DualMind: Towards Understanding Cognitive-Affective Cascades in Social Opinion via Multi-Agent Simulation

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Abstract

We demonstrate DualMind, an interactive multi-agent LLM platform for simulating public opinion dynamics during PR crises. Built on a validated cognitive-affective agent framework (PAACM), our demo highlights two core scenarios: (1) Strategy Simulation, where users input custom PR strategies and visualize their real-time propagation and impact, and (2) Real-world Reproduction, where users simulate historical cases and compare the results against ground-truth data. DualMind provides organizations with a crucial digital twin to proactively rehearse and refine communication strategies, mitigating reputational risk.

CCS Concepts

• **Computing methodologies → Multi-agent systems**.

Keywords

Multi-Agent Systems, Large Language Models, Crisis Communication, Social Simulation

1 Introduction

In the contemporary digital environment, the diffusion of public opinion across online social networks has become both highly influential and increasingly difficult to anticipate. Public relations (PR) crises can emerge and escalate with exceptional speed, posing significant risks to the reputation, market position, and operational stability of corporations, public figures, and institutions [5]. Recent high-profile cases illustrate that even a single misjudgment in communication can trigger large-scale consumer boycotts, lead to substantial losses in market capitalization, and cause enduring reputational damage [7]. Beyond corporate impacts, the rapid circulation of unverified information and polarizing narratives can undermine public trust in institutions and exacerbate societal tensions. The dynamics underlying these events, shaped by heterogeneous user groups, intricate social structures, and platform-specific algorithmic curation, create substantial challenges for strategic communication and crisis management. Effectively forecasting these dynamics remains a major hurdle. Traditional sentiment assessment methods, like surveys and focus groups, are too slow and coarse-grained to capture real-time online discourse. Even traditional computational and agent-based models, while faster, typically oversimplify human interaction by reducing complex, nuanced opinions to single numerical values or predefined categories [8]. This failure to model the rich semantic and emotional context of online conversations underscores an urgent need for advanced simulation tools capable of modeling complex social processes, supporting proactive strategic planning, and enabling more effective risk assessment in high-uncertainty scenarios [1].

The advent of Large Language Models (LLMs) has catalyzed a paradigm shift in computational social science, leading to the widespread application of LLM-based autonomous agents in research. A growing body of work demonstrates that these agents can effectively simulate complex human social behaviors and decision-making processes [2]. When instantiated within simulated environments, LLMs serve as viable *computational subjects*, capable of replacing or augmenting human participants in scientific studies and social simulations [6]. This agent-based simulation approach offers a novel and scalable avenue for exploring complex societal dynamics, such as opinion formation and information diffusion, in a controlled yet realistic manner.

Despite this potential, existing simulations often lack the specific architecture for high-stakes PR crises. Current LLM-agent studies focus on general belief evolution through prompt-engineered biases [3] or use hybrid models where LLMs only handle specific tasks like information alteration [4]. While these advance beyond traditional numerical models that reduce opinions to single scores [8], a critical gap remains for specialized, accessible platforms. To bridge this gap, we introduce DualMind, a novel multi-agent simulation platform powered by LLMs, designed specifically to model the evolution of public opinion during critical events. Our system

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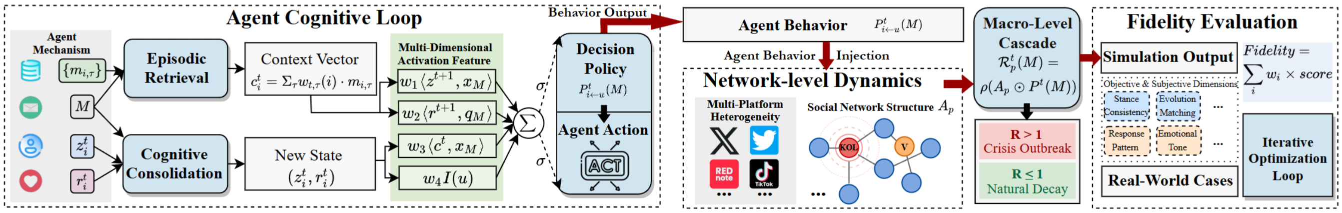

Figure 1: The overall framework of DualMind.

constructs a virtual social network populated by a large cohort of LLM-based agents, each endowed with a distinct persona, a memory module for cognitive continuity, and platform-specific behavioral protocols. These agents perceive information, interact with one another, and express opinions according to their unique characteristics and the structural constraints of simulated platforms (e.g., Weibo, Twitter, forums), thereby creating a high-fidelity digital microcosm for studying crisis dynamics.

To demonstrate the validity and utility of our platform, we conduct a rigorous evaluation grounded in real-world events. We employ a set of foundational LLMs whose knowledge bases are verifiably truncated before August, 2024 (including both open-source and proprietary models) to prevent data contamination. We then simulate the public response to 15 high-profile PR crises that occurred after August, 2024 across diverse geopolitical regions, including China, the United States, and Europe. Our experimental results reveal a strong correspondence between the simulated opinion trajectories generated by DualMind and the actual, documented evolution of public sentiment in these historical cases. This validation underscores the platform's potential as a reliable tool for both academic research and practical PR strategy testing.

2 Framework

DualMind formalizes opinion dynamics as a coupled evolution of agent cognitive states and network-level, content-sensitive diffusion. Each agent i possesses a dual latent state: a slowly evolving *semantic persona* $\mathbf{z}_i^t \in \mathbb{R}^d$ and a rapidly fluctuating *affective state* $\mathbf{r}_i^t \in \mathbb{R}^K$, complemented by an episodic memory store $\{\mathbf{m}_{i,\tau}\}$. When a message M (with embedding $\mathbf{x}_M$ and emotion $\mathbf{q}_M$) arrives, the agent retrieves a context vector $\mathbf{c}_i^t$ via attention-weighted, recency-decayed aggregation over its memory, implementing agent-level RAG:

$$\mathbf{c}_i^t \;=\; \sum_{\tau<t} \underbrace{\frac{\exp\{\beta\,\langle \mathbf{x}_{i,\tau}, \mathbf{x}_M\rangle\}\,\delta^{t-\tau}}{\sum_{\ell<t}\exp\{\beta\,\langle \mathbf{x}_{i,\ell}, \mathbf{x}_M\rangle\}\,\delta^{t-\ell}}}_{w_{t,\tau}^{(i)}}\,\mathbf{m}_{i,\tau}, \tag{1}$$

where $\beta > 0$ controls semantic selectivity and $\delta \in (0,1)$ implements recency.

The dual cognitive state updates via a gated, coupled rule preserving the slow–fast separation. Let $\sigma(\cdot)$ be the logistic function, $\Pi(\cdot)$ a projection operator (ensuring $\|\mathbf{z}\|_2 = 1$), η emotional persistence, γ adaptation rate, and α affective gate gain:

$$\begin{bmatrix}\mathbf{z}_i^{t+1}\\ \mathbf{r}_i^{t+1}\end{bmatrix} = \begin{bmatrix}\mathbf{z}_i^{t}\\ \eta\,\mathbf{r}_i^{t}\end{bmatrix} + \gamma\,\sigma\!\Big(\alpha\,\langle \mathbf{r}_i^t, \mathbf{q}_M\rangle\Big)\begin{bmatrix}\Pi\!\Big(\mathbf{x}_M - \langle \mathbf{x}_M, \mathbf{z}_i^t\rangle \mathbf{z}_i^t\Big)\\ \mathbf{q}_M - \mathbf{r}_i^t\end{bmatrix}. \tag{2}$$

This mechanism ensures that emotional resonance $\sigma(\cdot)$ gates the update to the long-term persona $\mathbf{z}_i^t$.

Decision-making follows the *Polarized Affective Cascade Model* (PAACM), a probabilistic policy. The activation probability $P_{i\leftarrow u}^t(M)$ integrates persona alignment, affective resonance, memory coherence ($\mathbf{c}_i^t$), source influence $I(u)$, platform bias $b_{p(i)}$, and agent threshold θ_i:

$$P_{i\leftarrow u}^t(M) = \sigma\Big(w_1\,\langle \mathbf{z}_i^t, \mathbf{x}_M\rangle + w_2\,\langle \mathbf{r}_i^t, \mathbf{q}_M\rangle + w_3\,\langle \mathbf{c}_i^t, \mathbf{x}_M\rangle + w_4\,I(u) + b_{p(i)} - \theta_i\Big). \tag{3}$$

This micro-level policy induces macro-level diffusion. The expected reproduction coefficient $\mathcal{R}_p^t(M)$ on a platform p (with adjacency $\mathbf{A}_p$) is the spectral radius $\varrho(\cdot)$ of the effective propagation matrix $\mathbf{P}^t(M)$ (where $[\mathbf{P}^t(M)]_{i,u} = P_{i\leftarrow u}^t(M)$):

$$\mathcal{R}_p^t(M) \;=\; \varrho\Big(\mathbf{A}_p \,\odot\, \mathbf{P}^t(M)\Big). \tag{4}$$

Supercritical cascades ($\mathcal{R}_p^t(M) > 1$) lead to self-sustaining opinion waves. This framework provides a closed, high-fidelity loop where PR interventions can be assessed by their ability to reduce $\mathcal{R}_p^t(M)$ below unity.

3 Demonstration and Case Studies

To validate the effectiveness of DualMind in simulating complex public relations (PR) crisis dynamics and to demonstrate its core functionalities, we designed and implemented an interactive demonstration system. This system supports two core simulation scenarios, fulfilling the distinct needs for **Strategy Effect Simulation** and **Real-world Case Reproduction**. The core of this demonstration system is a **Fidelity Evaluation Framework**, which is built upon a high-quality benchmark case library and a multi-dimensional evaluation schema. We will now elaborate on the simulation functionalities and this evaluation framework.

3.1 System Architecture

The system employs a decoupled front-end/back-end architecture, comprising a React front-end, a FastAPI back-end, and a LangChain-based agent layer.

The **front-end** utilizes a React (v19.1.1) and TypeScript stack with Ant Design. Social network visualization leverages the native Canvas API, chosen over libraries like D3.js for high-performance dynamic propagation effects.

The **back-end** simulator runs in a Python environment, employing the high-performance asynchronous framework FastAPI (over traditional Flask or Django) to serve RESTful APIs via Uvicorn.

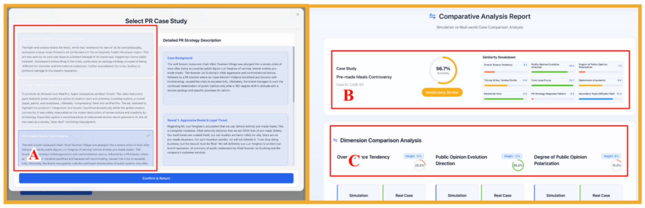

Figure 2: User interface of Case Study 1. (A) The user selects a real-world event from the "Select PR Case Study" window to set the ground truth; (B) The "Comparative Analysis Report" provides an immediate, top-level "Similarity Score" for feedback; (C) The user then assesses fidelity in detail via the "Dimension Comparison Analysis" module, which shows a side-by-side breakdown of simulated vs. real data.

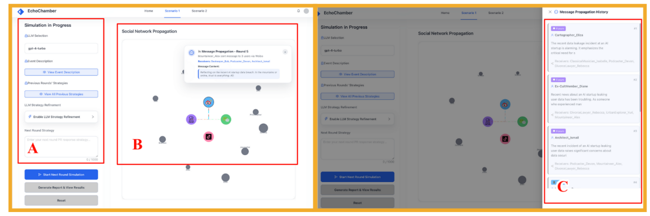

Figure 3: User interface for Case Study 2. (A) The user iteratively inputs natural language PR strategies in the left panel; (B) The center panel provides a real-time visualization of the opinion propagation network; (C) The right "Message Propagation History" panel tracks agent posts. Users analyze feedback from (C) to refine strategies in (A) and observe the new strategy's diffusion in (B).

The core **agent layer** utilizes LangChain and LangGraph to establish a structured cognitive workflow. Agent execution follows a controlled concurrency model: active agents execute sequentially in random order per round to avoid API concurrency limits. We employ a multi-model LLM strategy: the lightweight `gpt-4o-mini` handles high-frequency agent tasks (e.g., generating posts, evaluating stances), while the more powerful `gemini-1.5-pro` generates the final, complex nine-dimension analysis reports.

3.2 Case Study 1: Real-world Fidelity

In this Case Study, the system first presents you with a **Select PR Case Study** window. Here, you can see a structured list of real-world cases. When you click on any case in the list, the **Detailed PR Strategy Description** instantly loads, helping you understand the event background and the actual evolution of public opinion.

After you select a case and click **Confirm & Return**, the system loads the case's pre-decomposed key nodes. The simulation then starts automatically, strictly following the real-world timeline. It takes the first node, which is the company's first real PR statement, as input to drive the agent cohort's first simulation round, and you will see a visualization interface similar to that in Scenario 1.

Upon the conclusion of that node's simulation, you can choose to continue the simulation, or you can choose to generate a public opinion analysis report to view the results. Unlike Scenario 1, the system will present a **Comparative Analysis Report** interface. On this report, you will first see an overall **Similarity Score** (e.g., 67.0%), which intuitively summarizes the proximity between the simulated opinion development and the actual real-world event.

For an in-depth analysis, you can scroll down to the **Dimension Comparison Analysis** module. This module uses a side-by-side view to clearly display the simulation data versus the real data, presenting detailed scores and comparisons across all nine dimensions (such as Stance Consistency and Evolution Matching), complete with brief justifications and analysis. This simulation process also allows you to pause at any key node of the case and generate a comparative report, thereby intuitively evaluating DualMind's fidelity in reproducing real-world opinion dynamics.This workflow allows you to pause at any key node of the case and generate a comparative report, thereby intuitively evaluating DualMind's fidelity. The qualitative assessment here provides an interactive validation for the quantitative experiments.

3.3 Case Study 2: User-specified Simulation

In this Case Study, you can conduct a simulation for a custom crisis topic. First, define an initial public opinion event background in the **Event Description** text box. Then, acting as the PR entity, you compose and input the first-round PR intervention strategy into the **Next Round Strategy** input field.

Next, after you click the **Start Next Round Simulation** button, the system samples from the 100-persona library and dynamically instantiates a virtual social network with diverse agents. You can then observe the dynamic **Social Network Propagation** view on the main interface, which features icons representing platforms as information sources and propagation hubs (e.g., Weibo, TikTok), as well as nodes representing the agent users.

Subsequently, messages begin to propagate across the network. You can observe real-time pop-ups, such as **Message Propagation - Round 1**, which detail how an agent (e.g., Barista_Dave) receives and responds to the initial strategy. Lines then dynamically connect the agent nodes (gray dots) to simulate information diffusion. You can hover over these nodes or pop-ups to inspect specific message content and recipients. As the simulation advances, you can clearly track the specific posts and stance evolution of different agents via the **Message Propagation History** sidebar.

Once the first round over, you can analyze current opinion landscape and iteratively input a new PR strategy into the **Next Round Strategy** field. Upon clicking **Start Next Round Simulation** again, you will observe how this new strategy diffuses through the network and how the agents' reactions change in response.

At any stage of the simulation, you can click the **Generate Report & View Results** button. The system immediately invokes the evaluation module, presenting you with a comprehensive, nine-dimension public opinion analysis report. This report will quantitatively display the cumulative effects of your PR strategies, helping you determine if the intended objectives have been achieved. Through intermediate results such as the propagation map and stance evolution, we can observe that the dynamic interactions between agents conform to the logic of opinion propagation, demonstrating the system's reasonableness as a rehearsal tool.

4 Experiments

We conduct rigorous quantitative experiments to assess DUALMIND's fidelity in reproducing both the *process* (opinion trajectory) and the final *outcome* (aggregate stance distribution) of real-world PR crises against empirical data.

4.1 Setup

We evaluate on a **curated set of 15 real-world PR crises** (late 2024–2025), balanced across China (5), the US (5), and Europe (5). All models use LLMs with knowledge cutoffs before August 2024 to prevent data contamination. We compare DUALMIND against three SOTA baselines:

- **LAID** [4]: An LLM-enhanced agent model for information propagation, evaluated on four hypothetical scenarios (e.g., viral marketing) rather than real-world crises.
- **LPOD** [8]: A SOTA agent-based model for public opinion prediction that integrates epidemiological (SIR) models, validated on 100 real-world Weibo events.
- **LLM-GA** [3]: A foundational study on LLM agents, notable for identifying the "truth-bias" limitation, where agents inherently converge on factual consensus, on 15 topics with known ground truth.

All simulated outputs, $\hat{\mathbf{y}}_e$ and $\hat{\mathbf{p}}_e$, are generated using the same protocol and averaged over 5 stochastic seeds.

4.2 Metrics

We measure **process fidelity** using Pearson's r (Eq. 5) to compare the empirical ($\mathbf{y}_e$) and simulated ($\hat{\mathbf{y}}_e$) opinion trajectories. A higher r indicates better temporal alignment. We measure **outcome fidelity** using Jensen-Shannon Divergence (JSD, Eq. 6) between the final stance distributions ($\mathbf{p}_e, \hat{\mathbf{p}}_e$). Lower JSD indicates a closer match.

$$r_e = \frac{\sum_{t=1}^{T_e} (y_{e,t} - \bar{y}_e)(\hat{y}_{e,t} - \bar{\hat{y}}_e)}{\sqrt{\sum_{t=1}^{T_e} (y_{e,t} - \bar{y}_e)^2} \sqrt{\sum_{t=1}^{T_e} (\hat{y}_{e,t} - \bar{\hat{y}}_e)^2}}, \tag{5}$$

$$\mathrm{JSD}_e(\mathbf{p}_e \| \hat{\mathbf{p}}_e) = \frac{1}{2}\mathrm{KL}(\mathbf{p}_e \| \mathbf{m}_e) + \frac{1}{2}\mathrm{KL}(\hat{\mathbf{p}}_e \| \mathbf{m}_e). \tag{6}$$

4.3 Results

As visualized in Figure 4, DUALMIND consistently and significantly outperforms all baselines across all 15 cases. Our model achieves the highest average trajectory similarity (overall $\bar{r}{\approx}0.78$) and the lowest average outcome divergence (overall $\overline{\mathrm{JSD}}{\approx}0.27$).

This result highlights two key findings. First, the model demonstrates strong **cross-cultural robustness**, showing high-fidelity performance across the distinct media environments of China, the US, and Europe. Second, DUALMIND shows **clear superiority over SOTA models**, significantly outperforming even the strong **LPOD** baseline [8] in its own validated domain.

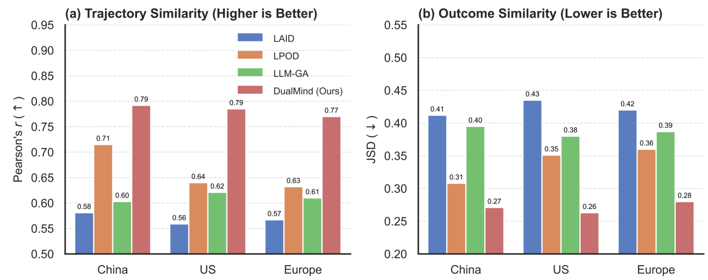

Figure 4: Fidelity comparison. DUALMIND (Ours) achieves the highest trajectory similarity (r, higher is better) and the lowest outcome divergence (JSD, lower is better) across all three regions.

Furthermore, while the **LLM-GA** [3] framework reported a "truth-bias" where agents default to factual consensus, our model's validation on real-world crises proves its ability to overcome this native LLM bias and faithfully simulate the complex, fact-resistant dynamics observed in human social networks.

5 Conclusion

In summary, we proposed DUALMIND, an LLM-based multi-agent platform that accurately simulates the dynamics of public relations crises. Our framework, validated against real-world 2025 events, demonstrated high fidelity in reproducing both opinion trajectories and final stance distributions, outperforming existing baselines. Limitations include the necessary simplification of agent cognitive models and the abstraction of complex platform algorithms and network scales. Future work will focus on enriching agent cognition with more complex reasoning, integrating external information streams (e.g., traditional media), and leveraging the platform for the automated discovery of optimal PR intervention strategies.

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