 'water supply', 'water system', 'water treatment', 'water usage'
2	'antibiotics', 'bottled water', 'brainjas', 'city of nokia', 'clean water', 'color', 'results', 'situation', 'system', 'wastewater', 'water', 'water cleanliness', 'water flow', 'water quality', 'water safety', 'water supply', 'water usage'
3	'groundwater', 'information', 'nokia missio', 'nokia mission', 'pregnancy', 'water', 'water consumption', 'water quality', 'water safety'
4	'air–water heat pumps', 'drinking water', 'heating', 'pump', 'temperature', 'treatment', 'water', 'water consumption', 'water quality', 'weight loss'
5	'birth', 'city', 'contractions', 'government', 'heat', 'pain relief', 'water', 'water distribution', 'water quality', 'water safety', 'water supply', 'weight loss'
6	'baby', 'electricity', 'nokia', 'water', 'water intake', 'water quality', 'water supply network', 'weight', 'weight loss'
7	'chocolate', 'food intake', 'food quality', 'insulation', 'nokia', 'residents', 'treatment', 'water', 'water circulation', 'water flow', 'water intake', 'water quality', 'water safety', 'water treatment', 'weight loss'
8	'city roof', 'diet', 'electricity', 'electricity generation', 'energy', 'energy consumption', 'food', 'food intake', 'pipes', 'salt', 'skin', 'water', 'water consumption', 'water quality', 'water safety', 'water temperature', 'water usage', 'weight loss'
9	'baby growth', 'calories', 'electricity production', 'energy', 'exercise', 'heating', 'installation', 'reading', 'water', 'water delivery', 'water flow', 'water quality', 'water usage', 'weight loss'
10	'diet', 'energy', 'food', 'groundwater', 'joints', 'life', 'sleep', 'water', 'water intake', 'water quality'
11	'electricity consumption', 'heat', 'hydropower potential', 'medication', 's.ach', 'water', 'water quality', 'water supply', 'weight loss'
12	'bottled water', 'electricity', 'food', 'surgery', 'tap water', 'vitamin c', 'water', 'water consumption', 'water distribution', 'water problems', 'water quality', 'weight loss'
13	'body', 'hydropower', 'medicine', 'nuclear power plants', 'walking', 'water', 'water quality', 'water safety'
14	'water', 'water quality'

Table B.8
Positive aspects clusters.

Cluster	Random Aspects (Positive)
0	'Nokia reputation', 'raw water quality puzzles revealed by new studies', 'city of Nokia', 'public information', 'official response', 'community involvement', 'director of the plant', 'investigation request', 'research', 'city development'
1	'fresh food', 'fresh juices', 'fish', 'drinks', 'juice content', 'organic wines', 'fruit consumption', 'diet', 'Nokia beer', 'food safety'
2	'hand hygiene', 'hygiene passport', 'sick people', 'doctor's advice', 'nurse', 'weight loss', 'fitness', 'healthy lifestyles', 'comfort', 'healing promises'
3	'Nokia's water disaster', 'water contamination', 'drinking water', 'raw water quality', 'clean water', 'water purification', 'water treatment plant', 'water supply network', 'water testing', 'water quality'
4	'heat pump', 'water-circulating floor heating', 'pipes', 'installation', 'floor heating', 'boiler', 'condensation insulation', 'temperature', 'ventilation', 'ground heat'
5	'Nokia employee', 'insurance', 'environmental permit conditions', 'emergency response', 'health', 'public transport', 'government', 'economic efficiency', 'recovery', 'public transportation'
6	'pipeline repair', 'energy supply', 'renewable energy', 'energy consumption', 'hydropower', 'electricity production', 'heat energy', 'heating', 'energy recovery', 'nuclear energy'
7	'wastewater', 'wastewater results', 'groundwater', 'filter exchange', 'wastewater management', 'wastewater cleaning', 'wastewater cleanliness', 'chemical recycling', 'sewer plant', 'water soluble medicines'
8	'treatment', 'diagnosis', 'healing', 'medicine', 'emergency bullet', 'hygiene', 'antibiotics', 'vaccine', 'surgery', 'doctorzide drug'
9	'well-being', 'vitamin intake', 'vitamin supplements', 'purity', 'cleanliness', 'vitamin C', 'hormones', 'epidural', 'homeopathic remedies', 'water:soluble vitamins'

Table B.9
Negative aspects clusters.

Cluster	Random Aspects (Negative)
0	'Nokia water crisis', 'contaminated Nokia water', 'drinking water', 'water purification', 'clean water', 'water contamination', 'tap water', 'water distribution', 'water supply', 'Nokia water problem'
1	'indirect damage to the water supply facility', 'water department apology', 'nokia authorities', 'Department of the Environment', 'wastewater entering the public network', 'city councilors', 'city officials', 'city of Nokia', 'city responsibility', 'municipality'
2	'wastewater fees', 'waste management', 'wastewater usage fee', 'water usage fee', 'cost of sewage', 'municipality economy', 'energy consumption', 'repair costs', 'public healthcare', 'financial problems'
3	'salmonella', 'cholera', 'diarrhea', 'intestinal infection', 'parasites', 'fever and vomiting', 'water vaccine virus', 'virus contamination', 'gut infections', 'infection risk'
4	'dirty water tower', 'toilet', 'pipe passage', 'rust pipes', 'contaminated room', 'toilet poison', 'mold exposure', 'sewer episode', 'dust spread', 'chloring and rinsing'
5	'Nokia contamination', 'wastewater contamination', 'groundwater contamination', 'nokia water plant', 'pipeline contamination', 'sewer', 'pollution', 'sewage', 'wastewater treatment plant', 'municipal sewage'
6	'pain and anxiety', 'health effects of water', 'environmental damage', 'child health', 'disease state', 'drinking difficulties', 'health risks', 'chlorine treatment', 'hospital capacity', 'symptoms of cambylobacter'
7	'food contamination', 'toxic substance', 'pharmaceutical residues', 'poison', 'chlorine content', 'urine contamination', 'drug residues', 'feed contamination', 'vitamin deficiencies', 'water:soluble substances'
8	'officials', 'Nokia crisis', 'government responsibility', 'crisis communication', 'legal responsibility for officials', 'official response', 'political pressure', 'government actions', 'responsible parties', 'information failures'
9	'contaminated tms', 'norovirus', 'chlorination', 'toxins', 'microbial content', 'wastewaters', 'stormwater', 'decision-makers', 'faucets', 'overflow'

samples were manually reviewed to ensure consistency of meaning, but minor shifts in nuance may persist. Future research could address these limitations by fine-tuning multilingual or Finnish-specific models such as FinBERT or TurkuNLP to improve native language representation. In addition, the scarcity of available data, stemming from the crisis's relatively short duration and localized impact, constrained corpus size and diversity. While the study analyzed a substantial amount of text, a larger multilingual dataset would likely strengthen generalizability and enable deeper cross-cultural comparisons in crisis discourse.

6. Conclusion

This study used Natural Language Processing (NLP) methods and Large Language Models (LLMs) to analyze public sentiment, stakeholder communication, and media coverage for a water contamination event happened in Nokia, Finland in November 2007. By combining Aspect-Based Sentiment Analysis (ABSA), Word embeddings, Clustering, and media bias detection, we explored how different organizations and individuals were perceived throughout the crisis. Findings show that public sentiment was initially dominated by fear, distrust, and frustration, especially during the early weeks marked by health risks and delayed communication. Over time, the emergence of visible recovery efforts, such as the deployment of the Defence Forces and emergency water distribution, helped shift discourse toward cautious optimism. Public perception proved to be responsive to the timing and transparency of institutional action. While media coverage remained mostly neutral, it might had limited influence on public sentiment, which appeared to be shaped more by lived experience and peer-to-peer communication. This is consistent with the official report of the crisis, indicating that most people first learned about the crisis through neighbors rather than through traditional media.

Compared to the prior study that focused on institutional communication, this research offers a more citizen-centered, data-driven perspective by analyzing thousands of public comments across time. It introduces a novel method, aspect-based sentiment clustering, and heatmap visualization to track emotional shifts and key concerns. The coexistence of positive and negative sentiment around shared themes like water supply and government response highlights the need for emotionally nuanced communication strategies. These insights align with existing crisis communication literature while advancing it with empirical depth. Importantly, they underscore the value of real-time sentiment monitoring as a feedback mechanism during crises. By incorporating public discourse analysis into preparedness and response planning, authorities can build more adaptive, trust-centered communication frameworks.

The limitations highlight a critical area for developing high-performing NLP models for low-resource languages, such as Finnish, or for exploring advanced cross-lingual methodologies. Such developments would enable a more comprehensive analysis, thereby minimizing information loss and translation artifacts that can distort interpretations of sentiments. Expanding the scope of analysis by including other platforms, such as X and Facebook, can provide a more comprehensive view of the public reaction and how platform-specific dynamics influence the discourse surrounding the crisis. Working on these areas will strongly improve the research framework and impact of research into public responses during these crisis events.

Abbreviations

ABSA	Aspect-Based Sentiment Analysis
AI	Artificial Intelligence
BERT	Bidirectional Encoder Representations from Transformers
COVID-19	Coronavirus Disease 2019
LLM	Large Language Model
PLM	pre-trained language models
PSHP	Pirkanmaa Hospital District
TAYS	Tampere University Hospital
NLP	Natural Language Processing

CRediT authorship contribution statement

Vishal Kumar: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis. **Frank Hopfgartner:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis. **Pekka M. Rossi:** Writing – review & editing, Funding acquisition, Data curation. **Mourad Oussalah:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Funding acquisition, Formal analysis, Conceptualization.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to refine the text. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. LLM prompts & fine-tuning parameters

This section presents the structure of the LLM prompt used in this study, and also describes the fine-tuning parameters applied to train our InstructABSA model for the Aspect-Based Sentiment Analysis (ABSA) task.

Zero-Shot Topic Modeling

Analyze each comment and categorize it into broad, meaningful topics. Avoid overly narrow topics and keep the number of categories small but relevant. Assign each comment a clear topic label in a maximum of two words, with no explanation.

Text to Analyze:
[Insert Text Here]
Output Topic:

Bias Detection

Analyze the following text for potential bias. If bias is detected, extract and provide only the specific biased statement without any explanation.

Text to Analyze:
[Insert Text Here]
Output (Biased Statement):

Aspect-Based Sentiment Analysis Prompt

Task: Extract all aspects mentioned in the following text related to a water contamination event, and identify their sentiment as positive, negative, or neutral. Return the result in the format: `aspect - sentiment`.
Examples:
Input: "The water smells strange and tastes metallic."
Output:
```
smell - negative
taste - negative
```

Input: "The response team acted quickly, but communication with the public was poor."
Output:
```
response time - positive
public communication - negative
```

Input: "Residents appreciated the free bottled water distribution."
Output:
```
bottled water distribution - positive
```

Input: "Contamination levels remain dangerously high despite efforts to clean the supply."
Output:
```
contamination levels - negative
cleanup efforts - neutral
```

Input: "Officials were transparent about the risks and regularly updated the community."
Output:
```
official transparency - positive
community updates - positive
```

Input: "There was no clear plan for long-term water safety."
Output:
```
long-term water safety planning - negative
```

Instructions: Read the text below and output only with aspect and sentiment without any explanation or additional text.
Text to Analyze:
[Insert Text Here]
Output:

Table A.6 shows the Hyper-Parameters used for fine-tuning the model for the Aspect-Based Sentiment Analysis task.

Appendix B. Aspect tables

See Tables B.7–B.9.

Data availability

Data will be made available on request.

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