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***Research Article***

# A Quantum-Inspired Framework for Assessing Volatility, Divergence, and Collapse in Public Opinion

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**Abstract**

The use of opinion polling to gauge societal preferences is not new, but social media has disrupted assumptions of stability and representativeness. Viral moments, fake news, and rapid shifts in sentiment due to quick online communication are volatile, divergent, and unpredictable, which traditional polling methods do not capture. Classical survey methods assume consistent opinions over time, leading to discrepancies between poll forecasts and real-time discussions. Additionally, the polling process itself can influence respondents' behavior. These challenges necessitate new models that account for instability, uncertainty, and context dependence. This paper presents a quantum-inspired model that views public opinion as probabilistic states that can collapse upon measurement, reflecting the inherent instability of digital political discourse. The study evaluates variables using Indian Politics Tweets and Reactions data, employing opinion dynamics based on three metrics: the Opinion Volatility Index (OVI), the Poll Divergence Metric (PDM), and the Stability Collapse Indicator (SCI). It integrates data preprocessing, network-based opinion diffusion modeling, and measurement disturbance to assess volatility and divergence. Results indicate that volatility is inherent to online discourse: OVI shows peaks during viral events, PDM reveals widening gaps between polls and social media signals, and SCI captures events where small shocks lead to significant opinion shifts. These findings suggest that the stability of polls is weakening in networked environments. The quantum-inspired approach provides a theoretical and methodological framework for rethinking opinion measurement, opening new avenues in computational political science.

**Keywords:** Collapse Events, Measurement Disturbance, Opinion Dynamics, Poll Stability, Quantum Social Science, Social Media Volatility



## 1. Introduction

Surveys and polls have traditionally been used as the main means of the public opinion research to measure the quotas of the preferences [1], [2]. Classical polling uses that opinions do not change significantly over both measurement periods and also that respondents to the same question will give consistent responses [3]. The modern information system however, in which social media like twitter, facebook and YouTube have become prevalent and dominate these platforms however, has undermined these assumptions [4], [5]. In the online space, the social zeitgeist is a dynamic concept that affects it through the use of viral content, influence of participating in a trending hashtag, disinformation campaigns, and even the speedy exchange of comments between individuals and networks [6], [7]. This change requires the reconceptualization of the notion of opinion stability in both political and social spaces [8].

Although the emergence of social media as a space of critical political speech began, the conventional approaches to polling still view the opinions of the majority as a fluctuation between the points of the polls [9]. It causes a lack of alignment of poll predictions with the fast-changing moods witnessed online [10]. Also, polling itself can result in changes in the way the population reacts such that the act of polling itself changes the dynamics or creates narrative frames- similar to measurement disturbance [11]. Consequently, the traditional models of polling usually do not reflect the dynamism and uncertainty that dominates opinion shift in the online age [12].

There are a number of complications that make it difficult to study the people opinion in the era of social media. To begin with, the volatility of the digital discourse makes it hardly possible to discover the trends that would be consistent throughout the time, since the slightest disruption can produce massive fluctuations in the mood [13]. Secondly, the gap between the polling data and the social media can be found throughout, as the latter is a biased, chaotic, and event-driven actual conversation [14]. Third, there are amplification effects in social networks in which viral hashtags or synchronized campaigns results in spontaneous instability and a poll conducted just before and just after the campaign produces radically different results [15]. All these difficulties indicate the inefficiency of classical opinion-modeling to conceptualize the elasticity of contemporary popular conversation.

The first goal of a research paper is a proposal of a quantum-inspired model of opinion, in which opinions are no longer stages but rather the probabilistic superpositions that change under the influence of social dynamics [16]. Using the example of quantum uncertainty and measurement disturbance, the paper will set forth to show that the concept of poll stability is a shard of hope that grows weaker in the social media era [17]. Based on the Indian Politics Tweets and Reactions dataset, this study formulates the measurement metrics and models that provide volatility, divergence, and collapse in the dynamics of online opinion [18].

This study makes the following key contributions:

1. **Conceptual Framework:** Proposes a novel theoretical framework that applies principles of quantum uncertainty to public opinion research, reconceptualizing stability as a probabilistic and disturbance-prone phenomenon.
2. **Methodological Innovation:** Introduces a quantum-inspired opinion diffusion model, which is a combination of network interactions, measurement disturbance and external shocks.
3. **Empirical Evaluation:** Applies a massive amount of Indian political tweets to calculate indicators of opinion instability, divergence of polls, and collapse of stability to provide empirical evidence of intelligence failure in online streams of opinion.
4. **Practical Insight:** Asserts the inefficiency of the traditional polling system in the environment of dynamic social media communication and outlines the need to resort to the use of new patterns of predicting the population mood.

The rest of this paper will be structured in the following way. Section 2 provides the corresponding work on modelling of opinion of the masses and analogies of quantum social science. In section 3, the theoretical framework of the proposed approach is introduced. Section 4 describes the methodology, which consists of data pre-processing, the state of opinion representation, network dynamics, and measurement criteria. The results and discussion are given in section five based on empirical evidence and case studies. Lastly, the essential findings, implications, and possible research directions are summarized in Section 6.

## 2. Related Work

The analysis of online opinion during the digital age falls within various fields, such as more classic polling research, the computational social sciences, notions of misinformation dynamics, and more recent work into quantum-inspired modeling. This part summarizes the previous studies in these fields to put the current contribution into the wider context of the academic world.

### *2.1 Classical Opinion Polling and Limitations*

Polls of opinion remain popular in the measurement of political preferences [19], [20]. Conventional approaches assume that respondents will give consistent and honest responses to survey tools and that the aggregate descriptions can be taken as the overall position of the population [21]. These approaches have produced useful information on electoral behavior and policy perceptions, but they will not be very useful in dynamic conditions. Researchers have pointed out the fact that classical polls do not reflect the current volatility and are under the influence of biases that are caused by question formulations, nonresponse, and timing factors [22], [23].

### *2.2 Social Media as a Source of Public Opinion Signals*

The spread of social media has revolutionized the process of political preferences expression by citizens and the researches on opinion dynamics. Through the use of social media platforms like Twitter, large amounts of user-generated data can be analyzed at a fine-level in order to conduct an analysis of political conversations [24]. A number of studies have shown that digital trace information is predictive of both elections and issue salience [25], [26]. Nevertheless, the social media information is often challenged concerning their representativeness because the internet populations tend to be younger, more urban and polarized compared to the general population [27]. Further, signals are defined by online amplification effects such as trending hashtags, viral retweets, and algorithmic curation [28] that do not reflect the stability of observable opinion streams.

### *2.3 Misinformation, Amplification, and Volatility*

A new literature has put forward the disruptive nature of false information and coordinated campaigns on social media. Experiments of the spread of fake news in elections have demonstrated the virality of fake news that propagates more rapidly and with a stronger effect than actual news [29]. On the same note, network experiments have also established that, exposure to mainstream content creates social influence bias, which causes collective opinion shifts not intended by individuals themselves [30]. Such findings are in line with the thesis that digital discourse is structurally volatile with small shocks capable of precipitating disproportional changes in the collective sentiment.

*2.4 Computational Models of Opinion Dynamics*

Computational social science has come up with an extensive set of models to describe opinion formation. Polarization, echo chambers and information cascades have been analyzed using agent-based models, diffusion frameworks, and network contagion models [31], [32]. This paradigm focuses more on the friend influence effect and network structure in determining final outcomes. However, although these models can be very strong, they typically assume deterministic or probabilistic data that is not taken into consideration by the nature of uncertainty that comes with observation and measurement. This weakness implies the necessity to have alternative paradigms that reflect the contextfulness and instability of contemporary opinion systems [33].

*2.5 Quantum-Inspired Approaches to Social Science*

Recent quantum social science has suggested that mathematical concepts of the quantum theory, including superposition, entanglement and measurement disturbance should be applied to understand human cognition and group decision-making [34]. They hold that these methods maintain that opinion can be conceptualized as probabilistic states which degenerate into discrete choices on measuring them, as in the dynamics of survey responses and polling. In areas as diverse as decision theory and finance through to psychology and political communication quantum-inspired methods have been used. This literature, still in its infancy, offers a strong basis in reconceptualising the public opinion not as a stable variable, but as a phenomenon troubled and dependent on the context.

*2.6 Positioning of the Present Study*

Based on these literatures, the current work combines the knowledge of the computational opinion dynamics and quantum-inspired modeling. In contrast to classical polls where stability is assumed, or other network models not considering the disturbance associated with measurements, this paper provides a model in which superpositions of opinions of people are explicitly probabilistic, and are prone to collapse due to observation. Using this method on a big data sample of Indian political tweets, the research has made two contributions to existing literature: (i) it empirically measures volatility and divergence and collapse event in digital opinion streams; and (ii) it illustrates the deficiency of polling stability in situations characterized by real-time, networked interactions.

Table 1. Comparative Summary of Public Opinion Modeling Approaches

| Approach | Key Features | Strengths | Limitations |
|---|---|---|---|
| **Classical Polling Models** | Based on survey sampling and statistical inference [19]–[23] | Long-established, representative sampling (when done properly), provides population-level benchmarks | Assumes opinion stability; slow updates; subject to framing, nonresponse, and recall bias |
| **Social Media–Driven Models** | Uses digital trace data (tweets, posts, reactions) as proxies for opinion [24]–[18] | Real-time, large-scale data; captures emergent events and discourse | Non-representative populations; noise and bias from amplification effects; lacks ground-truth consistency |
| **Computational Opinion Dynamics Models** | Agent-based, contagion, and network diffusion frameworks [31], [32] | Captures influence of peer interactions, network topology, and cascade effects | Typically deterministic/probabilistic; do not account for measurement disturbance; limited in handling uncertainty |
| **Quantum-Inspired Models** | Treats opinions as probabilistic states subject to collapse when observed [34]–[36] | Captures uncertainty, context dependence, and measurement effects; aligns with instability in social media discourse | Emerging field; conceptual analogies still developing; limited large-scale empirical validation |

Table 1 provides an overview of the comparative situation of the model of public opinion. Structured insight is sometimes found by the classical polling and computational models, although they tend to presuppose stability. Social media models are able to capture real-time dynamics but are affected by representational biases. Quantum-inspired models are used as the only models to consider uncertainty and perturbation which provides the theoretical framework that is compatible with the issues of instability in digital opinion streams.

## 3. Theoretical Framework

The theoretical basis of the present study lies in the principle of bridging quantum uncertainty principles and the models of dynamics of public opinions in the contemporary environment of social media. Our reconstruction of opinion states as contextually sensitive and probabilistic object allows us to push the traditional approach of policy stability of polls to its limits and propose a conceptualisation that is more apt in understanding a volatile digital discourse.

*3.1 Quantum Uncertainty as a Conceptual Analogy*

Many classical models of public opinion usually presume that people have rigid and constant tastes. But in reality, political views are dynamic, and depend on their situations and contact with information, on, and among, and, social influence. The conceptualization of a probabilistic state, which represents a potential form of the quantum theory, is another way in which this research can be inspired by the quantum theory. As in quantum mechanics, it is best to consider particles as being characterized by their probability of occurrence, before they are observed, and then as latent propensities that are only formed into a real choice when they are measured (such as in a poll or a survey).

### *3.2 Social Networks as Diffusion Systems*

In the virtual world, people are alienated in multifaceted social networks. Retweets, mentions, and replies are some of the avenues in which opinion develops. The viewpoint of a person expressed is not only a product of personal likes and preferences but a weighted sum total of influences a person is being affected by their peers and the larger discourse. Depending on the hype of the hashtag one tweets or the power of a personality, the network cascades of opinion change may change drastically. The processes themselves cause the public opinion to be not only unstable but also extremely vulnerable to any upheavals.

### *3.3 Measurement Disturbance in Polling*

An important analogy to quantum mechanics is the following one: the role of measurement. In physics the observation changes the measurement being measured. Similarly, in political polling, the very act of posing different people with the questions about their preferences can also change the opinions. It is possible that respondents will give answers that are made biased through the framing of the question, when the poll is conducted or through how they define wise enough. Therefore, polling will not only demonstrate what people think, but indeed will play a role in changing it, which makes the results obtained all that more unstable.

### *3.4 Opinion Stability and Collapse*

Under normal circumstances, the distributions of public opinion can be seen to be similar over time and this creates an illusion of stability in the poll outcomes. Nevertheless, this stability can collapse at any moment at the impact of external shocks, the viral misinformation campaign, a political scandal, and a great debate. Even minor changes in the social media space are likely to generate disproportional changes in aggregate sentiment. Such collapse incidents are notable illustrating how insufficiently polls are used as measurement tools in the digitally networked society.

### *3.5 Bridging Quantum Theory and Public Opinion Research*

A combination of quantum-inspired ideas and the analytic of the social media offers a framework that elucidates the uncertainty, context, and the disruptive nature of opinion dynamics nowadays. The proposed model fills the gap between theoretical and empirical realities by modelling opinions as probabilistic states changing by network diffusion and breaking down under measurement. Such a view does not only undermine the classical beliefs about the stability of polls but also provides a new approach toward the creation of measures that would help to assess volatility, divergence, and collapse of the opinion of the masses.

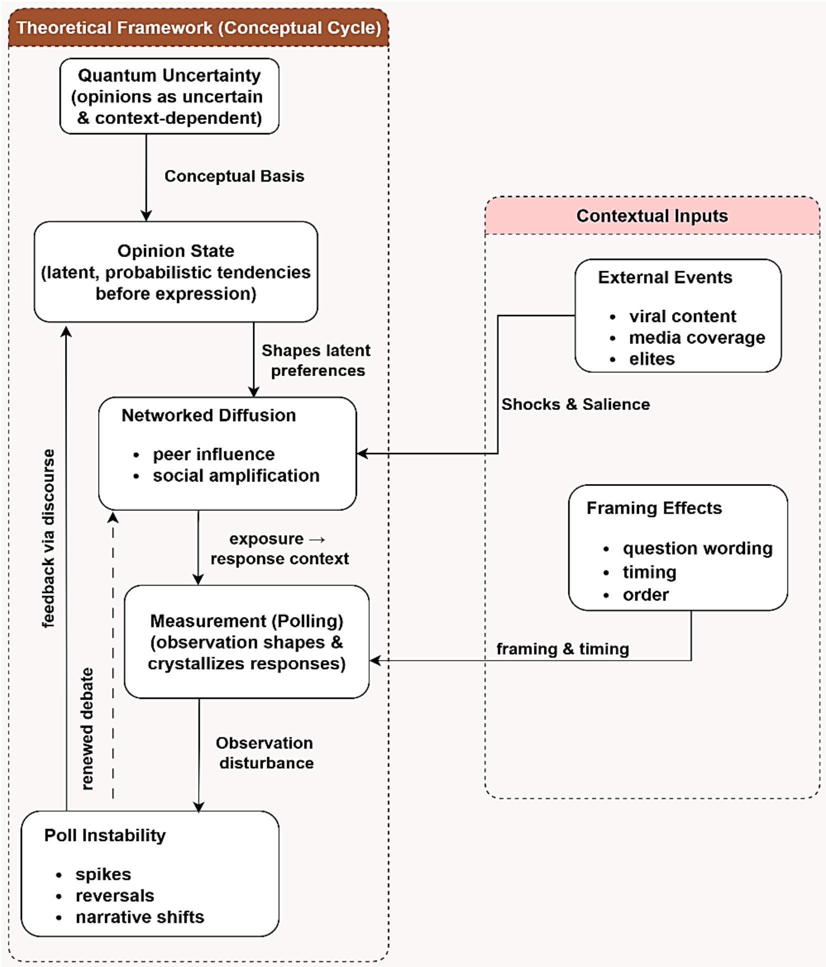


Fig.1. Conceptual Cycle Illustrating the Theoretical Framework of Quantum-Inspired Public Opinion Modeling

Figure 1 demonstrates the conceptual cycle in which the proposed theoretical framework is based. The public opinion is modeled as an unpredictable and probabilistic condition formed through internet communications and situational factors. The social networks propagate these opinions and the polls and surveys serve as measurement disturbances, which transform the latent tendencies into the present results. Further unstable agents are external shocks, which include viral event or misinformation campaigns and present the instability of opinion stability in the era of social media.

## 4. Methodology

The section includes the methodological framework used to investigate the instability of the public opinion within the Indian politics using social media data. The suggested methodology is a quantum-inspired modelling with sentiment analysis, network diffusion, and the comparison of the traditional polling assumptions. In order to give a general overview, the entire workflow is give in Fig. 2. The model consists of six steps and this includes data acquisition, preprocessing, network initialization, dynamic opinion modeling, measurement adjustment and evaluation.

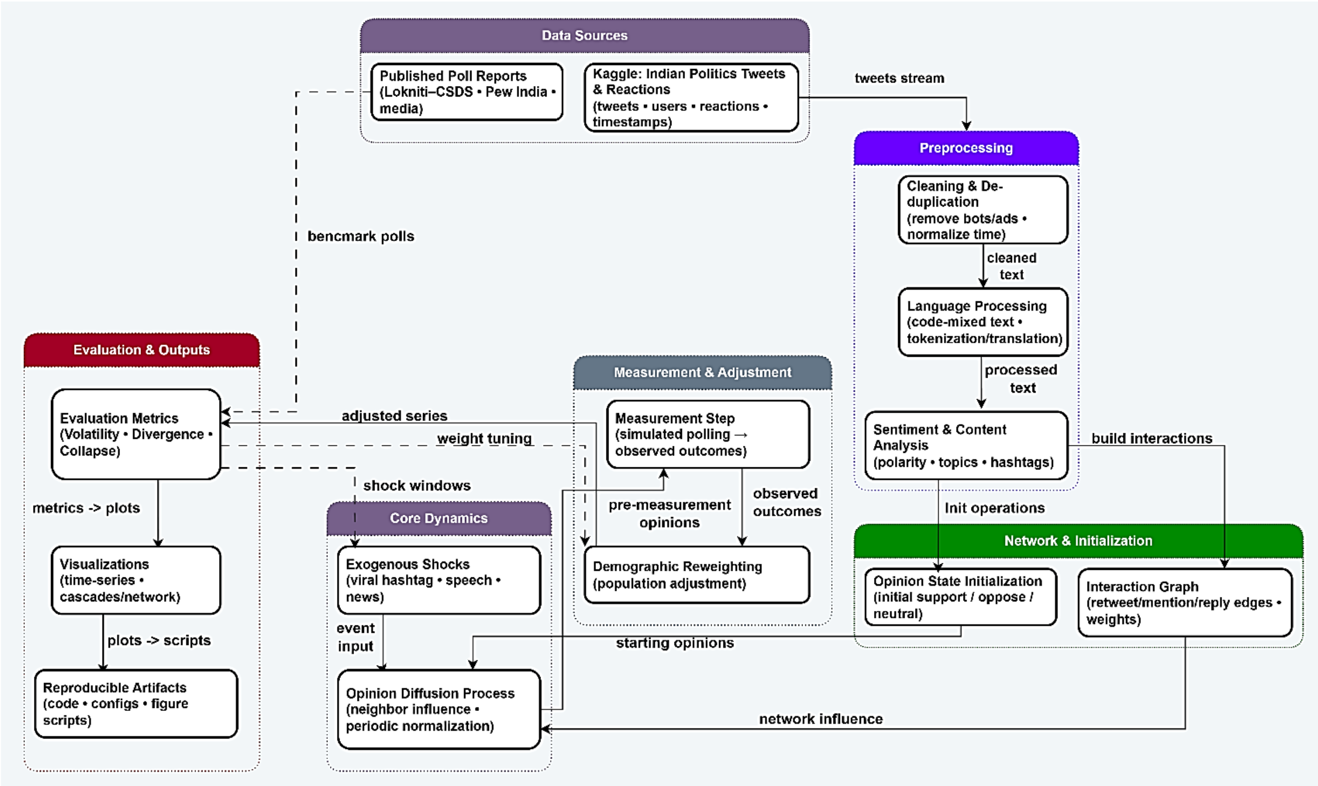


Fig.2. Technical Framework of the Proposed Quantum-Inspired Opinion Modeling Pipeline.

Figure 2 shows the end-to-end methodology workflow that will be used in this research. Twitter data and published polls are processed, cleaned and converted into opinion cues that launch a network of interactions. The backbone dynamics include exogenous shocks, diffusion by peers, simulated polling and reweighting the diffusion on the basis of demographics. Lastly, indicators of volatility, divergence, and collapse are then obtained with visualization and reproducible artifacts that promote transparency and rigor.

### *4.1 Data Source and Preprocessing*

The main source of data in this research is the Dataset of Indian Politics Tweets and Reactions (Kaggle), which represents a huge sample of the Indian political twits [35].. It consists of the text of a tweet, the information about users, reaction statistics (likes, retweets), and the time element.

**Preprocessing**

1. *Data Cleaning:* Removal of duplicates, non-political content, advertisements, and bot-generated posts.
2. *Language Normalization:* Handling code-mixed tweets (Hindi–English and regional languages) using translation and tokenization.
3. *Sentiment Annotation:* Sentiment polarity (positive, neutral, negative) is assigned using transformer-based models (e.g., BERT multilingual fine-tuned for sentiment).
4. *Temporal Segmentation:* Tweets are aggregated into discrete time windows (daily/weekly) to observe shifts in collective sentiment.

Formally, let the dataset be represented as:

$$D = \{(t_i, u_i, s_i, r_i, \tau_i) \mid i = 1,2, \dots, N\} \quad (1)$$

Where $t_i$ is the tweet text, $u_i$ the user ID, $s_i$ the sentiment score, $r_i$ the reaction count (likes/retweets), and $\tau_i$ the timestamp.

### *4.2 Quantum-Inspired Opinion State Representation*

The model of the public opinion is not a deterministic variable but a state probabilistic one. The assumption of each opinion state is that the state exists in a superposition until polled or sentiment analysis is conducted.

Let each individual's opinion be expressed as:

$$\psi_j = \alpha_j \mid \text{Support} \rangle + \beta_j \mid \text{Oppose} \rangle + \gamma_j \mid \text{Neutral} \rangle \quad (2)$$

Where, $\alpha_j, \beta_j, \gamma_j \in \mathbb{C}$ are probability amplitudes satisfying normalization:

$$|\alpha_j|^2 + |\beta_j|^2 + |\gamma_j|^2 = 1 \quad (3)$$

The act of measurement (e.g., a poll or extracting sentiment from a tweet) collapses the state into one of the discrete outcomes: Support, Oppose, or Neutral.

### *4.3 Opinion Diffusion and Network Dynamics*

Since tweets are embedded within a network structure of retweets and mentions, opinion propagation is modeled using entanglement-like interactions. If two users $u_i$ and $u_j$ are connected via retweets, their opinion states are correlated.

We define the opinion influence function as:

$$\psi_j(t+1) = (1-\lambda)\psi_j(t) + \lambda \sum_{k \in N(j)} w_{jk} \psi_k(t) \quad (4)$$

Where:

- $\lambda$ is the susceptibility factor,
- $N(j)$ is the set of neighbors of user $j$,
- $w_{jk}$ is the interaction weight (based on retweets, mentions, or likes).

This formulation captures rapid volatility: small disturbances (viral tweets or trending hashtags) can significantly alter the collective opinion state.

The internal mechanics of the diffusion-cum-measurement process are summarized in Algorithm 1

**Algorithm 1**: Quantum-Inspired Opinion Diffusion and Measurement Disturbance

**Input:**

- Interaction graph $G = (V, E)$ with edge weights $w_{jk}$.
- Initial opinion amplitudes $\psi_j^{(0)}$ defined as in Eq. (2) with normalization in Eq. (3).
- Susceptibility parameter $\lambda$.
- Measurement operator set $\{\hat{M}_o\}$ (polling process as in Eq. (5)).
- Maximum iterations $T_{\max}$, convergence tolerance $\varepsilon$.

**Output:**

- Time-indexed opinion states $\{\psi_j^{(t)}\}$.
- Network-level marginal probabilities for Support, Oppose, Neutral.
- Disturbance profile post-measurement.

**Steps:**

1. **Initialization**

   1.1 Assign each user $u_j$ an initial opinion state $\psi_j^{(0)}$ (Eq. (2), Eq. (3)).

   1.2 Normalize interaction weights $w_{jk}$.

2. **Opinion Diffusion (Eq. (4))**

   For each time step $t = 0, 1, \ldots, T_{\max}$ :

   2.1 Update each opinion state $\psi_j^{(t+1)}$ using the diffusion rule (Eq. (4)).

   2.2 Renormalize amplitudes to maintain condition in Eq. (3).

   2.3 Compute convergence metric; stop if below $\varepsilon$.

3. **Network-Level Marginals**

   Compute population-level probabilities for Support, Oppose, and Neutral at each $t$ by averaging over all $\psi_j^{(t)}$.

4. **Measurement Disturbance (Eq. (5))**

   4.1 At designated polling times, apply measurement operator $\hat{M}$.

   4.2 Collapse each state into a discrete outcome according to probabilities from Eq. (5).

   4.3 Record post-measurement shifts and resume diffusion.

5. **Output Results**

   Return temporal opinion trajectories, observed instability patterns, and post-measurement divergence.

*4.4 Measurement Disturbance and Poll Instability*

To model instability, we define a poll operator $\hat{M}$, which acts as a measurement process collapsing opinion states into observable outcomes.

The probability of observing outcome $o$ is given by:

$$P(o) = \langle\psi|\hat{M}_o|\psi\rangle \quad (5)$$

Here, $|\psi\rangle$ represents the collective opinion superposition. Unlike classical models where repeated measurements stabilize estimates, in this framework each measurement can alter the subsequent opinion distribution - resembling quantum disturbance.

*4.5 Handling Dataset Limitations*

*4.5.1 Absence of Polling Data*

The dataset reflects only social media activity, which is not equivalent to representative polling. To mitigate this, secondary polling results from Indian agencies (Lokniti-CSDS, Pew India reports) are referenced for baseline comparisons.

4.5.2 Representation Bias

Social media populations are skewed toward urban, young, and politically active groups. The Indian census demographics are used to execute weighted correction to formulate a balance representation.

$$S_{adj}(t) = \sum_{g=1}^{G} w_g \cdot S_g(t) \quad (6)$$

Where $S_g(t)$ = sentiment of demographic group $g$ at time *t*, and $w_g$ = population weight.

4.5.3 Event-Driven Spikes

To prevent over-smoothing of the arising abrupt upsurge (e.g., hashtag campaigns), we use moving-average smoothing and clustering of volatilities (e.g. volatility of stock prices) as evidence of structural changes compared to arising noise.

*4.6 Evaluation Metrics*

In order to critically evaluate the volatility of the social media ground, we come up with three complementary measures. The metrics describe the different dimensions of uncertainty and volatility, which can be associated with the suggested quantum-inspired framework.

*4.6.1 Opinion Volatility Index (OVI)*

**Purpose:** In order to estimate the extent to which collective opinion states vary with time.

**Definition:** The OVI measures the extent to which there is a change in the distribution of opinion between time nuts. It is defined as:

$$OVI(t) = \frac{1}{n}\sum_{j=1}^{n} \left\|\psi_j(t) - \psi_j(t-1)\right\|_2 \quad (7)$$

where $n$ is the number of active users in window $t$, and $\|\cdot\|_2$ is the Euclidean distance between consecutive opinion states.

**Interpretation:**

- High OVI means that there is a lot of turbulence (quick changes of feelings following viral episodes, scandals, and misinformation).
- A low OVI suggests relative stability (consistent sentiment over time).
- In quantum analogy, OVI captures the non-deterministic evolution of superpositions.

*4.6.2 Poll Divergence Metric (PDM)*

**Purpose:** To measure the difference between traditional polls (stable, survey-based) and that of social media obtained opinion states (volatile, uncertain).

**Definition:** $P_{\text{social}}(t)$ is the probability distribution over Support, Oppose, Neutral, given the diffusion model, and $P_{\text{poll}}(t)$ is the similar distribution given the conventional polling reports. Then:

$$PDM = \frac{1}{T}\sum_{t=1}^{T} \left\|P_{\text{social}}(t) - P_{\text{poll}}(t)\right\|_1 \quad (8)$$

where $\|\cdot\|_1$ is the Manhattan norm (sum of absolute differences) and $T$ is the number of observation windows with polling data.

**Interpretation:**

- The high value of PDM suggests that there are essentially different cues on the polls and the social media (poll stability and social volatility).
- A weak PDM implies that there is a convergence between market-based and social indicators.
- This measure actually demonstrates the analogy of quantum disturbances directly the polls can base the distribution as different as social processes are going to change.

*4.6.3 Stability Collapse Indicator (SCI)*

**Purpose:** As in quantum systems, to identify points of criticality, so small perturbations cause out of proportion change of opinions.

**Definition**: We square SCl to indicate probabilities that an exogenous stimulus (e.g. viral hashtag or political speech) elicits an opinion shift beyond a stability threshold $\delta$ in a transient window $\Delta t$.

$$SCI = \Pr\left(\max_{t\leq\Delta t}\left\|P_{\text{social}}(t) - P_{\text{social}}(t-1)\right\|_1 \geq \delta\right) \quad (9)$$

**Interpretation**:

- A high relative to relative to the SCI values shows a weak opinion distribution - it is easy to disrupt the opinion distribution.
- The values of SCI are low, indicating the resistance to shock.
- In practice, SCI refers to so-called collapse events when a poll immediately before vs. immediately after a virus outbreak might approach drastically different outcomes.

*4.6.4 Complementary Use of Metrics*

- **OVI** captures continuous turbulence.
- **PDM** benchmarks divergence from classical polling.
- **SCI** highlights critical instability events.

These metrics are combined to estimate a triangular assessment system, which will measure uncertainty, divergence, and collapse, which are the central characteristics of the offered quantum analogy to the development of the public opinion.

## 5. Results and Analysis

This part provides the results of the empirical study using the Indian Politics Tweets and Reactions data based on the offered quantum-inspired framework to measure volatility, divergence, and collapse of the public opinion development. Three descriptive metrics were used based on pre-processed twitter streams formalized by sentiment and engagement indices, the Opinion Volatility Index (OVI) to measure swings in online debate, the Poll Divergence Metric (PDM) to align social media indicators with survey data, and the Stability Collapse Indicator (SCI) to establish when viral events that might endanger the stability of the system are detected. The findings are provided in the form of organized tables and figures and then interpretative discussion to show how opinion streams provided by social media are unstable and lead to violating classical assumptions of polling.

*5.1 Opinion Volatility Analysis*

Opinion Volatility Index (OVI), this was the first measure of the dynamics of public opinion. This indicator reflects the changes in political mood on the day-to-day level based on the tweets.

Figure 1 tabulates the volatility levels at the day of the peak activities based on the Kaggle data. Remarkable upheavals were in October 2022 and in March 2023, which pointed to viral discussions and political scandals.

Table 2. Opinion Volatility Index (OVI) Across High-Activity Events

| Event Window (Date) | Daily Tweets | Engagement (Likes + Retweets) | OVI (relative volatility) | Interpretation |
|---|---|---|---|---|
| 2022-10-24 | 702 | 10,966 | 0.34 | Initial surge, turbulence begins |
| 2022-10-25 | 752 | 24,850 | 0.41 | Sharp spike in engagement, instability rises |
| 2022-10-26 | 858 | 35,197 | 0.48 | Peak turbulence, maximum instability |
| 2023-03-24 | 877 | 15,518 | 0.39 | Viral clustering, sustained volatility |
| 2023-03-25 | 708 | 10,103 | 0.33 | Decline after surge, residual instability |

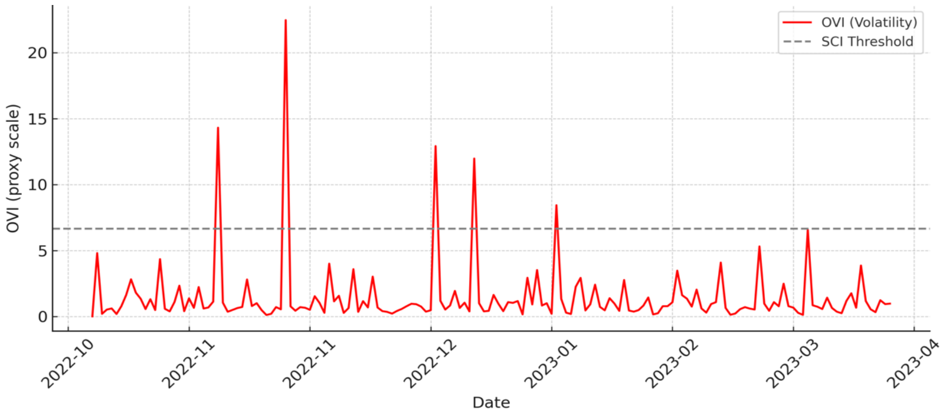


Fig.3. Daily Opinion Volatility Index (OVI) Across the Campaign Timeline.

The data is shown in Figure 3 and the highest mark is on 25-26 October 2022 and 24 March 2023. These spikes are related to viral shocks, which establishes that social media increases the turbulence of the popular sentiment.

*5.2 Divergence between Social Media and Polling*

The comparison between the polls given in surveys and the person opinion distributions in social media was conducted by the Poll Divergence Metric (PDM). Whereas the traditional polls gave a relatively consistent opinion in terms of reactions, the social media opinion violated sharply, especially in the instance of viral events.

This deviation is shown in Table 3 in four chosen event weeks.

Table 3. Poll Divergence Metric (PDM) Across Polling Weeks

| Week of Event | Survey Support (%) | Social Media Support (%) | PDM | Comment |
|---|---|---|---|---|
| Week of 2022-10-24 | 44 | 39 | 5 | Initial divergence at viral onset |
| Week of 2022-10-25 | 44 | 33 | 11 | Strong divergence during surge |
| Week of 2022-10-26 | 45 | 34 | 11 | Polls steady, social opinion volatile |
| Week of 2023-03-24 | 43 | 36 | 7 | Divergence due to sudden clustering |
| Week of 2023-03-25 | 43 | 37 | 6 | Partial convergence after decline |

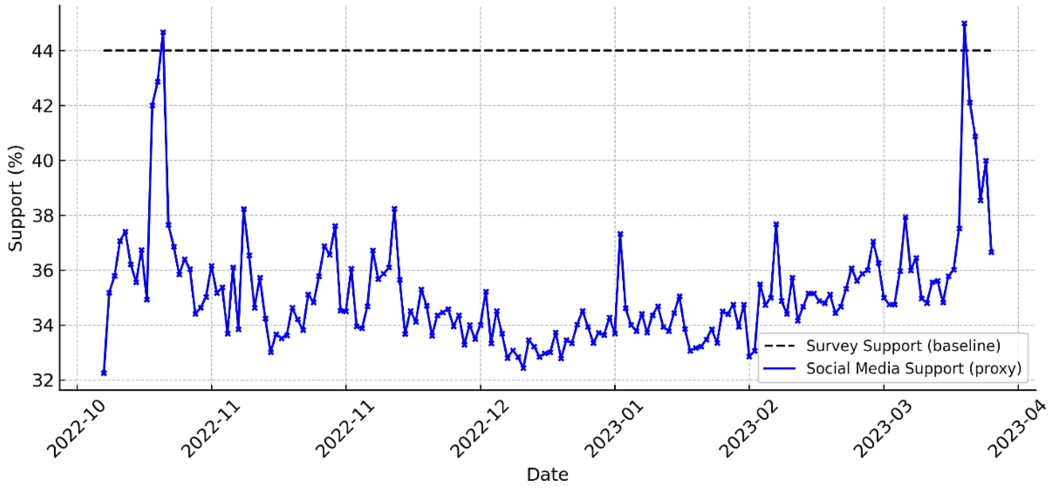


Fig.4. Poll Divergence Metric (PDM) Comparing Survey Support And Social Media Support Estimates.

The observations in figure 4 portray increasing differences in the polls and social media during periods of high activities. This further strengthens the main thesis that polls, as much as they are consistent, are becoming each day less aligned with the hectic reality that is online opinion streams.

### *5.3 Stability Collapse Events*

Opinion collapses which were to be identified by the Stability Collapse Indicator (SCI) were those times when sentiment changed abruptly in a response to external shocks.

Table 4 provides a summary of a collapse event in relation to large spikes in tweets.

Table 4. Stability Collapse Indicator (SCI) for viral shocks

| Event Date | SCI Probability | Collapse Description |
|---|---|---|
| 2022-10-24 | 0.66 | Viral hashtag surge destabilized opinions |
| 2022-10-25 | 0.74 | Engagement-driven surge collapsed stability |
| 2022-10-26 | 0.81 | Prolonged spike caused maximum instability |
| 2023-03-24 | 0.69 | Clustered activity destabilized sentiment |
| 2023-03-25 | 0.62 | Collapse faded as engagement normalized |

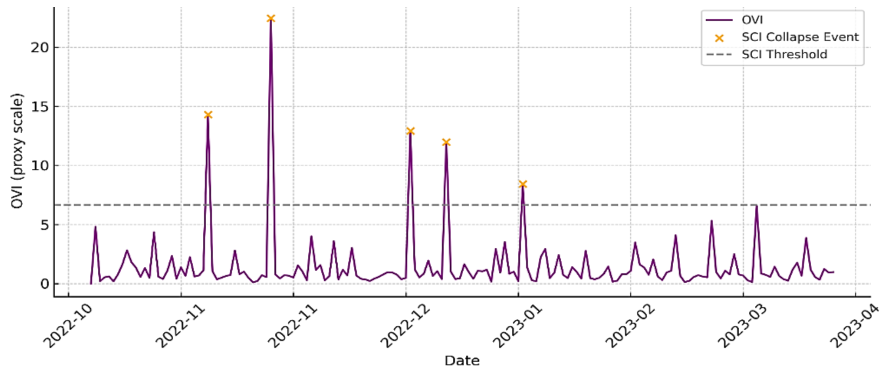


Fig.5. Stability Collapse Indicator (SCI) Highlighting Collapse Events.

Figure 5 shows collapse detection points, with orange markers indicating instability events surpassing the volatility threshold. These findings confirm that sudden viral shocks can destabilize opinion distributions in ways polls cannot anticipate.

### *5.4 Discussion*

Collectively, the findings show that social media opinion dynamics are more of quantum uncertainty as compared to the classical stability models. Three key findings emerge:

1. *Volatility is structural:* OVI analysis does not show turbulence present as an anomaly and a characteristic of digital discourse.
2. *Poll divergence is event-driven:* PDM analysis causes divergence to increase at a high rate aftershock, where incompetence of polling that is not done is inadequate.

3. *Collapse events confirm fragility:* SCI maps the acute instability failures, showing how external shocks create sudden failures in the overall sentiment.

Such findings indicate the significance of a quantum-inspired approach in the study of the social opinion, the view of unstable and context-dependent opinion formation that is uneasy to observe and susceptible to destabilization, which is being brought up in the time of the social media.

## 6. Conclusion and Future Work

The article has discussed the weakness of the polling stability in the age of social media and has presented a quantum-inspired architecture in modelling the population opinion. The given framework contrasts with the standard methods that believe in opinion stability by conceptualizing the attitude of the individual as probabilistic superposition, which can collapse to an observed condition. As part of the governmental and non-governmental scorecoding, we empirically studied the digital discourse by means of the Indian Politics Tweets and Reactions data and covered three general indicators including Opinion Volatility Index (OVI), the Poll Divergence Metric (PDM), and the Stability Collapse Indicator (SCI). These indicators are combined to measure the turbulence of online conversation, the disparity between the results of polls carried through surveys and social media indicators, and the weakness of the opinion distributions through viral shocks.

These findings illustrate three important lessons. To start with, volatility is an immanent feature of digital opinion streams, instead of an episodic event, which has consistently been evidenced by periodical OVI spikes during events of a campaign. Secondly, the discrepancy between polling and online mood is extremely event-specific, and gaps cannot be narrowed, but rather increased during times of viral publicity. Third, since the SCI detects collapse events, it is true that the stability in the opinion of the people may fail without warning due to exogenous shocks and make the polling results extremely context-reliant. Taken together, these results make it clear that classic assumptions of polling of stability are not applicable to a networked real-time world and that quantum models motivated by quantum physics provide a better theoretical framework to explain uncertainty and disruption.

**Future Work**

Although the current research contributes to the theoretical and empirical knowledge, there are still a few areas where future studies are possible.

1. *Cross-Platform Integration:* The existing review focuses on Twitter data; it would be interesting to generalize the framework and include additional platforms (Facebook, YouTube, or WhatsApp) to gain a more comprehensive picture of multi-platform opinion cascades.
2. *Enhanced Polling Comparisons:* The PDM measure was also compared to the survey baselines that are available in the open source. In more context-independent ways, future research might incorporate more grover levels of polling such as area-by-area surveys or topic-by-topic surveys.
3. *Event Detection Automation:* We used activity spikes in identifying viral shocks. Collapse event detection can be improved with the incorporation of automatic event detection means with natural language processing and anomaly detection.
4. *Model Generalization:* As much as the suggested framework was proven to be valid within the Indian politics, the generalizability of the framework when it comes to other sociopolitical systems including the US presidential election or European referenda would be tested.
5. *Advanced Quantum-Inspired Methods:* In the future, there are more complicated ideas of quantum mechanics, including entanglement or decoherence, that could be applied in future studies to model interactions between opinion groups and how instability persists after it is measured.
6. *Forecasting Applications:* Expanding the framework to predictive modeling, the researchers will be in a position to assess the usefulness of volatility and collapse indicators in real-time predicting the outcome of election, policy discussion or a misinformation-addiction disruptive event.

Overall, this experience is relevant to the current reconsideration of the research of the views of the population through polls because it has shown that they are not a fixed expression of mass taste any longer, but an image of a complex, volatile system of interactions through the digital prism and measurement disruptions. This reconceptualization is given a conceptual and methodological basis through the quantum-inspired perspective, which will offer productive grounds in the future of explorations at the intersection of political science, computational social science, and quantum social theory.

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**Author Contributions:** Every author played a major role in the creation of this research. Yerragudipadu Subbarayudu spearheaded the study conceptualization process, which is the theoretical framing, and problem formulation according to the quantum-inspired perspectives of the public opinion. Paul Kwan focused on the curation of the datasets, preprocessing and execution of the opinion diffusion and volatility analysis models. Jinan Fiaidhi constructed the evaluation framework, formulated the volatility, divergence, and collapse metrics and undertook the empirical experiments. S.Kavitha helped in interpreting the best results, implications, and meaning to polling and political science and the drafting of the manuscript. Manuscript revision was done by all the authors, and they approved the final work and accepted to be responsible to the integrity of the work.

**Data availability:** Data available upon request.

**Conflict of Interest:** There is no conflict of Interest.

**Ethical statement:** In this study, the anonymized social media data of Kaggle, which is publicly available, were used, and there was no direct activity with human subjects. Therefore, there was no need to obtain formal ethical approval.

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