PolarWeather: Visual Analysis of Multi-Platform Polarization Dynamics on Social Media

Jianing Yin, Tan Tang, Haobo Zheng, Buwei Zhou, Lu Ying, Songela Nurdawuliet, Yuan Tian, Tai-Quan Peng, Dazhen Deng, and Yingcai Wu

Abstract—Polarization dynamics analysis seeks to understand how opposing stances on specific issues and the hostility between them evolve over time. These evolutions become particularly complex in today's multi-platform social media environment, where shifting topics, platform-specific polarization patterns, and cross-platform influence intertwine. Existing studies typically focus on single-platform scenarios or merely rely on macro statistics, oversimplifying fine-grained evolution patterns. To bridge the gap, through expert collaboration and a literature review, we characterize polarization dynamics at a detailed level and systematically summarize underlying factors that can inform hypotheses about possible mechanisms. To effectively visualize these detail-level dynamics, we propose a novel weather-inspired visual metaphor, in which temperature (encoded by colors) represents stances, air masses depict polarization dynamics, and fronts illustrate interaction patterns between dynamics. The metaphor is implemented by our polarization visualization algorithm, which places multi-platform polarization dynamics with a hierarchical force-directed layout and visualizes their intensity and interaction patterns with a stance-based scalar field. We further present PolarWeather, a visual analytics system that enables experts to explore multi-platform polarization dynamics and conduct factor-informed hypothesis generation. We validate the effectiveness and usability of PolarWeather through real-world case studies, expert interviews, and a user study.

Index Terms—Polarization dynamics analysis, social media visualization, visual metaphor, multi-platform analysis

1 Introduction

Polarization describes the phenomenon in which people adopt opposing stances on specific issues, often accompanied by distrust and hostility [32,36]. Polarization dynamics on social media refer to the evolving patterns of polarization, as stance-aligned groups form, shift, and interact with each other [3,35,58]. In today's multi-platform social media, polarization dynamics have become increasingly complex. Shifting topics and oppositional groups' activities can yield highly variable polarization patterns [27]. Moreover, diverse platforms can exhibit distinct forms of polarization [49,69], and information flows between platforms further amplify this complexity [55]. Therefore, understanding polarization dynamics helps explain digitally mediated opinion formation and group alignment [10,46] and inform polarization mitigation [7,22].

Prior research has primarily examined polarization dynamics within a single platform [4, 5, 27, 36, 37]. A growing line of work takes a multi-platform perspective by comparing polarization dynamics on different platforms [35, 69] or building cross-platform propagation relationships [21,49]. However, existing studies typically reduce polarization dynamics to a few platform- or period-level aggregates, such as the average stance extremity and the proportion of each stance. These macro statistics can oversimplify the nuanced evolution and complex interaction patterns inherent in real-world social media. Moreover, the absence of a systematic summary of underlying factors makes it difficult to generate hypotheses about possible mechanisms. To our knowledge, detailed analysis of multi-platform polarization dynamics and support for factor-informed hypothesis generation remain underexplored.

Due to the lack of effective analytical tools and the proven value of interactive visualization for polarization dynamics analysis [53], we are motivated to propose a visual analytics solution to help experts explore multi-platform polarization dynamics and generate factor-informed hypotheses. Our target users are experts in social media polarization analysis. Developing such a solution faces three challenges:

C1. Formulating polarization dynamics and organizing underlying factors. Polarization dynamics are latent and multifaceted, making them hard to characterize directly from raw data, and prior work lacks fine-grained formulations. Capturing such dynamics requires integrating heterogeneous aspects into a unified representation, which is conceptually non-trivial. Furthermore, hypothesizing about possible mechanisms of such dynamics requires considering various underlying factors. Identifying and organizing these factors demands significant effort and expertise, making it a complex and labor-intensive endeavor.

C2. Effective visualization of complex dynamics in a multi-platform environment. Given the inherent complexity of polarization dynamics, especially when observed in multi-platform scenarios, clear and interpretable visual representations are essential. The visualizations must clearly convey the multiple aspects of dynamics and the interaction patterns between them. They also need to organize both intra-platform and inter-platform trends without overwhelming users. Maintaining interpretability and visual organization in a unified visualization is particularly difficult given the density and temporal nature of the data.

C3. Enabling flexible exploration of multi-platform dynamics and diverse factors. Comprehensively exploring multi-platform polarization dynamics and generating hypotheses about their mechanisms is challenging, due to the massive volume of social media data and the diversity of underlying factors. Supporting flexible analysis requires deliberate design that coordinates across different analytical dimensions while balancing information granularity and cognitive load.

To address the first challenge, we collaborate with experts and conduct a literature review to formulate a detail-level characterization of polarization dynamics. We integrate key information from multiple aspects at an appropriate scale, upon which the interaction patterns between dynamics can also be characterized. Furthermore, based on prior research, we work with experts to systematically summarize the underlying factors that can inform hypotheses about possible mechanisms. To address the second challenge, we propose a novel weather-inspired visual metaphor, namely polarization weather. Stance is represented as temperature (cold-to-warm color), stance-aligned dynamics as cold or warm air masses, and their confrontations as fronts, helping users interpret evolving structures and conflicts more intuitively. This metaphor is realized by a polarization visualization algorithm that places multi-

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Manuscript received xx xxx. 202x; accepted xx xxx. 202x. Date of Publication xx xxx. 202x; date of current version xx xxx. 202x. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org. Digital Object Identifier: xx.xxxx/TVCG.202x.xxxxxxx

platform dynamics with a hierarchical force-directed layout and visualizes their intensity and interaction patterns via a stance-based scalar field. To address the third challenge, we introduce PolarWeather, a visual analytics system that enables interactive analysis of polarization dynamics from macro to detailed levels and facilitates inductive hypothesis generation based on a variety of underlying factors.

Our contributions are summarized as follows:

- A problem formulation for polarization dynamics analysis, including a **detail-level characterization of polarization dynamics** and a **systematic summary of underlying factors**.
- A **weather metaphor** with an algorithm for visualizing multi-platform polarization dynamics, and a **visual analytics system** for multi-level exploration and inductive hypothesis generation.
- **Case studies**, **expert interviews**, and a **user study** that validate the effectiveness and usability of our system.

2 Related Work

This section reviews research on polarization dynamics analysis and visual analytics for social media dynamics that are related to our work.

2.1 Empirical Analysis of Polarization Dynamics

Current approaches to analyzing social media polarization dynamics mainly focus on a single platform. Flamino et al. [27] studied polarization on Twitter during the 2016 and 2020 US elections and linked its increase to new influencers. Lai et al. [37] found that Twitter users more frequently used replies to express conflicting stances during the 2016 Italian constitutional referendum debate. Other content analyses linked polarization or depolarization to screenshots, intergroup interactions, framing, and identity-based frame adoption [15, 24, 30, 48]. Some researchers simulated polarization dynamics with agent-based or network-based models [8, 10], and examined polarization through human-subject experiments or surveys [4, 5, 40]. However, a single-platform lens provides only a partial view of contemporary social media [36], limiting the comprehensiveness of findings [55]. Some studies have considered multiple platforms through comparative studies or by modeling cross-platform propagation relationships. Comparative studies found significant differences among polarization dynamics on Facebook, Twitter, and WhatsApp [69], and found that platform-specific expression styles can contribute to different polarization patterns [19, 51]. Other work examined polarization by considering cross-platform processes, such as platform migration following platform governance decisions [49], viral spillover from Facebook to Twitter [50], and coordinated inauthentic activity within and across platforms [21].

However, previous research mainly used macro statistics to measure polarization dynamics, which can obscure the fine-grained evolution and interaction patterns on real-world social media platforms. Meanwhile, the lack of a systematic summary of underlying factors limits experts' ability to hypothesize about possible mechanisms behind polarization. In this work, through expert collaboration and a literature review, we characterize polarization dynamics in detail and systematically summarize the underlying factors into five categories. By characterizing them appropriately in real-world situations, our system enables experts to analyze multi-platform polarization dynamics closely and generate hypotheses about their mechanisms inductively.

2.2 Visual Analytics on Social Media Dynamics

Many works mentioned in Sec. 2.1 have employed visualization charts to analyze results. However, these basic statistical charts focus solely on isolated data aspects at a macro level, lacking appropriate encoding for multi-faceted information, interactive features, and coordination between views, which hinders a comprehensive understanding. Santos et al. [53] demonstrated the value of interactive visualizations for polarization analysis by conducting a survey with experts.

To facilitate visual analysis of social media dynamics, researchers have proposed map-based, node-link-based, flow-based, and circular-layout-based designs. R-Map [18] and E-Map [16] employ map-based metaphors to visualize posts and repostings of an event on Weibo. D-Map [17] leverages a map-based ego-centric visualization to show users' reposting behavior during a message's diffusion. However, those map-based methods, which strictly follow the reposting tree sequence, lack aggregation and refinement of polarization dynamics, making it difficult to capture the interaction patterns between polarization dynamics. Similar problems appear in other works using node-link diagrams [42, 52, 60, 66]. Flow-based visualizations are also commonly utilized to represent the temporal spread of information [41, 57, 63, 67, 68, 72]. EvoRiver [57] employs stacked flows to show the cooperation or competition between topics. CausalMap [41] arranges a map-like view along an x-axis timeline to trace causal sentiment propagation as topics evolve. However, as the flows are typically laid out along the x-axis in time order, they are not well-suited to visualize relationships between multiple platforms or the interaction patterns between polarization dynamics within a platform, which require a more spatial, relative, and confrontational organization. Circular layout designs such as Whisper [14] inherently emphasize a center-periphery structure, hindering the simultaneous analysis of multiple platforms' dynamics. Therefore, while these methods effectively capture certain aspects of social media dynamics, they fall short in addressing the visualization challenges posed by multi-platform polarization dynamics.

Several studies have extended visual analytics to multiple platforms. TopicPanorama [64] merges different platforms' topic graphs to support comparisons of shared and distinctive topics. With flower glyphs to represent topic clusters and wind paths to depict cross-platform propagation, BloomWind [70] employs the visual metaphor of blowing seeds across gardens to illustrate how information spreads from one platform to another. However, these systems' designs cannot capture key characteristics of polarization dynamics within and across platforms in an integrated manner, such as how oppositional stances evolve, extend influence, and interact. To bridge the gap, we propose a weather metaphor that represents stances as temperature, polarization dynamics as air masses, and their confrontations as fronts, together with a hierarchical force-directed layout for multi-platform visualization.

3 Background and Design Requirements

In this section, we collaborated with three domain experts and conducted a literature review to formulate the problem and summarize the design requirements. Our experts included a professor with expertise in media and communication, one senior researcher specializing in social media opinion analysis, and another in public discourse analysis.

3.1 Problem Formulation

To formulate polarization dynamics analysis, we worked with the experts through weekly meetings and a concurrent literature review. Building on this process, we first focused on two prominent types of polarization that are commonly observed and studied on social media. We then used a "What-Where-When-How" framework as an operational characterization of a detail-level polarization dynamic. To facilitate hypothesis generation about mechanisms behind these dynamics ("Why"), we finally conducted an extensive literature review to identify and organize underlying factors that can inform such hypotheses.

In this work, we focus on two prominent forms of polarization:

- **Stance Polarization** refers to the conflict of stances on an issue, resulting in opposing groups. It is important to understand how people perceive an issue through social media, where individuals can express their voices freely on topics they care about [61].
- **Affective Polarization** refers to the distrust and animosity between opposing groups, going beyond disagreement over issues to include negative sentiment toward members of the other group. Group hatred is a very serious problem that requires significant attention [7].

Detail-level Polarization Dynamics. Previous work often characterizes polarization dynamics with macro-level statistics [1, 35, 69], but such summaries often miss situational details needed to analyze how polarization manifests and evolves in depth. Guided by experts and literature [37, 69], we narrow the granularity to a semantically cohesive group of posts within a platform that express a common stance toward a specific issue. We term such a stance-aligned group **a detail-level polarization dynamic**, and characterize it along the dimensions in Table 1. These dimensions focus on attributes that are necessary for locating a detail-level dynamic and characterizing how polarization is manifested within it [24,37,69]. Within the same platform and semantic context, two detail-level dynamics with oppositional stances can exhibit diverse interaction patterns, ranging from dominance by one dynamic to balanced competition. Polarization dynamics on different platforms may influence each other through cross-platform propagation.

Underlying Factors (Why). Social media polarization dynamics have been discussed in relation to various mechanisms [3], such as filter bubbles [9], selective exposure [23], network homogeneity [38], and media endorsement [39]. To support mechanism-oriented hypothesis generation, we associated detail-level polarization dynamics with underlying factors that serve as observable cues. Specifically, drawing from the literature review and expert insights, we systematically organized these factors into five categories [32] (see Table 2): source, platform, message, user profile, and environment factors. Source factors may play a guiding role in shaping dynamics. Platform factors describe platform-level features that may influence how polarization spreads. Message factors refer to content characteristics that can reflect or provoke polarized discussions. User profile factors capture historical behaviors that may relate to users' susceptibility to polarized thinking and in-group bias. Environment factors describe broader contextual conditions that may influence polarization.

Table 1: Characterization of a Detail-Level Polarization Dynamic.

Dimension	Description
What (Posts)	A group of posts expressing a common stance on a given issue.
Where (Platform)	The social media platform on which these posts were published.
When (Time)	Time span over which the posts were published.
How (Polarization Properties)	• *Stance polarization index*: quantifying the stance strength within this group [37]; • *Affective polarization index*: capturing emotional antagonism toward posters with opposite stances [69]; • *Frame evolution*: identifying and tracking how the frames used in these posts evolve. A frame refers to a way of selectively presenting and interpreting an issue from a particular angle (e.g., by highlighting, explaining, or blaming certain aspects), thereby shaping how the issue is understood [24,25,30].

Table 2: Categories of Underlying Factors.

Category	Factors & References
Source	Influential users / posts [12], salient events [8].
Platform	Platform affordances [35], algorithms [40], norms [44], cross-platform propagation [55].
Message	Emotional, uncivil, or sarcastic content [34]; divisive discourse [58]; content related to social significance, value, morality, or self-identity [11,31,46].
User Profile	Out-group contact, knowledge level, intolerance level, in-group identification [5,20,56].
Environment	Interpretative diversity [6], homophilic interactions [38].

3.2 Data Description

The input to this problem consists of three types of social media data: *Post data* includes post content, engagement metrics, author information, repost/comment relationships, and post type (original post, repost, comment). *User profile data* consists of basic user information, historical posts, and follower/followee relationships. *Platform data* captures metadata revealing platform attributes.

3.3 Requirement Analysis

To develop an effective visual analytics approach for analyzing multi-platform polarization dynamics, we conducted semi-structured interviews with experts to understand their workflow and analysis needs. Based on the interviews, we summarized the design requirements of our visualization system as follows.

R1. Support polarization analysis along topic sequences. When analyzing social media posts on a specific issue, multiple related topics may emerge over time, often linked by shared keywords or common event protagonists. These connections can reveal interesting changes in polarization dynamics over time. Beyond gaining a topic overview, experts are particularly interested in exploring polarization dynamics along sequences of related topics.

R2. Support hierarchical exploration of polarization. Given the volume of posts, experts prefer to start with a macro-level overview of polarization statistics and then delve into details. Specifically, they want to examine macro statistics of stance and affective polarization at the topic and topic–platform levels, so as to form an overall impression and spot patterns for deeper exploration.

R3. Present temporal evolution of multi-platform dynamics. The evolution of polarization dynamics involves single-dynamic progression, interactions between dynamics, and changes in the multi-platform polarization landscape, which should be presented in an integrated manner. Experts also expect flexible time selection to focus on the period of interest and progressively examine the evolution.

R4. Facilitate comparison between different polarization dynamics. To uncover patterns that may be overlooked when examining a single dynamic or platform in isolation, the experts need to compare polarization dynamics both within a platform and between platforms. Therefore, the system needs to provide a shared view of multi-platform dynamics to facilitate such comparisons.

R5. Co-present key aspects of polarization dynamics with intuitive visual encodings. Since the key aspects of multi-platform detail-level polarization dynamics are interpretively dependent, experts expect them to be co-presented through intuitive visual encodings to preserve analytical context, reduce cognitive load, and enhance analytical efficiency.

R6. Enable systematic exploration of various underlying factors. Experts are particularly interested in hypothesizing about possible mechanisms behind polarization dynamics in an inductive style. Specifically, they want to inspect and compare the underlying factors of different polarization dynamics, which helps them develop such hypotheses from observed patterns. Additionally, to support authentic and context-sensitive analysis of polarized narratives, experts emphasized presenting posts in their original language.

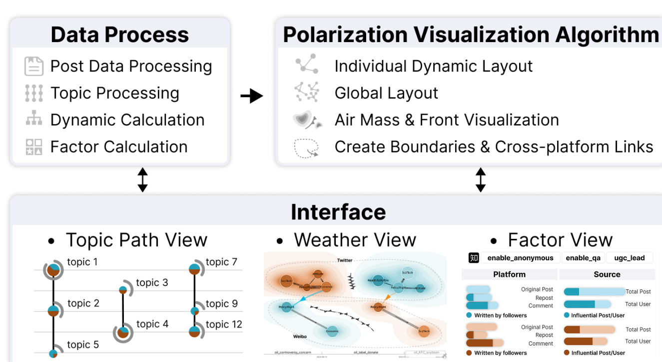

Figure 1: System overview of PolarWeather. The system is composed of three parts: a data processing module, a polarization visualization algorithm module, and an interface module.

3.4 System Overview

To meet the above requirements, we propose PolarWeather, a visual analytics system with three modules: a data processing module, a polarization visualization algorithm module, and an interface module (Fig. 1). The data processing module transforms the collected data by processing post data, clustering topics, and computing polarization dynamics and underlying factors. The polarization visualization algorithm module renders the computed dynamics as a weather metaphor, using a hierarchical force-directed layout and a generated scalar field. The interface module integrates three views to support hierarchical exploration of multi-platform polarization dynamics and inductive hypothesis generation based on underlying factors.

4 POLARIZATION WEATHER

In this section, we first describe the data processing procedure. Next, we discuss the motivation for proposing a weather metaphor to visualize multi-platform detail-level polarization dynamics. Finally, we present the specific visual encodings and the construction algorithm for polarization weather.

4.1 Data Processing

We process the collected data (Sec. 3.2) as follows. Specific implementation details are provided in Sec. D of the supplementary material.

Post Data Processing. Given the large quantity of posts and the demonstrated effectiveness of large language models (LLMs) in stance detection [71], targeted sentiment analysis [33, 45], and frame analysis [2, 54], we use GPT-4o [47] for post-level annotation. Each post is annotated with stance (support/oppose/none [37]), affective polarization (positive/neutral/negative/unknown), and a frame label (expert-defined categories based on the literature [25, 59]). To enhance reliability, three GPT-4o instances respond to the same prompt independently, and the final labels are decided by majority vote. For both polarization types, the instances also assign seven-point Likert scores (1 = strongly oppose/negative, 7 = strongly support/positive), which are then averaged and normalized to [-1, 1]. As evaluated in Supplementary Sec. C, this LLM-based annotation method achieved Weighted-F1/Cohen's κ of 0.90/0.82 for stance polarization, 0.86/0.78 for affective polarization, and 0.89/0.87 for frames against expert-consensus gold labels.

Topic Processing. To satisfy **R1**, we first apply BERTopic [29], a widely used method [26, 62, 65], to cluster posts into topic clusters $\{C(h)\}$ based on their content and publication time, where h indexes a topic. Then, we build topic paths by linking related topics chronologically through shared keywords or event protagonists.

Polarization Dynamics and Factors Calculation. To satisfy **R2**, we compute polarization measures at three levels. (1) *Topic-level statistics* calculate stance distribution and average affective polarization score of a topic. (2) *Topic-platform-level statistics* track stance distributions over time within each platform for a given topic. (3) To capture *detail-level polarization dynamics*, we partition each topic cluster $C(h)$ into units $\{C(h)_{i,m}\}$, where m indexes a unit and each unit $C(h)_{i,m}$ is a semantically cohesive set of posts on platform i. Based on stance labels, we further extract two detail-level dynamics from each unit: a support dynamic $C(h)_{i,m}^{\text{sup}}$ and an opposition dynamic $C(h)_{i,m}^{\text{opp}}$. For each dynamic $k \in \{C(h)_{i,m}^{\text{sup}}, C(h)_{i,m}^{\text{opp}}\}$, we model its frame evolution as a directed graph, *FrameGraph*(k). Each node represents a frame and corresponds to posts with that frame label. Directed edges are induced by interactions or temporal order between posts, capturing transitions from one frame to another. Within each unit, the interaction pattern between $C(h)_{i,m}^{\text{sup}}$ and $C(h)_{i,m}^{\text{opp}}$ is determined by their post-volume ratio, ranging from dominance by one dynamic to a balanced competition. Following Yin et al.'s formulation [70], we compute the post-level cross-platform propagation probability $P_{x \to y}$ for each cross-platform source–target post pair and retain those with sufficiently high probabilities as eligible pairs. For two detail-level dynamics A and B, cross-platform influence from A to B is computed by summing eligible post-pair probabilities from A to B and dividing the sum by the number of unique target posts in those pairs, which represents the average inbound information strength. Supplementary Sec. D.3.3 further provides a sensitivity probe supporting the robustness of the inferred cross-platform influence topology. In addition, *underlying factors* (Table 2) are computed for each detail-level dynamic and can be aggregated over a set of dynamics.

4.2 Motivation: Weather Map

Existing designs reviewed in Sec. 2.2 capture certain aspects of social media dynamics, such as diffusion sequences or single-platform temporal trends, but they do not offer an integrated view of detail-level polarization dynamics, including stance-aligned groups, their evolution, within-platform confrontations, and cross-platform influence. This gap motivates a new visual design for multi-platform polarization dynamics.

We explored combinations and variants of existing approaches, but found that straightforward integrations either fragmented the multi-platform context, lacked the expressive capacity to capture all required aspects, or were hard to understand. We therefore drew inspiration from weather maps for our visual design for three reasons (Fig. 2-a). First, polarization dynamics are inherently volatile and evolving, similar to weather patterns. Stances of opposition and support resemble cold and warm temperatures, and their conflicts are analogous to the interactions between cold and warm air masses that result in the formation of fronts. Second, the visual structure of weather maps, especially air masses and fronts, offers an effective spatial organization and expressive form for representing multi-platform polarization dynamics. The flexible combination of different visual elements on a weather map (e.g., map color, object shape, and boundaries) naturally supports the joint representation of evolving dynamics, their interactions, and the broader multi-platform context, making the metaphor well suited to **R3** and **R4**. Third, weather maps are commonly encountered in everyday life and education, making them cognitively accessible and easy to interpret. Therefore, using a weather metaphor can reduce cognitive load and help users better understand polarization dynamics, aligning with **R5**.

4.3 Polarization Weather Design and Visual Encoding

Polarization weather is designed to visualize detail-level polarization dynamics in a multi-platform environment. Multifaceted characteristics of these dynamics are encoded in different elements on the weather map, including air masses, temperature (color), node-link diagrams, isotherms, fronts, boundaries, and links (Fig. 2-b). These elements are chosen not only for their meaningful correspondence with the data features (**R5**), but also for their ability to reveal evolution patterns (**R3**) and facilitate comparative analysis (**R4**).

Air Mass & Temperature (Polarization Dynamic): An air mass represents one detail-level polarization dynamic (Fig. 2-c). Visually, it consists of the dynamic's *FrameGraph* and the local filled-isotherm region surrounding the graph. The stance of the dynamic is encoded by **temperature (color):** a cold-to-warm color gradient with cyan for opposition and burnt orange for support (Fig. 2-b).

Node-link Diagram (Frame Evolution): Inside each air mass, a node-link diagram represents the *FrameGraph* of the dynamic, where each node corresponds to a frame (Fig. 2-b). The text label indicates the specific frame. Node size encodes the number of posts with this frame label, and node color encodes the average stance score of these posts. Edge direction indicates transitions from one frame to another, and edge width reflects the transition volume.

Isotherm (Intensity): Isotherms reflect how the stance intensity of nodes influences their surrounding space (Fig. 2-b). Local isotherms surrounding a node-link diagram form the spatial extent of an air mass.

Front (Interaction Pattern): The front between two air masses represents their conflict pattern (Fig. 2-d), ranging from clear dominance by one air mass to a balanced competition. Front styles vary from single-sided to double-sided triangles pointing towards the opposing air mass. The ratio of triangle counts indicates the two air masses' post-volume ratio (Fig. 2-b), showing which air mass is more dominant in the confrontation. Larger triangles indicate more negative sentiment toward the opposing air mass, i.e., a lower affective polarization score.

Boundary (Platform Landscape): A platform boundary is depicted as a gray dashed curve enclosing all air masses on that platform (Fig. 2-e). It highlights a platform's polarization landscape, making platform-specific polarization distributions more discernible.

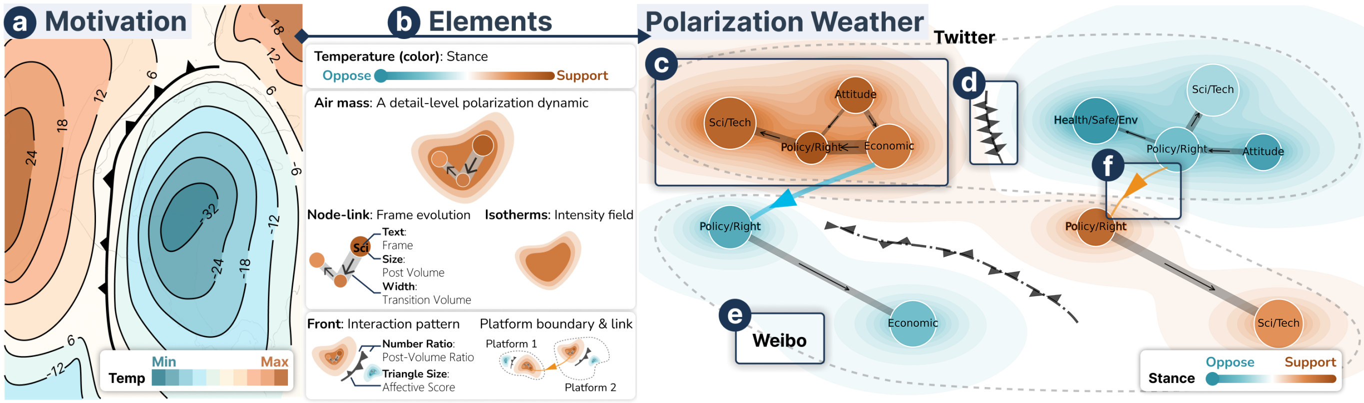

Figure 2: Visual encodings of polarization weather. Inspired by weather maps, polarization weather visualizes detail-level polarization dynamics in a multi-platform environment: detail-level dynamics as air masses, stances as temperature (color), frame evolution as node-link diagrams, intensity field as isotherms, interaction patterns as fronts, platform landscapes as boundaries, and cross-platform influence as links.

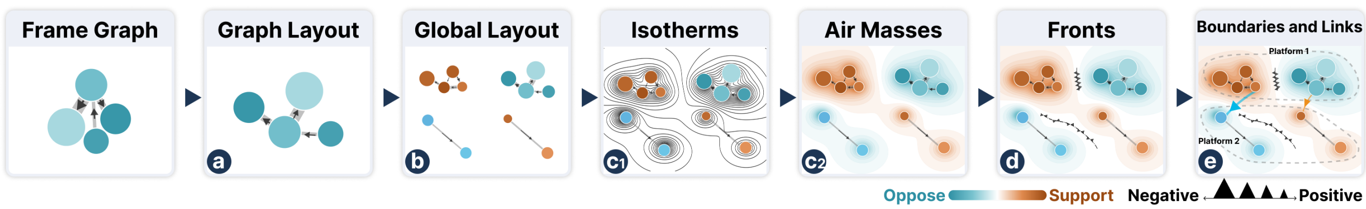

Figure 3: Polarization visualization algorithm: (a) graph layout for an individual dynamic; (b) global layout for dynamics; (c1) stance-based scalar field computation and isotherm generation; (c2) air mass visualization; (d) front visualization; (e) platform boundaries and cross-platform links.

Link (Cross-platform Influence): An arrowed curve linking two air masses (Fig. 2-f) represents the cross-platform influence between them. The curve's color encodes the target air mass' stance, and its width encodes the cross-platform influence from the source air mass to the target air mass.

4.4 Polarization Weather Construction

To construct polarization weather, we propose a polarization visualization algorithm, which uses a hierarchical force-directed layout to spatially organize multi-platform dynamics, and generates a stance-based scalar field to reveal their intensity and interaction patterns (Fig. 3).

4.4.1 Force-Directed Layout for an Individual Dynamic

For a detail-level polarization dynamic k, we apply the Fruchterman–Reingold algorithm (FR, [28]) to its $FrameGraph(k)$ and denote the resulting positioned graph as $FD(k)$ (Fig. 3-a).

4.4.2 Higher-Level Force-Directed Layout as Global Layout

To place multiple polarization dynamics, we treat each $FD(k)$ as a *super-node* in a higher-level force-directed layout (Fig. 3-b). These *super-node*s' positions are determined by FR's inherent repulsion and three levels of attraction: 1) strong attractive forces between *super-node*s belonging to the same unit, ensuring local cohesion; 2) medium attractive forces between *super-node*s from the same platform, preserving platform-level structures; and 3) weak attractive forces between *super-node*s with cross-platform propagation links, capturing cross-platform influence. Iterative updates based on these forces yield a clear and informative spatial arrangement.

4.4.3 Isotherm and Air Mass Visualization

With global layout fixed, we overlay a uniform grid on the canvas and compute an influence score $Z_{(x,y)}$ at each grid point (x,y):

$$Z_{(x,y)} = \sum_{k} \sum_{v \in FD(k)} \frac{v[\text{“stance\_score”}] \cdot v[\text{“weight”}]}{\|(x,y)-(x_v,y_v)\|_2^2 + 0.1}, \qquad (1)$$

where v refers to each node in every $FD(k)$, and (x_v, y_v) is its coordinate in the global layout. This formulation represents the aggregated stance influence exerted by all nodes at each point, yielding a scalar field of stance intensity. According to the Z-values, we generate isotherms (Fig. 3-c1) and fill them with a cold-to-warm color gradient (Fig. 3-c2). Accordingly, each air mass emerges visually as its corresponding $FD(k)$ together with the local filled-isotherm region surrounding $FD(k)$.

4.4.4 Front Visualization

Zero isotherms ($Z = 0$) denote boundaries where influences from oppositional stances cancel out. To effectively illustrate the interaction pattern between polarization dynamics within the same unit, we visualize the front along the zero isotherm between their air masses (Fig. 3-d). The numbers and sizes of triangles on each side of the front are determined by the two dynamics' post counts and affective polarization scores.

4.4.5 Platform Boundaries and Cross-Platform Links

Platform boundaries and cross-platform links are generated based on the coordinates of nodes in the corresponding dynamics (Fig. 3-e).

Platform Boundaries: For polarization dynamics on the same platform, we use the convex hull of the nodes to construct a gray dashed curve enclosing their collective region.

Cross-platform Links: For polarization dynamics with significant cross-platform influence, we use an arrowed Bézier curve to connect them. The color of the curve reflects the stance of the target dynamic, and its width is proportional to the computed cross-platform influence.

5 System Interface

PolarWeather's interface contains three coordinated views (Fig. 4). After users select platforms and an issue, Topic Path View provides an overview of topic paths and macro-level statistics (Fig. 4-a, **R1**–**R2**). Weather View then employs polarization weather to illustrate detail-level polarization dynamics along the selected path over a selected period (Fig. 4-b, **R3**–**R5**). Factor View shows underlying factors and post details for the selected dynamics (Fig. 4-c, **R6**). Cyan and burnt orange consistently encode opposition and support.

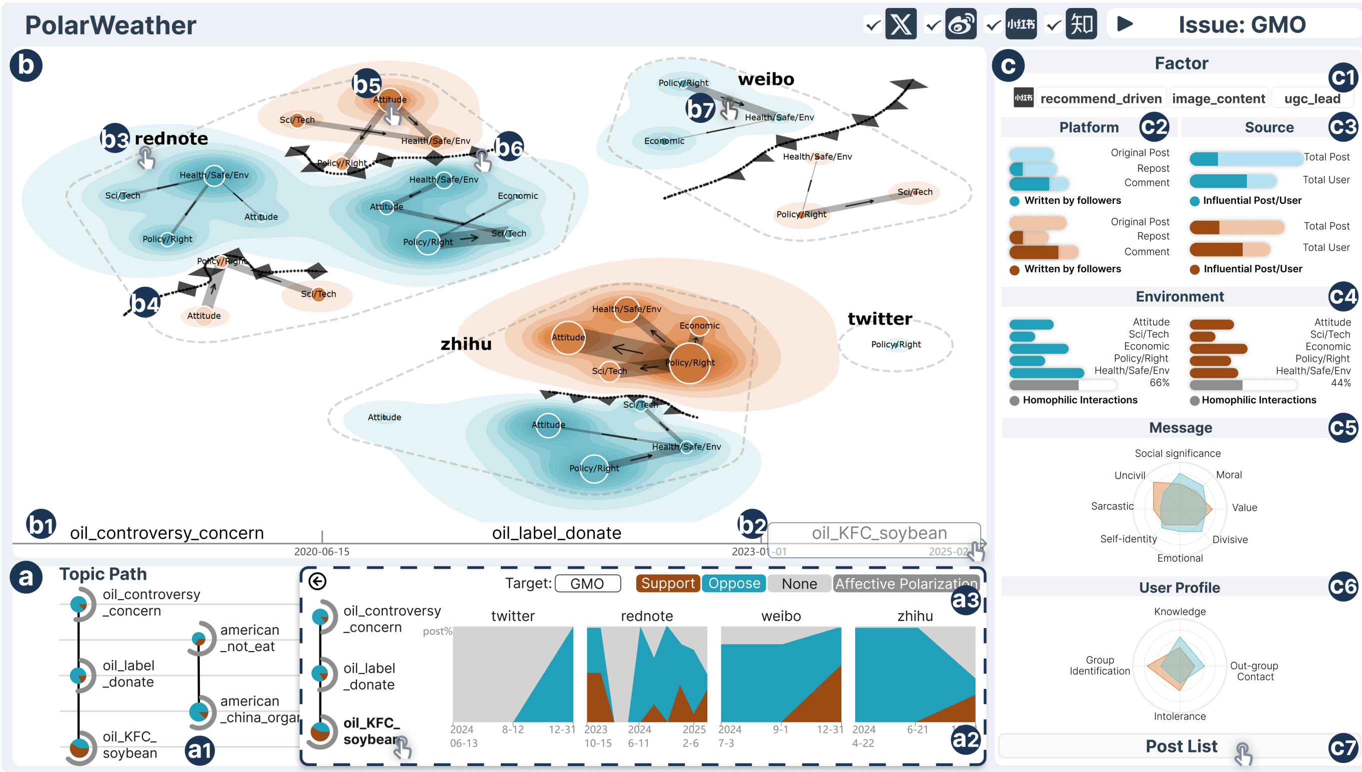

Figure 4: System interface of PolarWeather. (a) Topic Path View, presenting the relationships between topics as paths and visualizing macro-level polarization statistics. (b) Weather View, employing polarization weather to visualize detail-level polarization dynamics in a multi-platform environment. (c) Factor View, visualizing the underlying factors of the dynamics (i.e., air masses) selected in Weather View and providing the post list.

5.1 Topic Path View

Topic Path View (Fig. 4-a) presents the relationships between topics as topic paths (**R1**) and visualizes macro-level polarization statistics (**R2**), with legends and the target of stances shown at the top right (Fig. 4-a3).

Encoding and Interaction. Each topic path (Fig. 4-a1) consists of several *topic-level glyphs* connected by a vertical line. Inspired by BioFabric [43], we adopt a grid layout: each vertical line represents a topic path, and each horizontal line represents a time bin (later bins placed lower). Each glyph is placed at the intersection of its path and time bin. The glyph contains an inner pie chart and an outer ring. The pie radius encodes the topic's post volume, while pie segment angles and colors encode the stance distribution. The outer-ring arc encodes the topic's average affective polarization score, with longer arcs indicating more negative values. After selecting a topic path, users can click a topic-level glyph to reveal its *topic-platform-level charts* (Fig. 4-a2). For the selected topic, the stacked area charts show how the percentage of posts in each stance evolves over time on each platform.

Justification. Initially, we tried structures such as topic trees [67] and topic graphs [64]. However, the former's hierarchical layout lacked a clear representation of connections between topics at the same level, while the latter's format was found to be unintuitive for experts to interpret. Therefore, we adopted the BioFabric layout that better supports the requirement **R1** for its clarity and structural readability. Moreover, the glyphs and the stacked area charts effectively meet experts' needs for examining macro-level statistics (**R2**).

5.2 Weather View

Weather View (Fig. 4-b) uses polarization weather (Sec. 4.3) together with an interactive time axis to support exploring detail-level polarization dynamics in a multi-platform environment (**R3**, **R4**, **R5**).

Encoding and Interaction. The time axis (Fig. 4-b1) shows the temporal span of the topic path selected in Topic Path View. Users can brush a time window on the axis (Fig. 4-b2) to see the polarization weather for that period on the selected topic path. Interactions on the polarization weather are primarily driven by mouse clicks. Left-clicking opens a pop-up window with representative information:

- *Left-clicking a frame node* (e.g., Fig. 4-b5) shows a word cloud and representative posts that use this frame (e.g., Fig. 5-a1).
- *Left-clicking a front* (e.g., Fig. 4-b6) shows representative posts with high affective polarization (e.g., Fig. 5-a3).
- *Left-clicking a cross-platform link* (e.g., Fig. 6-a1) shows representative cross-platform propagation instances (e.g., Fig. 6-a4).

To link the observed visual patterns to their underlying factors, users can right-click to select air masses, which triggers the display of their underlying factors in Factor View (Sec. 5.3).

5.3 Factor View

Factor View (Fig. 4-c) supports systematic factor exploration by visualizing underlying factors of the air masses selected in Weather View and providing contextual details through the post list (**R6**).

Interaction. Factor View updates its content in response to user interactions in Weather View:

- *Right-click a platform boundary* (e.g., Fig. 4-b3): Factor View presents burnt orange charts for all warm air masses (supportive dynamics) and cyan charts for all cold air masses (opposed dynamics) on that platform. This interaction also updates the post list accessible via the "Post List" button (Fig. 4-c7).
- *Right-click a specific air mass* (e.g., Fig. 4-b7): Factor View shows the factor charts and post list for this air mass and its oppositional air mass on the other side of the front.

Encoding. We design charts for each factor category (Table 2). Within each category, factor charts for the supportive and opposed dynamics are laid out to facilitate visual comparison. To make magnitudes comparable at a glance, the bar charts displayed simultaneously share a common scale. Different factor categories are represented with chart types suited to their data characteristics. *Platform factors* use platform labels (Fig. 4-c1) and stacked bar charts to encode the numbers of different post types and follower-written reposts/comments (Fig. 4-c2).

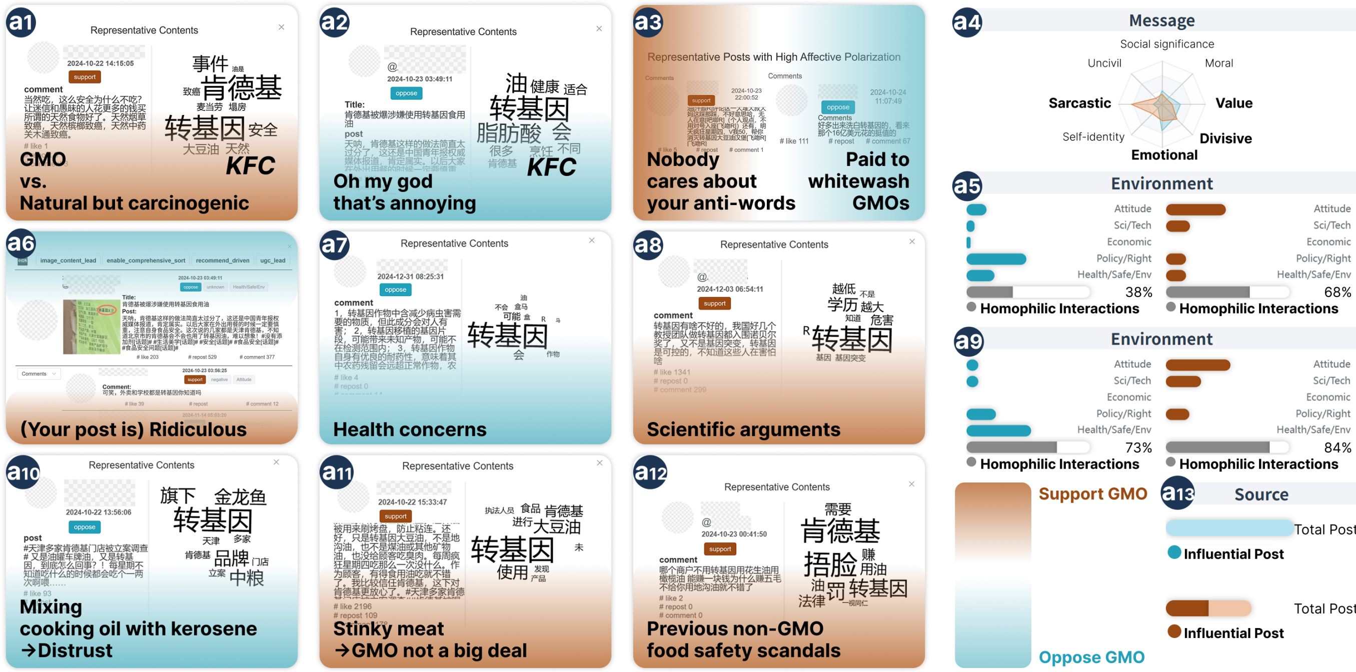

Figure 5: Case 1 "Support or Oppose GMO": (a) topic "oil_KFC_soybean" in the oil-related topic path. (a1–a13) illustrate how experts analyzed supportive and opposed dynamics on Rednote, Weibo, and Zhihu. They explored representative posts (a1–a3, a6–a8, a10–a12), and underlying factors such as homophilic interactions, content characteristics, and influential posts (a4, a5, a9, a13).

Source factors also use stacked bar charts to encode the numbers of posts, influential posts, users, and influential users (Fig. 4-c3). *Environment factors* (Fig. 4-c4) use bar charts for interpretative diversity (post count per frame) and percentage bars for the proportion of homophilic interactions (comment or repost interactions between posts with the same stance). *Message* and *User Profile factors* use radar charts to display the percentage of posts containing specific content characteristics (Fig. 4-c5) and the percentage of users exhibiting specific historical behaviors (Fig. 4-c6). Besides these charts, users can click the *"Post List"* button (Fig. 4-c7) to read posts in detail (e.g., Fig. 5-a6).

Justification. To visualize the underlying factors, we initially tried overlaying their values as annotations in Weather View. However, this approach introduced excessive visual clutter and hindered expert analysis. We also tried using one custom glyph per factor category. However, with five distinct glyphs containing various visual elements, experts found them difficult to interpret and cognitively demanding. Therefore, we adopted bar charts and radar charts as familiar visual forms that better balance comprehensiveness and interpretability. These design alternatives are illustrated in Supplementary Sec. A.1.

6 Evaluation

We evaluated PolarWeather's effectiveness and usability in polarization dynamics analysis through case studies, expert interviews, and a user study. These studies received institutional approval at our university.

6.1 Case Study

We invited three experts to conduct two case studies, including our collaborator in media and communication (E1), a senior researcher in opinion dynamics analysis (E2), and an experienced social media visualization engineer (E3). E2 and E3 had not participated before the case studies. We selected two real-world cases, "Support or Oppose GMO" and "DeepSeek: Useful or Not", to represent a long-standing social issue (GMO) and a suddenly viral technology-related issue (DeepSeek). Data were collected from Twitter, Weibo, Rednote, and Zhihu using paired English/Chinese keywords (e.g., "GMO/转基因", "DeepSeek Useful/DeepSeek好用"). These platforms were selected for their diverse platform characteristics and user demographics, creating an environment that facilitates more comprehensive observation, comparison, and analysis of polarization dynamics. The GMO dataset spanned from 2012 to 2025, including 1548 Weibo posts, 2260 Twitter posts, 1335 Zhihu posts, and 495 Rednote posts. The DeepSeek dataset spanned from late Dec. 2024 to late Mar. 2025, including 937 Weibo posts, 616 Twitter posts, 175 Zhihu posts, and 1507 Rednote posts. Each expert independently explored the cases. In Secs. 6.1.1 and 6.1.2, "they" denotes shared findings, while "E1/E2/E3" indicates individual discoveries.

6.1.1 Case 1: Support or Oppose GMO

In this case, experts used PolarWeather to study the polarization dynamics about supporting or opposing GMOs (Genetically Modified Organisms). Along the **oil-related topic path** (i.e., the left path in Fig. 4-a1), experts noticed a sharp rise in both the proportion of pro-GMO posts and the overall discussion volume at the topic "oil_KFC_soybean". They examined its macro statistics and found a surge of supportive voices since late 2024, especially on Weibo, Zhihu, and Rednote (Fig. 4-a2). So they brushed the corresponding time window and observed huge platform differences in Weather View (Fig. 4-b): on Rednote, cold (opposed) and warm (supportive) air masses were evenly balanced; on Zhihu, the warm air mass dominated; on Weibo, the cold air mass prevailed; and Twitter had limited discussion.

Rednote had two units of cold and warm air mass confrontation. In the first confrontation (Fig. 4-b6), by reading representative content of the frame nodes, they found discussions centered on the use of GMO oil in some KFC branches (Fig. 5-a1,a2). Supportive posts often used comparative rhetoric to justify their stance, such as contrasting GMO oil with natural but carcinogenic foods. Opposed posts primarily expressed anger over the event. Clicking the front between these two air masses (Fig. 4-b6), the experts observed that opponents accused supporters of being paid to whitewash GMOs, while supporters regarded opposed voices as negligible (Fig. 5-a3). The message factors (Fig. 5-a4) revealed that opposed posts frequently used value-related and emotional content, while supportive ones often used sarcastic and divisive content. The post list also confirmed that pro-GMO comments often appeared under opposed posts with an unfriendly tone (Fig. 5-a6). Therefore, despite the presence of some heterogeneous interactions (i.e., 100% minus the homophilic interaction percentage shown in Fig. 5-a5), E1 and E2 did not regard this as evidence of depolarization. In the

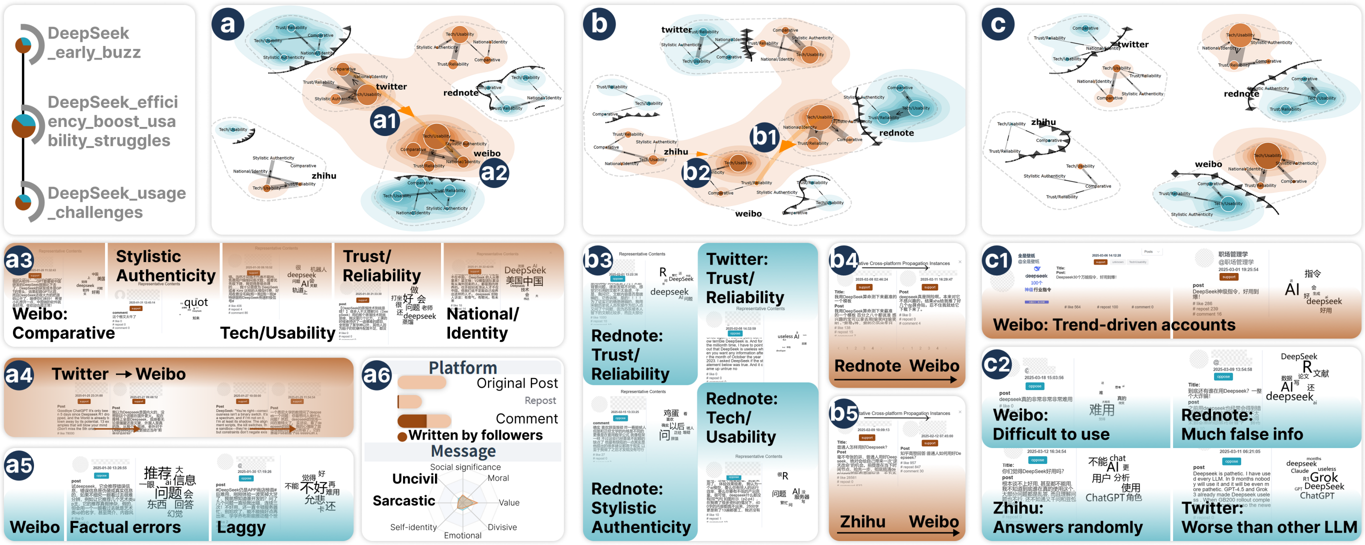

Figure 6: Case 2 "DeepSeek Useful or Not". (a) Topic "DeepSeek_early_buzz" (January 2025): supportive posts dominated. (b) Topic "DeepSeek_efficiency_boost_usability_struggles" (February): supportive posts remained dominant, but opposed posts were relatively substantial on Twitter and Rednote. (c) Topic "DeepSeek_usage_challenges" (March): supportive posts persisted, but with a smaller lead over opposed posts.

second confrontation (Fig. 4-b4), E2 observed a more rational tone. Opponents raised health concerns and criticized supporters for lacking expertise (Fig. 5-a7). Supporters presented scientific arguments, describing GMOs as controllable and safe (Fig. 5-a8). Both sides exhibited a high proportion of homophilic interactions (Fig. 5-a9), which E2 suggested helped maintain the rational tone, as users implicitly countered oppositional views by engaging with like-minded posts.

On Weibo, when discussing the use of GMO oil in KFC branches, representative posts from both sides frequently referenced non-GMO food safety scandals, such as the kerosene-contaminated cooking oil and the "stinky meat" incident (Fig. 5-a10,a11). Opponents interpreted all these events as reinforcing public distrust, while supporters claimed GMO oil was not a big deal compared to those non-GMO food safety scandals. Source factors showed that the supportive dynamic featured more influential posts (Fig. 5-a13), leading experts to infer that past non-GMO scandals may have been more effectively leveraged to support pro-GMO narratives. On Zhihu, they found that a similar use of non-GMO scandals appeared to reinforce supportive voices (Fig. 5-a12). Experts concluded that external shocks likely played a key role in the surge of pro-GMO voices during this period. Prior non-GMO food safety scandals could have broadened what was socially acceptable to say in public, making the pro-GMO stance easier to voice and circulate. Experts also explored other topic paths and found that platform-to-platform differences in polarization dynamics may relate to platform-specific characteristics or local contexts (see Supplementary Sec. A.2).

6.1.2 Case 2: DeepSeek Useful or Not

In this case, experts used PolarWeather to investigate whether users on Twitter, Weibo, Rednote, and Zhihu regarded the large language model DeepSeek as useful (supportive) or not useful (opposed).

In *January* 2025, supportive voices dominated on all platforms, with a smaller share of opposition (Fig. 6-a). On Weibo, the framing of supportive discussions evolved from praising DeepSeek's great usability and its GPT-like performance at lower cost to recognizing its eloquent responses, reliability, and its development team's Chinese identity (Fig. 6-a2,a3). Pro-DeepSeek tweets (e.g., claiming it outperformed ChatGPT or showcasing impressive responses) were circulated to Weibo (Fig. 6-a1,a4). Experts regarded these tweets as external validation that likely increased supporters' confidence and strengthened the pro-DeepSeek narrative on Weibo. Opponents on Weibo criticized DeepSeek for frequent factual errors and laggy performance (Fig. 6-a5). Examining underlying factors (Fig. 6-a6), E3 found that many supportive comments were written by followers, suggesting a stable user base around technology-related issues. Posts contained little uncivil or sarcastic content, and E1 associated this with the lower conflict severity in the technical domain, which was also reflected by the relatively small front triangles. Experts also noted a high proportion of original posts, suggesting active public participation around DeepSeek. In *February*, supportive posts remained dominant, but opposed posts were relatively substantial on Twitter and Rednote (Fig. 6-b). Opposed posts often criticized DeepSeek's hallucinations, poor response quality, slow performance, and overly ornate or formulaic wording (Fig. 6-b3). Supportive posts exhibited two cross-platform propagation patterns (Fig. 6-b1,b2): Rednote posts about using DeepSeek for fortune-telling sparked discussion on Weibo (Fig. 6-b4); a practical guide on Zhihu about using DeepSeek effectively was spread to Weibo (Fig. 6-b5). Experts noted that these patterns reflected different cultural emphases of Rednote and Zhihu, while also suggesting that cross-platform propagation could amplify polarization dynamics on the receiving platform. In *March*, supportive posts remained substantial, especially on Weibo, but with a smaller lead over opposed posts on all platforms (Fig. 6-c). E2 found that many supportive Weibo posts were DeepSeek usage guides posted by trend-driven accounts, reflecting users' interest in learning to use the model effectively (Fig. 6-c1). Moreover, based on the content and low engagement metrics of representative opposed posts, experts inferred that these posts were mainly written by grassroots users to share their unsatisfactory experiences with DeepSeek (Fig. 6-c2).

Finally, the experts compared the two cases. Affective polarization was more severe in the GMO case, as evidenced by the longer outer-ring arcs in the topic-level glyphs. Moreover, the GMO case revealed more pronounced platform-specific differences, whereas the DeepSeek case suggested a catalytic role for cross-platform propagation in polarization dynamics. The experts proposed issue maturity as a plausible explanation for this contrast: long-standing controversies such as GMO tend to develop entrenched divisions that keep users within platform-bound silos, whereas rapidly rising issues such as DeepSeek are more likely to trigger substantial cross-platform information flow.

6.1.3 Expert Interviews

We engaged five experts: E1–E3 (introduced above), E4 (platform policy and content safety analyst; 7 years), and E5 (senior UX researcher in visual analytics and HCI; 10+ years). E2–E5 participated only in the evaluation sessions. Following informed consent, each 1.5-hour session included an introduction, a 10-minute free exploration, two 30-minute case studies for E1–E3 (shown to E4–E5), and a 20-minute interview.

Positive feedback. First, all experts quickly understood the visual designs and navigated the system with ease. They described the interface as intuitive, clear, and easy to use. They praised that the weather metaphor made abstract polarization dynamics immediately graspable and reduced cognitive load. E5 highlighted the interface's clarity from a UX standpoint, and E4 remarked that "*at first glance you can already tell where the contention lies and which representative posts are fueling it—this fits decision-making practice much better than conventional charts.*" They also appreciated Factor View's familiar charts, neat layout, and factors commonly examined in polarization research, which made factor inspection and comparison straightforward. Second, experts highlighted the effective and elegant design of the weather metaphor. The effective combination of weather elements not only captured key aspects they care about compactly in a single view, but also supported within-platform analysis and side-by-side multi-platform exploration without switching views. E3 added that the metaphor brought out the relational patterns in the data. Finally, experts endorsed the system's workflow—from macro to micro, from surface patterns to mechanism hypotheses—as natural for exploratory analysis. They stressed that the inclusion of various underlying factors greatly facilitated their hypothesis generation. Reflecting on case studies, E1 and E2 valued the system's support for analyzing across platforms, as their analyses suggested that cross-platform propagation may affect polarization dynamics unevenly across issues. They found this insight valuable and expressed interest in using PolarWeather to further explore the issues and conditions under which this influence emerges.

Forward-looking suggestions. E2 suggested that, given the frequent loss of social media data, future versions of the system could support real-time analysis. E3 suggested refining our polarization visualization algorithm by introducing attractive forces between platforms with similar attributes to enhance the semantic richness of the layout.

6.2 User Study

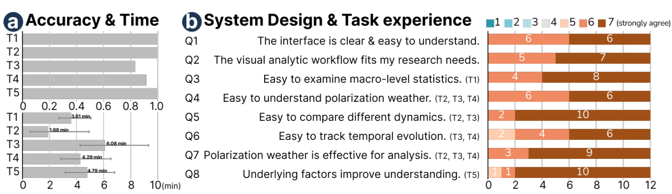

Figure 7: Results of the user study. (a) Task passing rate and task completion time. (b) Participant ratings on 7-point Likert-scale items.

We conducted a user study to evaluate whether users could understand the weather metaphor and use the system for analysis. We recruited 12 participants (5 male, 7 female), each with at least one year of research experience in social media polarization. They participated only in the user study. Following informed consent and a 10-minute tutorial, participants were asked to use PolarWeather to complete five tasks based on the datasets from case studies. Each task corresponded to one or more design requirements: (**T1**) describe macro-level patterns [R1–R2]; (**T2**) summarize the overall polarization weather [R4–R5]; (**T3**) examine and compare a pair of opposing detail-level dynamics [R3–R5]; (**T4**) analyze temporal evolution across periods [R3, R5]; (**T5**) compare underlying factors to develop mechanism hypotheses [R6]. We recorded participants' answers and completion time. Participants then completed a questionnaire including the System Usability Scale (SUS) [13] and several 7-point Likert-scale items about system design and task experience. The results are summarized in Fig. 7.

As shown in Fig. 7-a, participants completed all tasks in 20.65 minutes on average. All participants passed T1, T2, and T5. For T3, two participants did not fully understand a representative post. We found that the post itself contained relatively long text, which likely increased the reading burden and made it harder for participants to locate stance-relevant cues in the post. For T4, one participant reversed the correspondence between supportive/opposed and useful/not useful in the DeepSeek case, indicating that generic stance labels may impose a mapping burden when stances have issue-specific meanings. The mean SUS score was 85.63, which is within the top 10% of SUS scores. As shown in Fig. 7-b, participants also gave consistently high ratings across all 7-point Likert-scale items, indicating that they found PolarWeather understandable, usable, and analytically effective. They appreciated the intuitiveness of the weather metaphor and expressed willingness to use PolarWeather for their social media polarization analyses. Some participants suggested highlighting key information in representative posts to improve the efficiency of reading detailed post content. Overall, the results suggest that PolarWeather can be readily understood and used to effectively support the analysis of social media polarization dynamics. Additional details are in Supplementary Sec. B.

7 Discussion

Implications. First, PolarWeather shows that a visual metaphor can do more than make complex data easier to interpret: it can support holistic analysis of heterogeneous, multi-faceted social-media data. By bringing stance-aligned dynamics, their interactions, and multi-platform context into a shared visual representation, PolarWeather expands the design space of visual analytics for complex social phenomena. Second, PolarWeather suggests that polarization dynamics analysis benefits from integrated support across analytical levels. Our system supports a top-down workflow from macro-level overview to detail-level pattern inspection and then to inductive hypothesis generation, which experts often follow but prior tools rarely support systematically. By integrating multi-platform analysis with factor-informed exploration, PolarWeather supports a more systematic understanding of polarization dynamics.

Design Lessons. Our experience suggests that, for heterogeneous data, the value of a visual metaphor lies not simply in making an interface more vivid, but in providing a coherent organizing logic that aligns diverse data facets with analysts' mental models. Our weather metaphor worked because, instead of encoding stance, interactions, and platform context as isolated variables, it organized them into a coherent visual language that experts could interpret holistically.

Limitations and future work. First, PolarWeather controls the visual density of Weather View by first hierarchically filtering posts and then organizing them into detail-level dynamics. However, the view may still become crowded in extreme cases when highly dispersed semantic units lead to many dynamics. We also clarify that the spatial layout in Weather View is intended to organize detail-level dynamics for joint comparison, so spatial proximity should not be interpreted as a causal relationship. Future work could further reduce visual density through adjustable granularity of detail-level dynamics and encode additional meanings in the layout when needed. Second, PolarWeather supports inductive hypothesis generation rather than causal identification, since the visualized signals alone cannot rule out confounding or reverse causation. Future work could support causal validation of mechanism hypotheses. Third, retrospective social media data are inherently incomplete due to deletion, visibility restrictions, and collection gaps. Although paired Chinese/English keywords are practical for collecting issue-related data, they may miss platform-specific or renamed terms that users adopt under platform norms or content moderation, resulting in uneven coverage that may bias the inferred cross-platform influence. Future work will extend PolarWeather into an online system and improve data collection through expert-guided query expansion and multimodal retrieval. Additionally, the user-study failure cases suggest that future versions could highlight stance-relevant snippets in the post content and directly show issue-specific stance meanings in the legend.

8 Conclusion

This paper presents PolarWeather, a visual analytics system for exploring multi-platform polarization dynamics. Grounded in a detailed problem formulation, the system uses a weather-inspired visual metaphor with a corresponding visualization algorithm to represent detail-level polarization dynamics in a multi-platform environment. The inclusion of various underlying factors further supports inductive hypothesis generation about possible mechanisms. Results from case studies, expert interviews, and the user study demonstrate the system's effectiveness and usability for polarization dynamics analysis.

ACKNOWLEDGMENTS

The work was supported by National Key R&D Program of China (2023YFB3107100), NSFC (62532011), Zhejiang Provincial Natural Science Foundation of China under Grant No. LD25F020003, NSFC (62421003), Zhejiang Provincial Natural Science Foundation of China under Grant No. LZ26F020001, NSFC (62402428), and Ningbo Yongjiang Talent Programme (2023A-396-G).

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