

# Save It for the “Hot” Day: An LLM-Empowered Visual Analytics System for Heat Risk Management

Haobo Li, Wong Kam-Kwai, Yan Luo, Juntong Chen, Chengzhong Liu,  
Yaxuan Zhang, Alexis Kai Hon Lau, Huamin Qu, Dongyu Liu

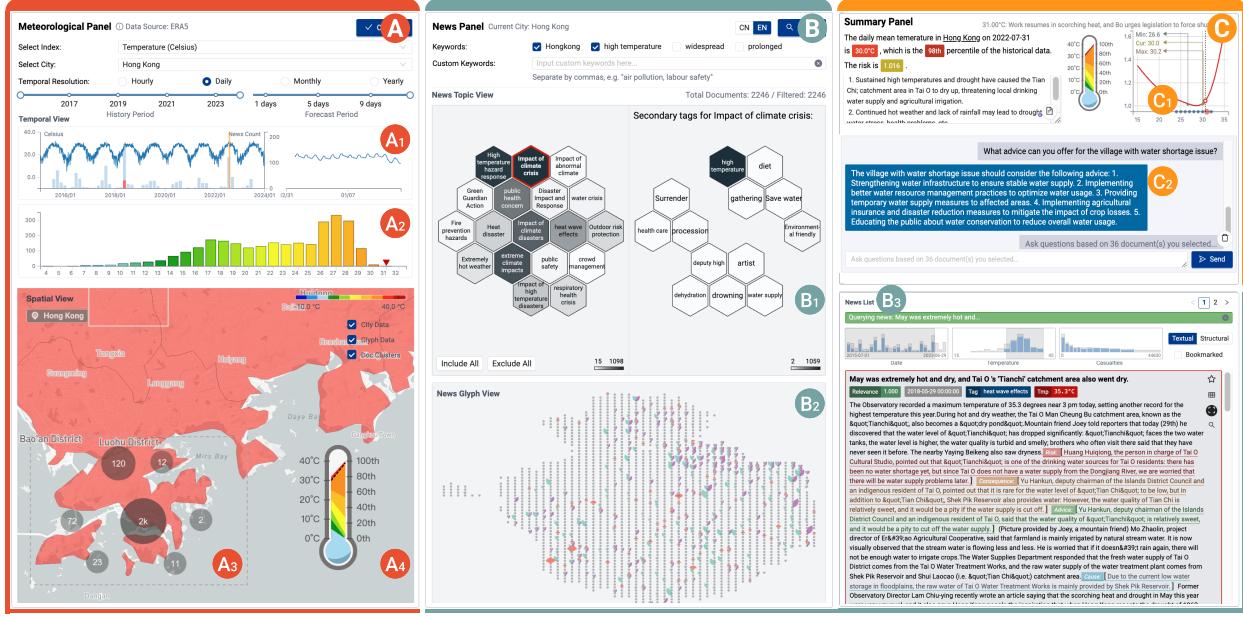


Fig. 1: The interface of *Havior* (Heat Savior). The Meteorological Panel (A) facilitates numerical understanding of meteorology, including temporal trends (A1), temporal distribution (A2), and spatial distribution (A3). The “thermoglyph” of Hong Kong (A4) intuitively shows the city-based pattern and correlation between temperature and percentile. The News Panel (B) supports human-in-the-loop news retrieval and enhancement in their semantic understanding, in terms of topic-based hierarchies (B1) and risk-based semantic proximity (B2) of retrieved news. The News List (B3) provides details of structural information in the retrieved news on demand with supportive visual cues. The Summary Panel (C) enables experts to examine the integration of news and numeric city risk model (C1), pose contextual questions (C2), and generate risk management reports.

**Abstract**— The escalating frequency and intensity of heat-related climate events, particularly heatwaves, emphasize the pressing need for advanced heat risk management strategies. Current approaches, primarily relying on numerical models, face challenges in spatial-temporal resolution and in capturing the dynamic interplay of environmental, social, and behavioral factors affecting heat risks. This has led to difficulties in translating risk assessments into effective mitigation actions. Recognizing these problems, we introduce a novel approach leveraging the burgeoning capabilities of Large Language Models (LLMs) to extract rich and contextual insights from news reports. We hence propose an LLM-empowered visual analytics system, *Havior*, that integrates the precise, data-driven insights of numerical models with nuanced news report information. This hybrid approach enables a more comprehensive assessment of heat risks and better identification, assessment, and mitigation of heat-related threats. The system incorporates novel visualization designs, such as “thermoglyph” and news glyph, enhancing intuitive understanding and analysis of heat risks. The integration of LLM-based techniques also enables advanced information retrieval and semantic knowledge extraction that can be guided by experts’ analytics needs. Our case studies on two cities that faced significant heatwave events and interviews with five experts have demonstrated the usefulness of our system in providing in-depth and actionable insights for heat risk management.

**Index Terms**—Heat risk management, climate change, numerical model, news data, large language model, visual analytics

## 1 INTRODUCTION

- H. Li, W. Kam-Kwai, C. Liu, Y. Luo, and H. Qu are with Department of Computer Science and Engineering of HKUST. Email: [hllem@ust.hk](mailto:hllem@ust.hk), [kkwongar@connect.ust.hk](mailto:kkwongar@connect.ust.hk) and [huamin@cse.ust.hk](mailto:huamin@cse.ust.hk).
- J. Chen is with School of Computer Science and Technology of ECNU. Email: [jtchen@stu.ecnu.edu.cn](mailto:jtchen@stu.ecnu.edu.cn).
- Y. Zhang and Alexis K. H. Lau are with Division of Environment and Sustainability of HKUST. Email: [yzhangkl@connect.ust.hk](mailto:yzhangkl@connect.ust.hk) and [alau@ust.hk](mailto:alau@ust.hk).

Extreme climate events [1], particularly those related to heat [27], have seen a marked increase in intensity, frequency, and duration in recent

- D. Liu is with Department of Computer Science of UC Davis Email: [dyliu@ucdavis.edu](mailto:dyliu@ucdavis.edu)

Manuscript received xx xxx. 201x; accepted xx xxx. 201x. Date of Publication xx xxx. 201x; date of current version xx xxx. 201x. For information on obtaining reprints of this article, please send e-mail to: [reprints@ieee.org](mailto:reprints@ieee.org). Digital Object Identifier: xx.xxxx/TVCG.201x.xxxxxxx

years, raising significant concerns globally. NASA has confirmed 2023 as the warmest year on record. Heat risks are associated with excess mortality due to temperatures above long-term averages during summer and specific extreme events like heatwaves [13]. The adverse impacts extend beyond personal health, as reduced workforce productivity is observed due to heat-related health issues among employees [48]. They can further cause severe damage to critical infrastructure, including buildings, power grids, roads, and rail lines, leading to disruptions in daily life and economic activities [41].

Developing effective strategies for heat risk management, therefore, becomes increasingly urgent. This typically involves three parts: identifying the extreme climate event, assessing the associated risk levels, and determining the actions to mitigate the adverse effects of such events [32, 58], such as issuing a severe heat warning or enforcing heat-specific workplace standards. However, this is not a trivial decision-making task as it requires a comprehensive understanding of the complex interplay between various factors, including meteorological, urbanization, demographic, and socioeconomic factors [13, 24, 62].

To assess the risk levels of heat-related extreme events, numerical models are dominantly used by environmental researchers [62, 64, 69]. However, they are limited in three aspects. Firstly, their sparse spatial and temporal resolution offers insufficient data-driven support for effective risk management. For instance, the fifth-generation reanalysis (ERA5) data [22], one of the most used domain data, yields only one estimate for an area spanning approximately  $27.75 \times 27.75 \text{ km}^2$  per hour. This coarse-grained resolution can only predict normalized results and overlook extreme conditions. Secondly, these approaches aim to predict meteorological variables (*e.g.*, temperature and humidity), failing to capture the complex risk dynamics involving human behaviors and social factors [53]. Thirdly, the preparedness and response of society to the risk and the instructions for citizens are absent.

Analyzing news articles about environmental issues is of high potential to let decision-makers have the knowledge and means to develop more effective preventive measures. News articles complement numerical models by describing extreme situations in detail, documenting the cause and consequences, and discussing city responses and specific advice [52] for handling heat-related events. This information offers retrospective evaluations of management strategies that experts can utilize to refine their approach. However, it is unclear how to systematically integrate the heterogeneous data types (textual news and numerical models) for consistent and insightful analysis.

The emergence of LLM offers a new opportunity to address the integration. We explore how LLMs can be utilized to retrieve relevant news, extract structural information, and summarize knowledge to facilitate actionable strategies. They have demonstrated abilities from information extraction [12] to question answering and even document retrieval [44]. Despite these strengths, integrating environmental news into heat risk management encounters technical challenges: First, the overwhelming volume of available news articles challenges the token limit of LLMs, affecting the efficiency of retrieval; Second, the task of leveraging LLMs to derive meaningful insights from a large corpus of news on heat risks remains largely unexplored; Third, the difficulty of fusing information from varied sources, such as numerical data and textual news, poses a barrier to obtaining a holistic view of heat risks, further complicated by the heterogeneous nature of these data sources.

To address those challenges, we implement *Havior* (Heat Savior), an LLM-empowered visual analytics system that integrates numerical data and textual news for heat risk management. *Havior* provides a novel “thermoglyph” design that utilizes metaphorical representations to enhance experts’ comprehension of meteorological conditions. *Havior* aims to support experts in efficiently retrieving, managing, and navigating a large volume of news articles within a human-in-the-loop retrieval process through hex bin visualizations of topics and news glyphs. To distill the news’ semantic meaning, *Havior* employs LLM, including prompt engineering and retrieval augmented generation (RAG) [37], to extract structural information and semantic understanding from the news articles. By combining the strengths of numerical models and the rich contexts from news articles, *Havior* empowers stakeholders to make informed decisions and take proactive measures to mitigate the

impacts of heat risks. This paper has the following contributions:

- ◊ A detailed analysis of heat risk management, identifying key goals and requirements for design considerations.
- ◊ A novel LLM-empowered pipeline, including the incorporation of RAG, that supports human-in-the-loop retrieval and heterogeneous data alignment in the context of heat risk management.
- ◊ A VA system, *Havior*, features “thermoglyph”, news glyphs, and visualization of hex bins, allowing experts to explore and visualize heat risk insights interactively. We implement *Havior* through an open-source prototype system<sup>1</sup>.
- ◊ Two case studies and expert interviews to demonstrate the effectiveness of *Havior*, showing that useful insights can be obtained by integrating numerical and textual data.

## 2 RELATED WORK

### 2.1 Visualizing Climate Risk

Climate risk is commonly defined as the “effect of uncertainty on objectives” [31], quantified by the probability and impact of hazards such as landslides, flooding [54, 57], and wildfires [7]. Meteorological visualization research primarily focuses on displaying and analyzing *weather simulation data* [4, 30, 43, 51] to derive insights for mitigating these hazards. However, existing tools often lack the necessary granularity to address the spatial-temporal complexity of meteorological predictions with adequate explanations [8]. Several visual analytics systems [10, 38, 47, 60] have thereby emerged to explore the multifaceted spatial-temporal dynamics between meteorological variables.

However, the analysis of *anthropogenic* factors, *i.e.*, human-induced causes of climate change, remains under-explored [43, 45]. An illustrative example is the dependency on air conditioning during heatwaves. While essential for coping with rising temperatures, it in turn contributes to climate change and triggers surges in energy consumption, stressing power grids and amplifying the risk of grid failures. Existing simulations largely ignore these anthropogenic effects, indicating a significant research gap in managing climate risks. The approach we proposed integrates meteorological simulation results with risk-related news data to provide a novel perspective on anthropogenic factors, using news as a lens to magnify and segment the unstructured simulation data stream [29]. This fusion of quantitative simulations with contextual news analysis offers a logical interpretation of quantitative variables and empirical support for subjective narratives [28]. Our integrative visualization designs aim to navigate users through both quantitative and qualitative meteorological phenomena, enhancing data communication and decision-making in climate risk management. Specifically, the “thermoglyph” enhances users’ understanding of local climate conditions. The hex bin layouts for hierarchical tags and news glyphs provide a stratified analysis of heat risks with progressing details.

### 2.2 Mining Large Text Corpus

Over the past decade, text visualization has focused on microblog data, notably Tweets, recognizing its utility in providing real-time insights for disaster response. This data offers a direct glimpse of public sentiment evolution (*e.g.*, panic during disasters) through topic modeling techniques like Latent Dirichlet Allocation (LDA), facilitating rapid reactions to emergencies [57] and public expressions [65]. However, microblogs’ casual format and unstructured nature present significant challenges, often omitting necessary context for analyzing periodic events [6]. It revealed the tendency of such data to amplify biases, whether from frequent posters or through politicized viewpoints, thus limiting its scope for analyzing broader meteorological phenomena.

News articles are more reliable in monitoring natural disasters than microblogs [45]. They often highlight extreme situations, which is a desired property in analyzing heat risks, and provide in-depth descriptions of local conditions, consequences, and underlying reasons behind heat-related incidents. Authored by professionals, these articles are richer, more coherent, and less noisy in analytical discussions [52] (*e.g.*, expert opinions and suggested mitigation strategies) than microblogs to support retrospective evaluations of management strategies. However,

<sup>1</sup><https://anonymous.4open.science/r/Havior-C58D>

the inherent complexity in these documents requires heterogeneous data sources and advanced techniques for effective data structuring and interpretation [66–68]. Moreover, mapping news to specific climate events has traditionally relied on fuzzy logic [70] due to the differing detail levels between meteorological data and journalistic reporting.

To connect news with climate events, textual descriptions can align with geospatial visualizations for spatial context and information relevance. Direct references and visual cues within the text can enhance user engagement and understanding of geospatial context [25, 34–36]. Our approach draws inspiration from these design guidelines to maintain close interactions between text and geospatial visualizations. *Havior* extracts structured information from news by LLMs and highlights the key information with novel visual designs. These designs maintain a good balance between the geospatial context of numerical models and the semantic understanding of textual information.

### 2.3 Steering Documents Retrieval

One of the great challenges in text mining is to retrieve content of interest from a vast volume of document corpus [40]. Due to the ambiguity in natural languages, the retrieval intent can usually be satisfied by multiple similar filtering conditions. To steer the process of document retrieval, previous visual analytic systems have proposed solutions based on ranking [6], similarity [11], and removing overlaps [18]. However, they can easily ignore some topics of low frequency, which is not negligible in dealing with heat risk management. As news articles contain dense information, we employ a hexagon layout to maintain a tight arrangement while retaining text similarity relations with the neighborhood to further facilitate content-focused navigation.

With the retrieval results, further computational support should be provided to facilitate the goal of text mining. Recent advances in LLMs have demonstrated promise in summarizing large documents, as their pre-trained intelligence is suitable for a wide range of analytical tasks. Nevertheless, adapting LLMs to specific domain tasks requires massive computing resources. Efficient alternatives such as prompt engineering [15] are limited by token lengths, such that analyzing multiple documents at once remains a challenge. On the contrary, incorporating a question-based document retrieval system, DocFlow [50] allows for the intuitive searching of documents by posing questions in natural language, thereby enhancing both accessibility and search efficiency. Inspired by these approaches, we explore using RAG, a promising solution that incorporates knowledge from external databases. This approach is particularly effective in mitigating common challenges LLMs face, including creating fabricated content (hallucinations), reliance on outdated information, and the lack of transparent, traceable reasoning processes [16]. By profoundly integrating LLM for semantics analysis and retrieval of news, our approach enhances machine reasoning and human-in-the-loop visual analysis, fostering effective human-AI collaboration in addressing environmental threats.

## 3 DESIGN STUDY

Over the past year, our collaboration with two domain experts, **E1** and **E2**, through weekly meetings, has largely shaped the design of our system. **E1** is a professor in environmental science with more than thirty years of research experience, while **E2** is a specialist in the environmental domain with over four years of research experience.

Together, we have identified the limitations of numeric domain models. While these models offer quantitative analysis, they often fail to capture the full complexity of urbanization, demographics, and socio-economic factors essential for developing effective heat risk management strategies. We have collectively recognized the potential of news sources to bridge this gap. News provides a factual and direct post-event perspective, enabling a better understanding of the intricate interplay between these socio-demographic factors and the numerical data on heat risks. The central challenge we faced was integrating heterogeneous data sources, including various data types, to create a comprehensive and human-steerable decision-support pipeline. Through our year-long collaboration, we have distilled three overarching design goals and six specific design requirements guiding the development of *Havior*.

### 3.1 Design Goals

**G1: Early warning function for potential heat risks.** Given the increasing impact of climate change, the system should incorporate an early warning function that alerts experts to potential heat risks based on real-time data and historical trends, aiming to minimize losses. **E2** expressed, “*The system is only considered valuable if it can provide assistance in real-world scenarios.*”

**G2: Location-adaptive heat risk analysis.** Considering the diverse meteorological conditions of different regions, employing weather measurements is insufficient to support bespoke risk management strategies for specific locations. **E1** provides an example: The temperature 28° is observed at the 98.6th percentile in Beijing, indicating its rarity. However, the same temperature is only at the 75.4th percentile in Hong Kong, implying that the city has more endurance and preparedness for a higher temperature. Despite experiencing the same temperature in magnitude, the two cities have different temperature distributions, thus they have different preparedness and strategies. The magnitude-based metrics (temperature in this case) denote the meteorological condition at a time point, while probabilistic-based metrics (percentile) concern multiple measurements in a time period (location-adaptive). The two metrics should both be considered in heat risk analysis.

**G3: Leverage historical knowledge from news for risk comprehension and informed decision-making.** The system should empower experts to understand heat risks comprehensively and map its insights to the numeric domain model’s results. The insights include causes, potential consequences, actionable strategies for decision-makers, and appropriate guidance for citizens. **E1** warned, “*The 2003 European heatwave, a case often mentioned, resulted in numerous casualties due to a lack of preparedness and improper instructions. In the future, we will experience similar extreme summers, or even worse.*”

### 3.2 Design Requirements

We defined six requirements that are grouped into three categories: numeric understanding from climate data analysis, semantic understanding from news, and integration of them.

**R1: Numeric Analyze historical and future trends.** To achieve **G1**, the system should support historical analysis and future forecasting functions. Experts should be able to load and analyze numerical data of interest at different time points, allowing them to examine past trends and forecast future scenarios effectively.

**R2: Numeric Examine spatial meteorological conditions.** To reach **G2**, the system should enable the analysis of spatial patterns using familiar visualization forms and analytical methods for domain experts. Features such as spatial zoom in/out and the ability to switch between different variables should be provided to facilitate insights.

**R3: Semantic Support human-in-the-loop news retrieval.** To support **G3**, a multi-step retrieval approach should be developed to retrieve a suitable number of news that align with experts’ interests. **E1** and **E2** stated, “*There are tons of news for me. I need a system to retrieve an appropriate amount of news in different stages of analysis.*”

**R4: Semantic Enhance management and navigation among large-scale news.** To further support **G3**, with the retrieved news list, efficient management should allow experts to filter and rank news based on numeric and semantic criteria. An easy navigation way among a large amount of news and similar news should be facilitated.

**R5: Semantic Extract insights from heat-related news.** To address **G3**, the system should possess the abilities of structural information extracting, semantic understanding, and contextual question-answering to help experts gain semantic insights from heat-related news.

**R6: Integration Integrate numeric and semantic insights for decision-making.** For **G1**, **G2**, and **G3**, the system should integrate the figurative impact of news into the figures in the numeric model’s results to generate location-specific insights. **E1** explained, “*If you ask our numeric model how many people die, it has no answer since it only calculates some meteorological variables.*”

## 4 HAVIOR

In this paper, we develop a novel pipeline (Fig. 2) for *Havior* leveraging the burgeoning capabilities of LLM to integrate numerical data analysis and semantic understanding to enhance heat risk management.

### 4.1 Data Preprocessing

**Climate data** were obtained from the ERA5 reanalysis dataset [22]. Its utilization and performance in heat risk research have been widely acknowledged for its quality, long-term availability, and accessibility [39, 55]. The hourly data is from 2015 to 2023 and has a spatial resolution of approximately  $27.75\text{ km} \times 27.75\text{ km}$ . While it might seem intuitive to focus on daily temperature extremes (*e.g.*, max and min) to assess heat risks, studies have shown that *daily mean temperature* (hereinafter temperature) is more appropriate because it is more comprehensive in representing the day’s temperature exposure [20, 61]. The average of 24-hour (in hours UTC) temperatures within a day was utilized for the temperature for each location. Moreover, we adopt the Pangu-Weather [3] model with ERA5 temperature estimates to obtain temperature forecasts up to 14 days (Fig. 2-A3).

To contextualize magnitude-based metrics, we also incorporated probability-based indicators for a holistic analysis of heat risks.

- **Temperature percentiles** offer contexts into the local climatology of a specific region, enabling cross-regional and temporal comparisons [33]. This is particularly important when considering variations in local tolerance and preparedness levels [2].
- **Return period** is a statistical measure indicating the estimated average interval between the occurrence of heat events. This measure suggests the likelihood of a certain temperature threshold being exceeded at least once a year. It evaluates the frequency and intensity of heat events [32].

The **heat risk model** [17] examines the relationship between heat-related mortality and temperature fluctuations in 384 locations (Fig. 1-C1). The resulting patterns are often represented as “U” curves, with the temperature range associated with the lowest mortality called the Minimum Mortality Temperature (MMT). Deviations from the MMT are generally associated with an exponential increase in the relative risk. Since the local climate conditions (*e.g.*, tropical or temperate) have a strong influence on individual locations’ MMT, our analysis adopts the corresponding heat risk models for each city (Fig. 2-A4).

**Environmental news dataset** was obtained from Wisers [59], which consisted of 7.7 million environmental (not limited to heat) news articles from Chinese news publishers, mainly covering East Asian regions. The dataset spans from July 2015 to June 2023. Each news article contains the title, content, character statistics, publishing date, publisher, and media type. The media types encompass both web and publication resources while excluding internet-based media sources primarily reliant on aggregating news reports from official news agencies. We extracted structural information from news articles by using LLM (GPT3.5 [5]), including extracted information (*e.g.*, location, time, risk description, and consequence) and inferred information (*e.g.*, advice and tag) (Fig. 2-A1). This structural information was developed together with our domain experts (E1-2). The prompts and examples can be found in the supplementary material.

### 4.2 Interactive Risk Understanding Integration

#### 4.2.1 Numerical Climate Data Understanding

Experts can analyze the numerical climate data to gain a quantitative understanding of the risk (R1, R2). After the numerical data was processed by the method mentioned before and displayed in *numeric panel* (Fig. 1-A), experts can analyze both magnitude-based and probability-based indices for heat risk and identify heat hazards. Additionally, the temporal and spatial information of heat events can help interpret and understand meteorology. The extracted time and location from news sources are visualized in the *temporal view* and *spatial view*, respectively. Integrating this information with the climate data facilitates experts’ numerical understanding of heat risk, which was challenging in the experts’ original workflow. The interpretability and contextuality

it introduced for the result of the climate numerical model empower experts to gain deeper insights into meteorological conditions.

By examining the temporal trend (Fig. 2-B1), experts can identify noteworthy patterns and fluctuations in the meteorological variables and the occurrence of news events over time (R1). This analysis facilitates the detection of temporal correlations and the identification of significant events or trends within the meteorological context. Similarly, the spatial distribution of news events (Fig. 2-B2) provides valuable information regarding the geographical patterns and localized impacts of meteorological phenomena (R2). By visualizing the spatial distribution of news articles, experts can discern clusters, hotspots, or areas of interest, aiding in the identification of regions affected by specific weather conditions or events. Furthermore, we extract numerical temperature from the news. Then we choose news with the highest number of casualties across different temperatures (Fig. 1-C1), allowing us to provide semantic explanations for numerical risk levels. It transforms the risk level from a mere numerical value into a relatable example, enabling experts to develop a more intuitive grasp of heat risks.

#### 4.2.2 Topic Understanding & Context Analysis

Experts can utilize the dataset of environment-related news to gain a semantic understanding of the risk in the city’s context.

**Keywords retrieving** (Fig. 2-Ba). The first step is to retrieve highly relevant news using keywords (R3), such as “Hong Kong,” “prolonged,” and “high temperature,” and automatically filter the retrieved news using semantic meaning. These keywords can be automatically generated based on the numerical analysis results or suggested by experts who have analyzed the numerical data. For instance, a 97.5th percentile with  $\geq 4$  days duration [21] can lead to the inclusion of the keyword “heatwave.” The experts’ choice of cities can result in the inclusion of the keyword “city name.” To provide experts with the most relevant news, we use the “is heat risk” and “location” from structural information to automatically filter the news. In addition to the automated semantic filtering, we offer experts numeric filters based on the criteria of “time,” “temperature,” and “casualty,” which can be extracted from the news.

**Topic modeling** (Fig. 2-Bb). We harness the capabilities of LLMs to cluster tags (one item of structural information, Fig. 2-A1) to generate descriptive topics (R3, R4, R5). They are the concise summarization and categorization of the retrieved news, facilitating efficient analysis and management (Fig. 2-B3, Fig. 2-B4). Therefore, it serves two objectives: topic discovery and retrieval. Utilizing LLM, a wide range of comprehensive topics related to heat risk in the specific city can be identified. Experts can gain an overview of the heat risk landscape and uncover unexpected heat risk topics by exploring these identified topics. Since the number of news articles retrieved about a city often exceeds the experts’ capacity to effectively read and analyze, leveraging topics as a criterion enables them to filter the news effectively. Consequently, they can focus their attention on delving deep into specific topics.

**RAG** (Fig. 2-Bc). To continue enhancing the ability to delve into specific topics, we employ RAG to provide the ranking function based on semantic meaning (R4). Therefore, experts can use natural language (sentences or documents) to rank news (Fig. 2-B5). This is achieved by designating the retrieved news as the knowledge source and leveraging the semantic meaning to rank the news articles within this source through Embedchain [56]. This approach allows news that aligns closely with the experts’ interests to be prioritized and placed higher in the ranked list. Moreover, experts can pose contextual questions and get more accurate answers from LLM (Fig. 2-B6) by utilizing the retrieved news articles and the numeric results as the knowledge source (R5). This integration of news articles and numeric data broadens the scope of potential questions posed by experts.

#### 4.2.3 Heat Risk Management

*Havior* integrates two essential perspectives of analysis: numerical and semantic (R6) for heat risk management. On the one hand, the numerical analysis provides valuable insights into the quantitative aspects of the risk, offering a solid foundation for understanding the magnitude, trends, and patterns of heat risk. Its results are also utilized for subsequent tasks such as news retrieval, filtering, and comprehension. On

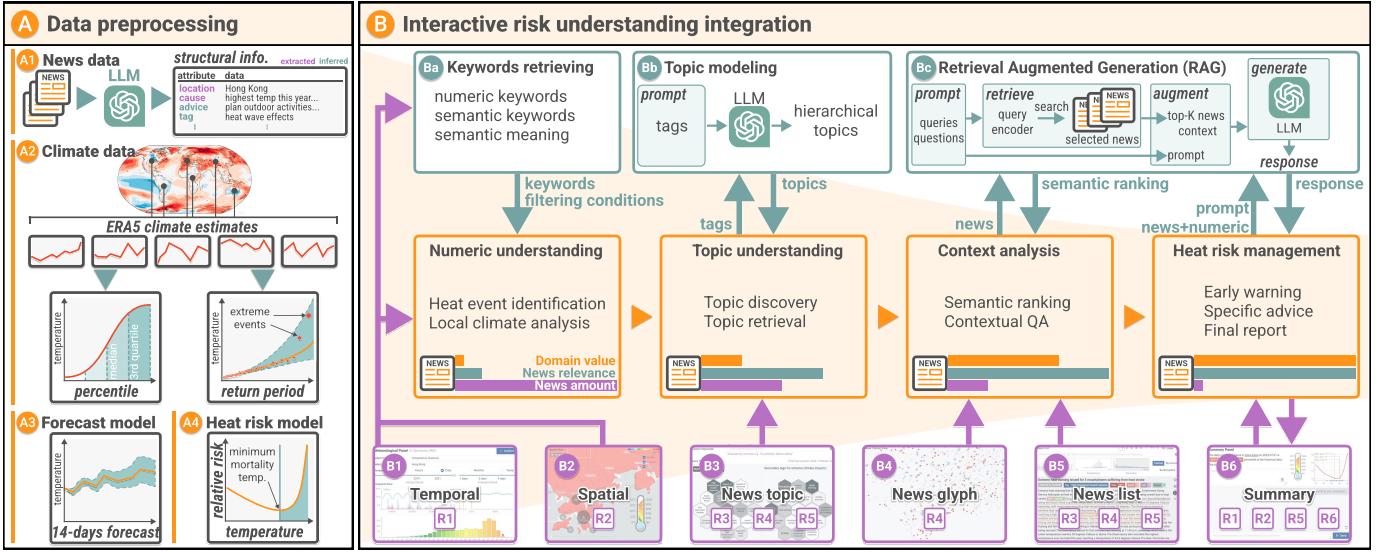


Fig. 2: The LLM-empowered pipeline contains two parts: data preprocessing (A) and interactive risk understanding integration (B). The data preprocessing involves extracting structural information using LLM (A1) and calculating climate indices (A2-4). In interactive risk understanding integration (B), heterogeneous understandings are integrated through keywords retrieving (Ba), topic modeling (Bb), and RAG (Bc). The interactive analysis process is supported by six views of *Havor* (B1-6) which fulfill the design requirements.

the other hand, the textual analysis retrieves, filters, clusters, ranks, and analyzes relevant news articles for an in-depth semantic understanding. This enables experts to delve deeply into the context, impacts, and complexities surrounding the risk. Moreover, these insights can assist experts in comprehending and explaining numerical meteorology. To summarize, the integration of numerical analysis and semantic understanding allows for a more nuanced assessment, enabling experts to identify potential correlations, causal relationships, and interdependences among various risk factors.

*Havor* provides a summary functionality (Fig. 2-B6) that assists experts in consolidating their insights, encompassing both numerical and semantic aspects. These insights, along with the numerical results, are analyzed using LLM. The analysis culminates in the generation of a comprehensive final report, which encompasses various elements such as meteorological conditions, descriptions of the heat risk scenario, historical events or disasters that have occurred, and corresponding advice for government entities to mitigate impacts or for citizens to address the risk. This final report serves as a valuable resource for facilitating informed and well-founded decision-making by experts, triggering more effective and rational risk management strategies. Decision-makers can develop proactive risk mitigation plans, allocate resources effectively, and implement targeted interventions to minimize the potential negative impacts on communities, economies, and the environment.

## 5 VISUAL DESIGN OF HAVOR

The interface of *Havor* is shown in the Fig. 1. To exemplify the connection between views in the interface, let us consider an expert (Zoe) utilizing *Havor* for heat risk research. Initially, to check the numerical meteorological condition, Zoe selects the index, city, and temporal resolution from the top menus of the *meteorological panel*. The temporal (R1) and spatial (R2) climate information is then displayed in the *temporal view* and *spatial view*, respectively. After gaining the numerical understanding, the next step involves exploring the semantic aspect. Zoe selects the recommended keywords or types the customized keywords (R3) in the top menus of the *news panel*. The *news topic* view displays topics of the retrieved news using hex bins. Zoe can make positive or negative selections of hex bins (R3, R4), resulting in different scatter plots in *news glyph* view and news lists in the *news list*. Zoe can easily locate news of interest with the assistance of *news glyph* view and delve into the structural information or full-text of news within the *news list* view (R4). The human-in-the-loop retrieval process and the contextual in the *news panel* question-answering interface in the *sum-*

*mary panel* can help her understand heat-related news (R5). Moreover, insights or knowledge that experts wish to summarize for subsequent reviewing or report generation (R6) for decision-making can be pinned to the *summary panel*. With the integration of numerical results, *Havor* is able to generate an informative report for decision-making.

### 5.1 Temporal View

The *temporal view* (Fig. 1-A1) is for experts to understand the temporal trends and distribution of meteorological variables (R1). Considering the history period (2015-2023) is typically much longer than the future forecasting period (14 days), line charts for historical and future data are on the same y-axis, but they are separated on the x-axis. This separation helps experts distinguish between the known historical data and the projected future data. To zoom in on a particular timeframe, experts can drag the node of start or end (2017, 2019, 2021, 2023).

Furthermore, they need to explore the temporal relationship between trends and the volume of news related to these parameters (R6). We use the bar chart (Fig. 1-A1) to show the number of news articles published. To save space and easily comparison between the relative magnitudes of changes in both meteorological data and news volume over time, we combine the bar chart and the line chart with the dual y-axis with both y-axes beginning from zero. This design helps in maintaining a visual consistency that can aid in understanding the relationship between the two datasets (Fig. 5-A, B) without overstating or understating the variations in either due to scaling issues [26]. In addition to the temporal trend, we provide a histogram (Fig. 1-A2) to display the frequency distribution of temperature (R1).

### 5.2 Spatial View

We provide the *spatial view* aiming to help experts visualize and comprehend the spatial distribution of meteorological variables (R2). To achieve this, we combine the citywide heat map of the variable and the geography map to display the spatial distribution. In determining the color scheme, we draw inspiration from ERA5's color scheme [14], which is chosen based on its association with human perception of temperature. The spatial relationship between the distribution of meteorological variables and the geographic locations of news articles is vital (R6). Thus, we plot news on the map (Fig. 1-A3). They will be automatically aggregated in cases of close proximity when zooming in/out, allowing for a more concise visualization.

**Thermoglyph.** G2 emphasizes both magnitude-based temperature and probability-based index. To effectively visualize them, we have devel-

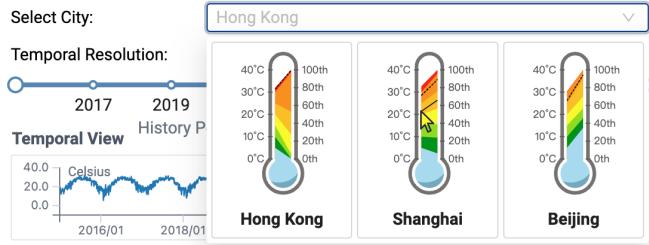


Fig. 3: The “thermoglyph” in the city gallery for selecting cities. They employ a metaphorical representation. The pattern of color blocks vividly depicts the relationship between temperature and percentile for each city. The black lines connect the current temperature (dashed) or the hovered temperature (bold) to its corresponding percentile.

oped the “thermoglyph.” They are presented in the city gallery (Fig. 3), alongside each city on the map (Fig. 1-A4), and in the summary panel, which caters to the varying needs of experts throughout different stages of analysis. The “thermoglyph” resembles a thermometer, where the color gradually fills from the bottom to the top, representing the rising mercury in a traditional thermometer due to heat. The “thermoglyph” consists of two parallel axes: temperature and percentile. Different temperature ranges and the associated percentiles are linked and encoded using the same color scheme in the *spatial view*. Consequently, unique patterns emerge in different cities (Fig. 3). For instance, the “thermoglyph” for Hong Kong exhibits a concentrated pattern on the left side, indicating that the temperature in Hong Kong is more concentrated for the majority of the time. On the other hand, the “thermoglyph” for Beijing showcases parallel distribution, representing the broader temperature range and distinct seasonal characteristics observed in Beijing. A dashed back line indicates the current value. We also add a solid black line to accurately illustrate the link when the mouse hovers. This feature fulfills the experts’ need for precise information.

**Design alternatives.** We consider a design alternative line chart (Fig. 2-A2) but find two issues: (1) It is challenging to differentiate between various patterns based on the changing slopes of the lines and (2) caused confusion among users because it implies a temporal change. Therefore, we opted for the design of the “thermoglyph,” which intuitively conveys the relationships between temperatures and percentiles.

### 5.3 News Topic View

Topic generation of news can help efficiently filter and manage news (R3, R4) and analysis of news (R5). For *news topic view* (Fig. 1-B1), we employ hex bins with text placed at their centers to represent topics for three reasons. Firstly, compared to a table list of topics, it has the advantage of conveying the information of overview. Secondly, the two-dimensional space of the hex bins preserves the relative spatial relationships between topics [42], enabling the keeping of semantic meaning relationships. Thirdly, in addition to being used as a container for displaying topics, hex bins are inherently well-suited to serve as buttons for experts to filter news. We encode the quantity of related news for each topic using a grayscale intensity scheme to avoid confusion with the color in the *spatial view*.

As mentioned in Sec. 4.1, we generated tags for each news. Then we employed the LLM to cluster those tags and generate the title for each cluster, resulting in a hierarchical structure. The first-level topics, which correspond to the cluster titles, provide an overview of the information in each cluster. The second-level topics, which are tags of news, offer more specific information pertaining to each cluster. The visual design for both first-level and second-level remains consistent.

For interaction, experts can simply click on first-level topic to display its second-level topics. By directly double-clicking on a topic, experts can choose to show or hide the relevant news in the *spatial view*, *news glyph view* and *news list*, enabling them to focus on specific aspects and in-depth analysis. Furthermore, when the mouse hovers over a topic, the associated bar (Fig. 1-A1) in *temporal view* and *news glyph* (Fig. 1-B2) in *news glyph view* will dynamically change color to red.

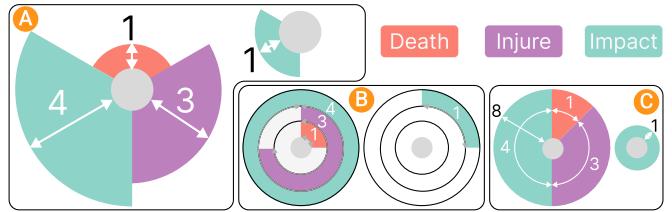


Fig. 4: We opt for the coxcomb glyph design (A) for the news glyph. Alternative design: target glyph design (B) and pie glyph design (C).

### 5.4 News Glyph View

The *news glyph view* (Fig. 1-B2) aims to leverage experts’ spatial memory for locating and navigating news effectively and enable experts to identify the news of interest quickly (R4) with each news represented as a glyph in a 2D space. In our design, we assume that news articles reporting higher casualties hold greater importance for experts (supported by E1-2). Thus, we encode the number of deaths, injuries and impacted individuals into the glyph. By incorporating this information visually, experts can quickly assess the severity and impact of each piece of news. For locating and navigating, they require a reasonable layout of news. To achieve this, each news is first encoded as a high-dimensional vector based on its semantic meaning and subsequently reduced to two dimensions using UMAP [42], maintaining semantic similarity. We also used a grid-based method [23] to avoid clutters and keep the relative distance of news glyphs. When the topic selection changes, the corresponding news will be shown or hidden without changing the position to keep the consistency of spatial memory.

We opt for dimension reduction and glyph visualization as opposed to ranking visualization methods like lineup [19], based on several considerations. Firstly, news articles encompass a diverse range of topics, and the absence of casualty information does not necessarily diminish their significance (E2). By organizing news articles based on their semantic meaning, we ensure that even those without casualty information are not overlooked entirely. Secondly, scalability was taken into account. Our glyph design, coupled with a 2D space, provides an effective solution for accommodating a large number of news articles. Lastly, the utilization of spatial memory aids in navigation. The spatial representation allows for better cognitive mapping and recall of specific articles. Thus, under the condition of a large number of news, we prioritized an intuitive and space-efficient design. As a result, we opted for a circular form of glyph to represent each news item.

**Coxcomb glyph.** For circular glyph form, we designed a modified version of the classical coxcomb visualization (Fig. 4-A) to represent the numbers of deaths, injuries, and impacts. To address cases where casualty information is absent, we added a grey node in the center. This modification ensures that each news article can be displayed, even if the casualty information is unavailable. The coxcomb glyph consists of three  $120^\circ$  sectors, each distinguished by a different color to represent deaths, injuries, and impacts. The number of casualties within each category is encoded by the length of the sector. By utilizing the coxcomb glyph, experts can easily identify important news that entails severe consequences. The news glyph is interconnected with both the *news list* and *spatial view*. When a glyph is clicked, the corresponding news will be automatically centered in the other two views.

**Alternative designs.** In addition to the coxcomb glyph, we have developed two alternative designs: the target glyph (Fig. 4-B) and the pie glyph (Fig. 4-C). However, there are certain limitations associated with them. The target glyph represents the number of deaths, injuries, and impacts using three individual arcs. It effectively conveys the information. However, a significant limitation is that it is spatially expensive. Regardless of whether a news article contains casualty information or not, the glyph occupies the same large size. The pie glyph employs size to encode the sum of deaths, injuries, and impacts. The angle ratio of the sectors is determined based on their respective numerical ratios. However, the pie glyph has been criticized for its lack of intuitiveness in expressing individual numbers within each category. Experts need to consider both size and angle to comprehend the magnitude of the

numbers. Considering these factors, we have chosen the coxcomb glyph as the preferred design option.

## 5.5 News List View

The *news list* (Fig. 1-B3) lists the headlines of news articles. It provides the functionality for filtering them based on criteria such as time, temperature (which is closely linked to results of domain models), and casualties (R3), ranking the news based on their semantic meaning (R4), and reading original text or structural information (R5). We plot three bar charts to display the number of news corresponding to each criterion. Then experts can directly brush the bar to apply the filters. The three bars are synchronized. When filtering is applied, a blue color emerges in all bar charts to indicate the number of remaining news.

Experts can use sentences to search and rank news so that they can easily access the news with similar semantic meanings. To get the details, they can expand the headlines to structural information or full-text. Additionally, visual cues are used to highlight relevant sentences pertaining to “risk,” “cause,” “consequence,” and “advice” within full text, which improves the efficiency of reading original text (Fig. 1-B3).

## 5.6 Summary Panel

The summary panel was designed to integrate insights of both numeric and semantic to facilitate further decisions to minimize the losses of potential heat risk (R1, R2, R5, R6). To achieve this integration, we incorporate insights from one side to the other.

**Numeric and semantic for numeric.** To provide numerical understanding, the line chart (Fig. 1-C1) illustrates relationships between city risks and temperatures. Experts can read the numerical risk level for decision-making. We also select news with the highest number of deaths at each temperature as representative examples. This approach allows experts to match impacts with different risk levels, contextualizing a mere number. These representative news articles are plotted as scatter points on the x-axis, which show a tooltip when hovered.

**Semantic and numeric for semantic.** Any semantic insights found during the entire process can be pinned and compiled to this panel for the purpose of reviewing findings and generating the final report. In order to enhance the comprehension of risk, we implement a contextual question-answering interface (Fig. 1-C2) that helps experts pose contextual questions. Contextual answers will be generated based on selected news articles from the *news list* using RAG. The key results derived from the numerical model are rephrased in natural language for experts to review. They are of utmost importance as they serve as references for generating the final report as well. By diligently curating and maintaining the content within this panel, a comprehensive final report can be generated using LLM. The report becomes a valuable reference for experts working on future actionable plans.

## 6 EVALUATION

For evaluation, besides E1-2 who we closely collaborate with, we involved three more experts (E3-5) to conduct case study. The panel of experts includes four professors with an average of 15 years of research experience (33, 10, 9, and 10 years respectively) and one specialist with 4 years research experience. Additionally, E1 is a representative in the ‘My Climate Risk’ scheme, launched by the World Climate Research Programme (WCRP) [49] to mitigate climate event risks.

The experts studied the 2022 extreme heatwave in China [71]. Prior to the case studies, a training session was conducted to familiarize the experts with the visual designs, interactions, and connections between different views of *Havior* [63]. Subsequently, the experts explored *Havior* to analyze their areas of interest. During the case studies, the experts derived valuable insights from *Havior*. Then we conducted 30-minute interviews with experts to collect their comments and feedback.

### 6.1 Case Study I - 2022 China Heatwave: Hong Kong

Hong Kong is an exemplary case to delve into the complexities of heat risks in light of the increasing occurrence of extreme heat events [24].

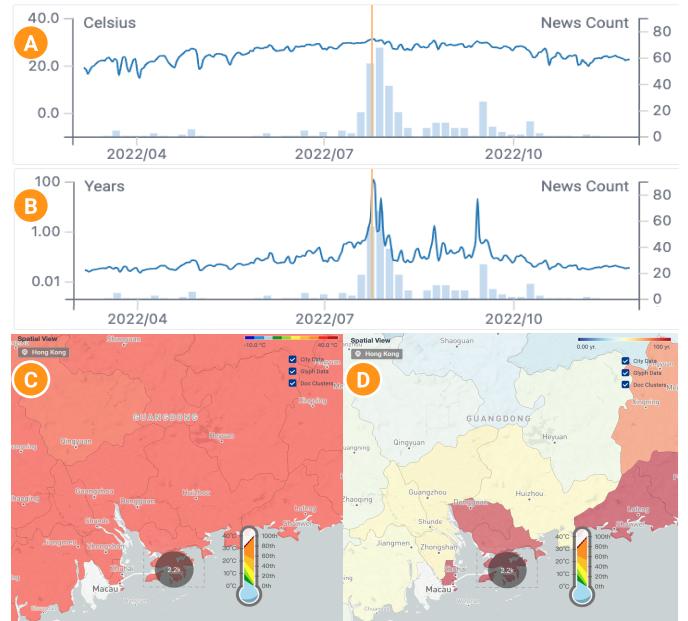


Fig. 5: The temporal trend (A) and the spatial distribution (C) of the temperature on 2022-07-24 in Hong Kong. The temporal trend (B) and the spatial distribution (D) of the return period on 2022-07-24 in Hong Kong. Bars in (A) and (B) are the number of news. Visualizations of the probability-based return period are better suited for studying extreme heat risk, as compared to magnitude-based temperature. The consistency of heterogeneous results (especially in (B)) enhances the interpretability of the system for heat risk research.

**Analysis of Numerical Climate Data** Firstly, experts choose the index, city and temporal resolution as “temperature,” “Hong Kong” and “daily” to check the meteorological condition. To research the 2022 China heatwave, experts set the date (single click on Fig. 1-A1) to be “2022-07-24” since it has the highest temperature (Fig. 5-A). The experts commenced their exploration by analyzing the *temporal view* (R1) and *spatial view* (R2), which effectively presented relevant meteorological information (E2-5). E2 commented, “*The geographical representations, color coding, and glyph design provide an intuitive and comprehensive means of understanding of the meteorological condition.*” They discovered that the temperature was anticipated to persist at an alarmingly high level of around 31 degrees Celsius, indicating a prolonged period of extreme heat (Fig. 5-A). Furthermore, the entire Greater Bay area was engulfed in high temperatures (Fig. 5-C). Then they checked the temporal distribution of temperature and found that 26-29 degrees is normal in Hong Kong. So they don’t know if it is severe. Thus, the experts realized they needed a deeper understanding of the meteorological condition.

Therefore, they decided to investigate probability-based indices. Using the “thermoglyph” (Fig. 1-A4), they gained a holistic understanding of the relationship between temperature and percentile data (E2-4). To their surprise, the current percentile for the temperature linked close to the 100th percentile, indicating an unusually severe situation. Seeking further validation, they delved into the detailed information on the return periods. The large return period (Fig. 5-B, D) signifies a low probability of the temperature occurrence, which raises concerns about the potentially severe consequences. The analysis of return periods provides additional support to the conclusion that Hong Kong is confronted with a substantial heat risk (E1, E3, E5).

**Analysis of Textual News Data** Experts turned to news to enhance their understanding. They conducted a search using the recommended keywords, resulting in the retrieval of 2,246 news articles. By incorporating meteorological variables and news articles (R6), the researchers discovered that the return period yielded more intriguing insights (Fig. 5). The consistency observed between the outcomes derived from heterogeneous climate and news data enhances the rationale

for utilizing news with climate data for heat risk research (**E1, E4-5**).

Then the experts obtained an overview of the potential heat risks in Hong Kong by examining topics (**R5**). The topics of news are automatically generated by LLM and visualized in the *news topic view* (Fig. 1-B1). These heat risks encompassed various aspects, including well-known topics such as “high temperature hazard response,” and “impact of climate crisis.” It was not surprising that the majority of news articles were related to these aspects. However, the experts also encountered unexpected topics, such as the “water crisis,” which received relatively less attention. They found this feature to be highly beneficial in expanding their awareness of previously unrecognized risk topics. They believed that it would enhance their considerations during decision-making processes, leading to more informed and rational decisions (**E1, E2, E5**). **E5** commented, “*The topics found here are not preprogramming, which I think is crucial. When some parameters change or new sources are included, the result can be automatically updated. This is intrinsically natural to pick up new things.*”

The experts observed a clear seasonal pattern by analyzing the bar plot (Fig. 1-A1) showcasing the number of news (**R6**). Notably, the number of news articles during the summers of 2018 and 2022 stood out significantly compared to other years. This observation aligned with the 2018 southern China heatwave [9] and the 2022 China heatwave [71]. Consequently, experts (**E4, E5**) could infer that a severe heatwave would likely occur if *Havor* were used in 2022.

Motivated by these findings, the experts aimed to explore how Hong Kong responded to heat risks and identify city-based features by deeply delving into specific topics (**R5**). This knowledge would enable the development of more appropriate strategies to assist in preparedness and provide guidance for governments and citizens alike (**E1-5**). They decided to explore the most well-known topics first by filtering news articles (**R3**) under the categories of “impact of climate crisis,” excluding others (Fig. 1-B1). Then they utilized the news glyph to identify the largest one (Fig. 6-A1) and clicked on it to access the details (**R4**). This particular news discussed the Marathon held in high temperatures that resulted in numerous athlete injuries. While severe, this outcome was somewhat expected. The experts bookmarked the news article for future review and pinned important sentences (**R4**) to the summary panel, which would contribute to generating the final report.

Subsequently, they came across another news glyph that indicated the highest number of deaths (Fig. 6-A2). With the help of visual cues for reading the full text (Fig. 6-B), they can easily gain insights (**R5**). **E3** commented, “*The visualization that maps structural information to the original news text is remarkably neat and useful. You must have dedicated considerable thought to this design.*”. They found that this news article highlighted the correlation between high temperatures and increased mortality among mental health patients, particularly in Hong Kong for its lack of sky view and green space. The experts found this insight unexpected, as it would have been challenging to identify this correlation solely based on numerical models.

The experts proceeded to investigate the unexpected topic, “water crisis” (**R5**). They identified only one news article that has casualty data with the help of the news glyph. They ranked the list of news based on the semantic meaning of the selected news (Fig. 1-B3). Structural information (Fig. 6-C) is very helpful for quickly analyzing news (**E2-4**). By examining the structural information of the first few news in the *news list*, the experts quickly discovered that heatwaves can give rise to water supply challenges, even in a prominent city like Hong Kong. By referring to the red proportion depicted in the bar (Fig. 1-A1), they observed that all news articles concerning tap water supply problems were reported solely during the previous heatwave in summer of 2018 (**R6**). Noting the government is criticized due to the absence of the tap water supply system for remote villages, the experts posed the question for advice and a considerable answer derived based on the 2018 summer news selected (Fig. 1-C2). Based on the observation that news regarding the unavailability of tap water was only reported during the summer of 2018, the experts inferred that the government had taken measures to tackle the issue. Our subsequent investigation proved this assumption, as evidenced by a government document [46]. Additionally, the measures taken by the government in 2018 autumn are

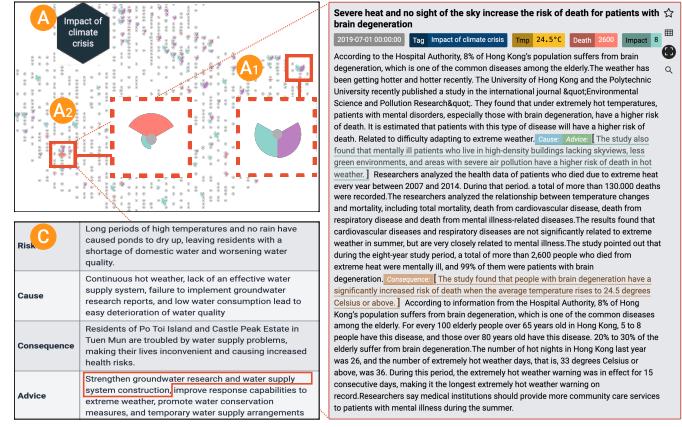


Fig. 6: News glyphs under the topic of “impact of climate crisis” (A). The largest news glyph (A1) and the news glyph with the largest number of deaths (A2) are likely to be selected. The structural information highlighted (B) in the original text helps experts understand the news quickly. The structural information (C) of the only news with glyph under the topic of “impact of climate crisis” helps experts understand the news easily. The advice generated based on summer’s news is similar to what the government has taken [46] in 2018 autumn.

very similar to the advice given by *Havor* (Fig. 1-C2) and structural information (Fig. 6-C). It verifies the ability of *Havor* to discover risk topics and facilitate informed decision-making (**E1-5**).

On the contrary, crop risks due to heat risk are inadequately handled. Experts uncovered another unexpected topic centered around “crop loss” and “crop damage,” revealing incidents of crop death and economic loss resulting from unforeseen insect infestations (butterflies that grow in tropical areas have migrated to Hong Kong) triggered by high temperatures and drought (**R5**). These risks were witnessed in 2018, 2021, and recurred in 2022. The lack of attention and proactive preventive measures towards these issues may explain their persistence. However, specific measures are expected to have a positive impact on the risk. we sought the *Havor*’s advice and received valuable advice such as “strengthening pest control,” “improving the irrigation system,” and “using shade nets to reduce plant heat stress.” By leveraging *Havor*, we not only identify unresolved heat-related risks but also devise informative strategies to effectively address them (**E1-5**). **E1** commented, “*This is the best practice I want to get from your system. It is helpful for me to do the risk management.*”

**Summary and Integration of heterogeneous insights (R6)** The experts compiled the semantic insights they discovered in the *summary panel*. Alongside these insights, the numerical conclusions were presented. Additionally, the experts examined the representative news related to the current ( $31^{\circ}$ ) temperature and identified the need for heightened attention to the risks faced by outdoor workers. By combining the numerical conclusions with the semantic insights from the news, the experts generated a final report on the heat risk in Hong Kong. This report provided them with a comprehensive understanding of the heat risk and helped them to make informed decisions and take appropriate actions (**E1-2, 4-5**). It can be found in the supplementary material. **E2** pointed out, “*The convergence of all heterogeneous data and model generates many insights to me. It is efficient to use LLM to integrate and summarize them. The report is a valuable reference for informing subsequent strategy considerations.*”

## 6.2 Case Study II - 2022 China Heatwave: Shanghai

To validate the ability of *Havor* to find city-specific insights (**R6**), we implemented *Havor* in another city: Shanghai. We examined the heat risk in Shanghai during the 2022 China heatwave, focusing on identifying any contrasting city-specific topics compared to Hong Kong. Following a process similar to that of the first case study, experts examined the meteorological conditions (**R1, R2**). Subsequently, they retrieved relevant news using the keywords “Shanghai” and “high tem-

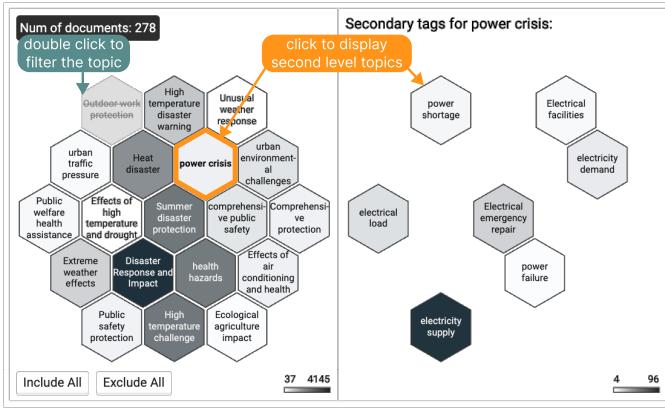


Fig. 7: The news topic view of Shanghai displays the hierarchical topics of the retrieved news articles. Left: the first-level topics. Right: the corresponding second-level topics upon clicking a first-level topic. Furthermore, double-clicking on a specific topic enables the filtering of news articles related to that topic in the subsequent analysis process.

perature.” Through the analysis of the first-level topics (Fig. 7), a distinct topic of heat risk: “power crisis” is found by experts.

They got in-depth knowledge about this topic by learning more subtopics through the second-level hex bins (R5). After their analysis of the news, they discovered that the 2022 extreme heatwave, characterized by historically high extreme temperatures, minimal rainfall, and soaring electricity demand, exacerbated the power supply-demand imbalance in Shanghai. To mitigate the impact on economic development and the well-being of residents, Shanghai implemented measures such as the suspension of landscape lighting to conserve power. Seeking guidance on this specific issue in Shanghai, the experts sought assistance from *Havior*. They received a comprehensive response, even including detailed information about the 24-hour power service hotline (95598) in Shanghai. The contrasting risks faced by Shanghai and the specific advice generated by the system highlight the significance of considering city-oriented factors and their unique circumstances in managing heat risks (E1-E5). E4 pointed out, “*The system demonstrates its ability to generate insights for different locations. It is important since the location-oriented strategy for risk management helps more.*”

## 7 DISCUSSION

### 7.1 Findings Discovered and Lessons Learned

**Anthropogenic factors in decision-making.** In the past, the inclusion of anthropogenic factors in climate analysis and heat risk management was hindered by the challenge of modeling these unstructured and non-numeric elements, which stand in stark contrast to the domain’s usual numerical models. However, our LLM-empowered pipeline marks a breakthrough, allowing the seamless incorporation of these factors and their contextualization with the climate model results. E5 expressed, “*By analyzing highly relevant news, the risk is no longer an abstract number to me. These multifaceted insights help me make informed decisions.*” Our findings reveal that the extensive documentation (e.g., in news and official documents) of anthropogenic factors is now accessible for various critical applications, enhanced by the efficiency of LLMs and the effectiveness of visual analytics.

**Yesterday’s news informs tomorrow’s risks.** The utility of incorporating historical news for dealing with unprecedented extreme events has sparked discussions among both our team and domain experts. A consensus emerged that while historical insights may have limitations when applied to new or intensely amplified risk scenarios, they can still aid in identifying risks with greater magnitude and tracking unresolved risks. E5 believed that “there’s nothing new under the sun,” suggesting that new heat extremes still echo those risks in the news. He expressed that identifying existing risks helps “*extend my scope of consideration by imagining how they scale.*” The LLM’s risk summaries enable experts to anticipate and develop preemptive strategies for more severe

extremes. The recurring risks in the news indicate unresolved problems that need more attention, as in the first case study. On the other hand, E1 praised the system’s capability to draw connections between seemingly irrelevant events and reveal new compounded risks. This analysis, spanning various spatial and temporal dimensions, alerts experts to emerging risks and suggests proactive measures. E1 noted that the significant changes brought by several climate events highlight the potential for risks to converge and intensify, like a chain reaction, eventually creating more significant issues. He further elaborated, “*These risks have been hidden and cannot be foreseen, but with your system, we now know that they exist and how they evolve.*

**Visualizations as the link for LLM and expert expertise.** “*Why use VA instead of directly asking LLM for the best heat risk management strategies?*” The answer lies in the fact that domain insights are derived from experts’ exploration. *Havior*, as an LLM-empowered VA system, effectively bridges the gap between LLM and expert expertise by employing carefully designed visualizations and interactions. E5 thought the LLM is embedded into the pipeline properly, “*Although I think the topics generated by LLM are not perfect, I find the result combined with hex bins useful to help me discover new topics. In the original workflow, I would only search for news related to the topic I had predetermined, which could cause me to miss out on something.*”

**While new visualizations are beneficial, domain experts may exhibit “inertia.”** We strove for simple, yet efficient visualizations recommended by experts during the collaboration. However, experts’ feedback still indicates that the visual design is helpful but requires time to be adapted. E3 commented, “*I have never seen visualizations like the ‘thermoglyph’ before. However, after a brief introduction, I understand its efficiency.*” The lesson we learned is the importance of considering the prevalent visualization used in the domain and the underlying reasons. This awareness enables us to design the most suitable visualizations that minimize the transition cost.

**Applicability and Generalizability** We confirmed *Havior*’s usefulness and effectiveness through expert interviews. They specifically appreciated the vivid “thermoglyph” and the valuable insights they obtained through interacting with *Havior*. In particular, E4 expressed the satisfaction of effectiveness with *Havior* and complained about the low efficiency and uninspired results of the manual investigation in their original workflow. E1 expected to use *Havior* in his research and considered the implementation of *Havior* at the city’s observatory to introduce impactful value. For generalizability, *Havior* provides a novel and feasible pipeline for integrating numeric results and insights from textual events. *Havior* can serve as a source of inspiration for tasks in other domains hurdled by heterogeneous data, especially numeric and textual. For example, E5 proposed the potential use of *Havior* in analyzing diverse numeric indices and financial events in green finance.

### 7.2 Limitations and Future Work

**The limitation in LLM,** like accuracy, hallucination, domain expertise, and timeliness, also affects *Havior*’s efficiency to provide precise analysis and up-to-date advice. It is surprisingly difficult to exclude instances like “real estate market overheating” from heat risks. Despite using the RAG model to filter timely news articles, we still encounter reliability issues. Our next step is to refine a domain-specific LLM, aiming for a deeper comprehension of heat-related risks.

**Visual scalability issue** arises when the news glyph view displays the topic with a large volume of news articles. To address this issue, we have designed a modified coxcomb glyph and implemented a grid-based algorithm to alleviate the problem of visual clutter. In future research, the exploration of more advanced visualization techniques and filtering methods holds the potential to further mitigate this limitation.

**Unexplored modalities**, such as satellite imagery and video footage about disasters, also contain information on risk events. We seek to incorporate multimodality capabilities in *Havior* for risk management.

## 8 CONCLUSION

In this study, we have undertaken the characterization of the risk management problem, with a specific focus on the integration challenges

posed by the heterogeneity of numerical results from domain models and risk insights derived from news sources. We then developed *Havior*, an LLM-empowered VA system, guided by the domain-characterized requirements. *Havior* aims to enhance the analysis of heat risk, improve heat risk management strategies, and mitigate heat-related threats. Two case studies and interviews with five domain experts were conducted for the evaluation. Their positive feedback and in-depth insights serve as evidence of the usefulness and efficiency of *Havior*. Significantly, the evaluation results demonstrate the potential for integrating quantitative model results with heterogeneous insights of risk derived from news reports to enhance the management of heat risks.

## SUPPLEMENTAL MATERIALS

All supplemental materials are available on OSF at [https://osf.io/dx5wt/?view\\_only=d44d6a39856d4c26b9452fc3f9be64b6](https://osf.io/dx5wt/?view_only=d44d6a39856d4c26b9452fc3f9be64b6), released under a CC BY 4.0 license. In particular, they include (1) A PDF file containing LLM Prompts used in the paper and some examples, (2) figure images in multiple formats, and (3) the process of expert interview.

## FIGURE CREDITS

The choropleth about ERA5 in Figure 2A2 is from C3S/ECMWF at <https://climate.copernicus.eu/how-c3s-era5-reanalysis-dataset-can-help-policymakers>. Figure 2Bc is a partial recreation of Fig. 1 from [37], which is in the public domain.

## ACKNOWLEDGMENTS

For IEEE VIS, this section may be included in the **2-page allotment for References, Figure Credits, and Acknowledgments**.

The authors wish to thank A, B, and C. This work was supported in part by a grant from XYZ (# 12345-67890).

## REFERENCES

- [1] G. Accarino, D. Elia, D. Donno, F. Immorlano, and G. Aloisio. A machine learning-powered digital twin for extreme weather events analysis. Technical report, Copernicus Meetings, 2023. doi: [10.5194/egusphere-egu23-6060](https://doi.org/10.5194/egusphere-egu23-6060) 1
- [2] B. G. Anderson and M. L. Bell. Weather-related mortality: how heat, cold, and heat waves affect mortality in the united states. *Epidemiology*, 20(2):205, 2009. doi: [10.1097/EDE.0b013e318190ee08](https://doi.org/10.1097/EDE.0b013e318190ee08) 4
- [3] K. Bi, L. Xie, H. Zhang, X. Chen, X. Gu, and Q. Tian. Accurate medium-range global weather forecasting with 3d neural networks. *Nature*, 619(7970):533–538, 2023. doi: [10.1038/s41586-023-06185-3](https://doi.org/10.1038/s41586-023-06185-3) 4
- [4] A. Biswas, G. Lin, X. Liu, and H.-W. Shen. Visualization of time-varying weather ensembles across multiple resolutions. *IEEE Transactions on Visualization and Computer Graphics*, 23(1):841–850, 2017. doi: [10.1109/TVCG.2016.2598869](https://doi.org/10.1109/TVCG.2016.2598869) 2
- [5] T. Brown, B. Mann, N. Ryder, M. Subbiah, J. D. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020. doi: [doi.org/10.48550/arXiv.2005.14165](https://doi.org/10.48550/arXiv.2005.14165) 4
- [6] J. Chae, D. Thom, H. Bosch, Y. Jang, R. Maciejewski, D. S. Ebert, and T. Ertl. Spatiotemporal social media analytics for abnormal event detection and examination using seasonal-trend decomposition. In *2012 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pp. 143–152, 2012. doi: [10.1109/VAST.2012.6400557](https://doi.org/10.1109/VAST.2012.6400557) 2, 3
- [7] C. A. T. Cortes et al. Analysis of wildfire visualization systems for research and training: Are they up for the challenge of the current state of wildfires? *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–20, 2023. doi: [10.1109/TVCG.2023.3258440](https://doi.org/10.1109/TVCG.2023.3258440) 2
- [8] C. V. F. de Souza et al. Prowis: A visual approach for building, managing, and analyzing weather simulation ensembles at runtime. *IEEE Transactions on Visualization and Computer Graphics*, 30(1):738–747, 2024. doi: [10.1109/TVCG.2023.3326514](https://doi.org/10.1109/TVCG.2023.3326514) 2
- [9] K. Deng, S. Yang, D. Gu, A. Lin, and C. Li. Record-breaking heat wave in southern china and delayed onset of south china sea summer monsoon driven by the pacific subtropical high. *Climate dynamics*, 54:3751–3764, 2020. doi: [10.1007/s00382-020-05203-8](https://doi.org/10.1007/s00382-020-05203-8) 8
- [10] Z. Deng et al. Airvis: Visual analytics of air pollution propagation. *IEEE Transactions on Visualization and Computer Graphics*, 26(1):800–810, 2020. doi: [10.1109/TVCG.2019.2934670](https://doi.org/10.1109/TVCG.2019.2934670) 2
- [11] A. G. Dias, E. E. Milios, and M. C. F. de Oliveira. Trivir: A visualization system to support document retrieval with high recall. In *Proc. DocEng*. ACM, New York, 2019. doi: [10.1145/3342558.3345401](https://doi.org/10.1145/3342558.3345401) 3
- [12] A. Dunn et al. Structured information extraction from complex scientific text with fine-tuned large language models. *arXiv preprint arXiv:2212.05238*, 2022. doi: [10.48550/arXiv.2212.05238](https://doi.org/10.48550/arXiv.2212.05238) 2
- [13] K. L. Ebi et al. Hot weather and heat extremes: health risks. *The Lancet*, 398(10301):698–708, 2021. doi: [10.1016/S0140-6736\(21\)01208-3](https://doi.org/10.1016/S0140-6736(21)01208-3) 2
- [14] ECMWF. 2 m temperature and 30 m wind. <https://charts.ecmwf.int/products/medium-2mt-wind30/>, 2024. [Online; Accessed 15-January-2024]. 5
- [15] Y. Feng, X. Wang, W. Kam-Kwai, S. Wang, Y. Lu, M. Zhu, B. Wang, and W. Chen. Promptmagician: Interactive prompt engineering for text-to-image creation. *IEEE Transactions on Visualization and Computer Graphics*, 30(1):295–305, 2024. doi: [10.1109/TVCG.2023.3327168](https://doi.org/10.1109/TVCG.2023.3327168) 3
- [16] Y. Feng, X. Wang, B. Pan, W. Kam-Kwai, Y. Ren, S. Liu, Z. Yan, Y. Ma, H. Qu, and W. Chen. Xnli: Explaining and diagnosing nli-based visual data analysis. *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–14, 2023. doi: [10.1109/TVCG.2023.3240003](https://doi.org/10.1109/TVCG.2023.3240003) 3
- [17] A. Gasparini et al. Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *The lancet*, 386(9991):369–375, 2015. doi: [10.1016/S0140-6736\(14\)62114-0](https://doi.org/10.1016/S0140-6736(14)62114-0) 4
- [18] E. Gomez-Nieto et al. Similarity preserving snippet-based visualization of web search results. *IEEE Transactions on Visualization and Computer Graphics*, 20(3):457–470, 2014. doi: [10.1109/TVCG.2013.242](https://doi.org/10.1109/TVCG.2013.242) 3
- [19] S. Gratzl, A. Lex, N. Gehlenborg, H. Pfister, and M. Streit. Lineup: Visual analysis of multi-attribute rankings. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2277–2286, 2013. doi: [10.1109/TVCG.2013.173](https://doi.org/10.1109/TVCG.2013.173) 6
- [20] Y. Guo. The role of humidity in associations of high temperature with mortality: A multicountry, multicity study. *Environmental Health Perspectives*, 127, 09 2019. doi: [10.1289/EHP5430](https://doi.org/10.1289/EHP5430) 4
- [21] Y. Guo et al. Heat wave and mortality: A multicountry, multicomunity study. *Environmental Health Perspectives*, 125(8):087006, 2017. doi: [10.1289/EHP1026](https://doi.org/10.1289/EHP1026) 4
- [22] H. Hersbach et al. The era5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730):1999–2049, 2020. doi: [10.1002/qj.3803](https://doi.org/10.1002/qj.3803) 2, 4
- [23] G. M. Hilasaca, W. E. Marcílio-Jr, D. M. Eler, R. M. Martins, and F. V. Paulovich. A grid-based method for removing overlaps of dimensionality reduction scatterplot layouts. *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–14, 2023. doi: [10.1109/TVCG.2023.3309941](https://doi.org/10.1109/TVCG.2023.3309941) 6
- [24] J. Hua, X. Zhang, C. Ren, Y. Shi, and T.-C. Lee. Spatiotemporal assessment of extreme heat risk for high-density cities: A case study of Hong Kong from 2006 to 2016. *Sustainable Cities and Society*, 64:102507, 2021. doi: [10.1016/j.scs.2020.102507](https://doi.org/10.1016/j.scs.2020.102507) 2, 7
- [25] N. Ingulfsen, S. Schaub-Meyer, M. Gross, and T. Günther. News globe: Visualization of geolocalized news articles. *IEEE Computer Graphics and Applications*, 42(4):40–51, 2022. doi: [10.1109/MCG.2021.3127434](https://doi.org/10.1109/MCG.2021.3127434) 3
- [26] P. Isenberg, A. Bezerianos, P. Dragicevic, and J.-D. Fekete. A study on dual-scale data charts. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2469–2478, 2011. doi: [10.1109/TVCG.2011.160](https://doi.org/10.1109/TVCG.2011.160) 5
- [27] P. Jyoteeshkumar reddy, S. E. Perkins-Kirkpatrick, and J. J. Sharples. Intensifying Australian Heatwave Trends and Their Sensitivity to Observational Data. *Earth's Future*, 9(4):e2020EF001924, 2021. doi: [10.1029/2020EF001924](https://doi.org/10.1029/2020EF001924) 1
- [28] W. Kam-Kwai, Y. Luo, X. Yue, W. Chen, and H. Qu. Prismatic: Interactive multi-view cluster analysis of concept stocks. *arXiv preprint arXiv:2304.05011*, 2024. doi: [10.48550/arXiv.2402.08978](https://doi.org/10.48550/arXiv.2402.08978) 2
- [29] W. Kam-Kwai, X. Wang, Y. Wang, J. He, R. Zhang, and H. Qu. Anchorage: Visual analysis of satisfaction in customer service videos via anchor events. *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–13, 2023. doi: [10.1109/TVCG.2023.3245609](https://doi.org/10.1109/TVCG.2023.3245609) 2
- [30] C. P. Kappe, M. Böttger, and H. Leitte. Exploring variability within ensembles of decadal climate predictions. *IEEE Transactions on Visualization and Computer Graphics*, 25(3):1499–1512, 2019. doi: [10.1109/TVCG.2018.2810919](https://doi.org/10.1109/TVCG.2018.2810919) 2
- [31] K. Keller, C. Helgeson, and V. Srikrishnan. Climate risk management. *Annual Review of Earth and Planetary Sciences*, 49(1):95–116, 2021. doi:

- [10.1146/annurev-earth-080320-055847](https://doi.org/10.1146/annurev-earth-080320-055847) 2
- [32] H. Kunreuther, G. Heal, M. Allen, O. Edenhofer, C. B. Field, and G. Yohe. Risk management and climate change. *Nature climate change*, 3(5):447–450, 2013. doi: [10.1038/nclimate1740](https://doi.org/10.1038/nclimate1740) 2, 4
- [33] W. Lass, A. Haas, J. Hinkel, and C. Jaeger. Avoiding the avoidable: Towards a European heat waves risk governance. *International journal of disaster risk science*, 2:1–14, 2011. doi: [10.1007/s13753-011-0001-z](https://doi.org/10.1007/s13753-011-0001-z) 4
- [34] S. Latif, S. Chen, and F. Beck. A deeper understanding of visualization-text interplay in geographic data-driven stories. *Computer Graphics Forum*, 40(3):311–322, 2021. doi: [10.1111/cgf.14309](https://doi.org/10.1111/cgf.14309) 3
- [35] S. Latif, Z. Zhou, Y. Kim, F. Beck, and N. W. Kim. Kori: Interactive synthesis of text and charts in data documents. *IEEE Transactions on Visualization and Computer Graphics*, 28(1):184–194, 2022. doi: [10.1109/TVCG.2021.3114802](https://doi.org/10.1109/TVCG.2021.3114802) 3
- [36] F. Lei et al. Geoexplainer: A visual analytics framework for spatial modeling contextualization and report generation. *IEEE Transactions on Visualization and Computer Graphics*, 30(1):1391–1401, 2024. doi: [10.1109/TVCG.2023.3327359](https://doi.org/10.1109/TVCG.2023.3327359) 3
- [37] P. Lewis et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. In *Proc. NeurIPS*. Curran Associates Inc., New York, 2020. doi: [10.48550/arXiv.2005.11401](https://doi.org/10.48550/arXiv.2005.11401) 2, 10
- [38] D. Liu, K. Veeramachaneni, A. Geiger, V. O. K. Li, and H. Qu. Aqeyes: Visual analytics for anomaly detection and examination of air quality data. *CoRR*, abs/2103.12910, 2021. 2
- [39] J. Liu et al. Mortality burden attributable to high and low ambient temperatures in China and its provinces: results from the global burden of disease study 2019. *The Lancet Regional Health—Western Pacific*, 24, 2022. doi: [10.1016/j.lanwpc.2022.100493](https://doi.org/10.1016/j.lanwpc.2022.100493) 4
- [40] S. Liu et al. Bridging text visualization and mining: A task-driven survey. *IEEE Transactions on Visualization and Computer Graphics*, 25(7):2482–2504, 2019. doi: [10.1109/TVCG.2018.2834341](https://doi.org/10.1109/TVCG.2018.2834341) 3
- [41] S. Mathew, B. Zeng, K. K. Zander, and R. K. Singh. Exploring agricultural development and climate adaptation in northern australia under climatic risks. *The Rangeland Journal*, 40(4):353–364, 2018. doi: [10.1071/RJ18011](https://doi.org/10.1071/RJ18011) 2
- [42] L. McInnes, J. Healy, and J. Melville. Umap: Uniform manifold approximation and projection for dimension reduction. *arXiv preprint arXiv:1802.03426*, 2018. doi: [10.48550/arXiv.1802.03426](https://doi.org/10.48550/arXiv.1802.03426) 6
- [43] T. Metze. Visualization in environmental policy and planning: A systematic review and research agenda. *Journal of Environmental Policy & Planning*, 22(5):745–760, Sept. 2020. doi: [10.1080/1523908X.2020.1798751](https://doi.org/10.1080/1523908X.2020.1798751) 2
- [44] L. Nan, E. Zhang, W. Zou, Y. Zhao, W. Zhou, and A. Cohan. On evaluating the integration of reasoning and action in LLM agents with database question answering. *arXiv preprint arXiv:2311.09721*, 2023. doi: [10.48550/arXiv.2311.09721](https://doi.org/10.48550/arXiv.2311.09721) 2
- [45] A. Noviello et al. Guiding environmental messaging by quantifying the effect of extreme weather events on public discourse surrounding anthropogenic climate change. *Weather, Climate, and Society*, 15(1):17–30, 2023. doi: [10.1175/WCAS-D-22-0053.1](https://doi.org/10.1175/WCAS-D-22-0053.1) 2
- [46] S. D. C. S. (Oct). Remote rural water supply plan - shatian meilin village. [https://www.districtcouncils.gov.hk/st/doc/2016\\_2019/sc/committee\\_meetings\\_doc/DHC/1389/st\\_dhc\\_2018\\_047\\_tc.pdf](https://www.districtcouncils.gov.hk/st/doc/2016_2019/sc/committee_meetings_doc/DHC/1389/st_dhc_2018_047_tc.pdf), 2018. Publication ID: DH 47/201 8, 8
- [47] R. Palaniyappan Velumani, M. Xia, J. Han, C. Wang, A. K. LAU, and H. Qu. Aqx: Explaining air quality forecast for verifying domain knowledge using feature importance visualization. In *Proc. IUI*, p. 720–733. ACM, New York, 2022. doi: [10.1145/3490099.3511150](https://doi.org/10.1145/3490099.3511150) 2
- [48] L. A. Parsons, D. Shindell, M. Tigchelaar, Y. Zhang, and J. T. Spector. Increased labor losses and decreased adaptation potential in a warmer world. *Nature communications*, 12(1):7286, 2021. doi: [10.1038/s41467-021-27328-y](https://doi.org/10.1038/s41467-021-27328-y) 2
- [49] W. C. R. Programme. <https://www.wcrp-climate.org/my-climate-risk>, 2021. [Online; Accessed 09-January-2024]. 7
- [50] R. Qiu, Y. Tu, Y.-S. Wang, P.-Y. Yen, and H.-W. Shen. Docflow: A visual analytics system for question-based document retrieval and categorization. *IEEE Transactions on Visualization and Computer Graphics*, 30(2):1533–1548, 2024. doi: [10.1109/TVCG.2022.3219762](https://doi.org/10.1109/TVCG.2022.3219762) 3
- [51] M. Rautenhaus et al. Visualization in meteorology—a survey of techniques and tools for data analysis tasks. *IEEE Transactions on Visualization and Computer Graphics*, 24(12):3268–3296, 2018. doi: [10.1109/TVCG.2017.2779501](https://doi.org/10.1109/TVCG.2017.2779501) 2
- [52] M. Roberts. What are the heat exhaustion and heatstroke symptoms? <https://www.bbc.com/news/health-62120167>, 2023. [Online; Accessed 08-January-2024]. 2
- [53] N. P. Simpson et al. A framework for complex climate change risk assessment. *One Earth*, 4(4):489–501, 2021. doi: [10.1016/j.oneear.2021.03.005](https://doi.org/10.1016/j.oneear.2021.03.005) 2
- [54] L. Styve, C. Navarra, J. M. Petersen, T.-S. Neset, and K. Vrotsou. A visual analytics pipeline for the identification and exploration of extreme weather events from social media data. *Climate*, 10(11), 2022. doi: [10.3390/cli10110174](https://doi.org/10.3390/cli10110174) 2
- [55] S. Sun et al. Increased moist heat stress risk across China under warming climate. *Scientific Reports*, 12(1):22548, 2022. doi: [10.1038/s41598-022-27162-2](https://doi.org/10.1038/s41598-022-27162-2) 4
- [56] D. Y. Taraneet Singh. Embedchain: The open source rag framework. <https://github.com/embedchain/embedchain>, 2023. [Online; Accessed 11-November-2023]. 4
- [57] D. Thom, R. Krüger, and T. Ertl. Can twitter save lives? a broad-scale study on visual social media analytics for public safety. *IEEE Transactions on Visualization and Computer Graphics*, 22(7):1816–1829, 2016. doi: [10.1109/TVCG.2015.2511733](https://doi.org/10.1109/TVCG.2015.2511733) 2
- [58] A. Vicedo-Cabrera et al. The burden of heat-related mortality attributable to recent human-induced climate change. *Nature Climate Change*, 18(2), 06 2021. doi: [10.1038/s41558-021-01058-x](https://doi.org/10.1038/s41558-021-01058-x) 2
- [59] Wisers. Wisers: best media monitoring. <https://login.wisers.net/>, 2024. [Online; Accessed 01-January-2024]. 4
- [60] Y. Wu, D. Weng, Z. Deng, J. Bao, M. Xu, Z. Wang, Y. Zheng, Z. Ding, and W. Chen. Towards better detection and analysis of massive spatiotemporal co-occurrence patterns. *IEEE Transactions on Intelligent Transportation Systems*, 22(6):3387–3402, 2021. doi: [10.1109/TITS.2020.2983226](https://doi.org/10.1109/TITS.2020.2983226) 2
- [61] Z. Xu, J. Cheng, W. Hu, and S. Tong. Heatwave and health events: A systematic evaluation of different temperature indicators, heatwave intensities and durations. *The Science of the total environment*, 630:679–689, 02 2018. doi: [10.1016/j.scitotenv.2018.02.268](https://doi.org/10.1016/j.scitotenv.2018.02.268) 4
- [62] J. Yang et al. Projecting heat-related excess mortality under climate change scenarios in China. *Nature communications*, 12(1):1039, 2021. doi: [10.1038/s41467-021-21305-1](https://doi.org/10.1038/s41467-021-21305-1) 2
- [63] L. Yang, C. Xiong, W. Kam-Kwai, A. Wu, and H. Qu. Explaining with examples lessons learned from crowdsourced introductory description of information visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 29(3):1638–1650, 2023. doi: [10.1109/TVCG.2021.3128157](https://doi.org/10.1109/TVCG.2021.3128157) 7
- [64] W. Yi and A. P. Chan. Effects of temperature on mortality in Hong Kong: a time series analysis. *International journal of biometeorology*, 59:927–936, 2015. doi: [10.1007/s00484-014-0895-4](https://doi.org/10.1007/s00484-014-0895-4) 2
- [65] F. Yuan, M. Li, and R. Liu. Understanding the evolutions of public responses using social media: Hurricane matthew case study. *International Journal of Disaster Risk Reduction*, 51:101798, 2020. doi: [10.1016/j.ijdrr.2020.101798](https://doi.org/10.1016/j.ijdrr.2020.101798) 2
- [66] W. Zhang, W. Kam-Kwai, Y. Chen, A. Jia, L. Wang, J.-W. Zhang, L. Cheng, and W. Chen. Scrolltimes: Tracing the provenance of paintings as a window into history. *IEEE Transactions on Visualization and Computer Graphics*, 2024. To appear. doi: [10.48550/arXiv.2306.08834](https://doi.org/10.48550/arXiv.2306.08834) 3
- [67] W. Zhang, W. Kam-Kwai, X. Wang, Y. Gong, R. Zhu, K. Liu, Z. Yan, S. Tan, H. Qu, S. Chen, and W. Chen. Cohortva: A visual analytic system for interactive exploration of cohorts based on historical data. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):756–766, 2023. doi: [10.1109/TVCG.2022.3209483](https://doi.org/10.1109/TVCG.2022.3209483) 3
- [68] W. Zhang, S. Tan, S. Chen, L. Meng, T. Zhang, R. Zhu, and W. Chen. Visual reasoning for uncertainty in spatio-temporal events of historical figures. *IEEE Transactions on Visualization and Computer Graphics*, 29(6):3009–3023, 2023. doi: [10.1109/TVCG.2022.3146508](https://doi.org/10.1109/TVCG.2022.3146508) 3
- [69] Q. Zhao et al. Global, regional, and national burden of mortality associated with non-optimal ambient temperatures from 2000 to 2019: a three-stage modelling study. *The Lancet Planetary Health*, 5:E415–E425, 07 2021. doi: [10.1016/S2542-5196\(21\)00081-4](https://doi.org/10.1016/S2542-5196(21)00081-4) 2
- [70] M. Zhizhin, E. Kihm, V. Lyutsarev, S. Berezin, A. Poyda, D. Mishin, D. Medvedev, and D. Voitsekhovsky. Environmental scenario search and visualization. In *Proc. GIS*, pp. 1–10. ACM, New York, Nov. 2007. doi: [10.1145/1341012.1341047](https://doi.org/10.1145/1341012.1341047) 3
- [71] B. Zhou, S. Hu, J. Peng, D. Li, L. Ma, Z. Zheng, and G. Feng. The extreme heat wave in China in August 2022 related to extreme northward movement of the eastern center of SAH. *Atmospheric Research*, 293:106918, 2023. doi: [10.1016/j.atmosres.2023.106918](https://doi.org/10.1016/j.atmosres.2023.106918) 7, 8