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Progressive Information Polarization in a Complex-Network Entropic Social Dynamics Model

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ABSTRACT The advent of social media and technologies augmenting social communication has dramatically amplified the role of rumor spreading in shaping society, via means of misinformation and fact distortion. Existing research commonly utilize contagion mechanisms, statistical mechanics frameworks, or complex-network opinion dynamics models. In this paper, we incorporate information distortion and polarization effects into an opinion dynamics model based on information entropy, modeling imprecision in human memory and communication, and the consequent progressive drift of information toward subjective extremes. Simulation results predict a wide variety of possible system behavior, heavily dependent on the relative trust placed on individuals of differing social connectivity. Mass-polarization toward a positive or negative consensus occurs when a synergistic mechanism between preferential trust and polarization tendencies is sustained; a division of the population into segregated groups of different polarity is also possible under certain conditions. These results may aid in the analysis and prediction of opinion polarization phenomena on social platforms, and the presented agent-based modeling approach may aid in the simulation of complex-network information systems.

INDEX TERMS Information theory, behavioral sciences, social dynamics, information propagation, information polarization, communicative distortion, agent interaction, complex networks.

I. INTRODUCTION

The information age is characterized by a distinct shift towards computerization and interpersonal networking technology, with a natural consequence of vastly accelerated information uptake and sharing by the average individual [1], [2]. Non-hierarchical content distribution, common on large-scale unrestricted social network platforms, have vastly accentuated the role of rumor spreading in social communication, with potential implications including the skewing of political alignments and election results [3]–[5], the molding of public opinion in countries [6], [7], and even the manipulation of financial markets [8], [9]. The pervasiveness of information propagation has been exploited by companies to further commercial interests [10]; rumor mongering has also led to the development of new algorithms applicable in computer networking and peer-to-peer file sharing [11], [12]. The dynamics of social communication is an area of active research [13]–[17], with realistic rumor-spreading models carrying major theoretical and practical significance.

A standard model of rumor spreading, known as the Daley-Kendall (DK) model [18], [19], is well-established and has been used extensively in the study of opinion dynamics. Various extensions of the model have since been reported, including the incorporation of complex network topologies [20]–[22], and the development of the stochastic Maki-Thompson model variant [23], [24], with analytical solutions derived via means of interacting Markov chains [25]. The effects of memory-facilitated opinion contagion have also been investigated [26]–[29]; in the

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Sznajd model, in particular, statistical mechanics models of ferromagnetic magnetization and phase change phenomena were successfully utilized to simulate the evolution of binary opinions [5], [30]–[32]. Many other relevant aspects, such as confidence levels [33], information density and associated majority-rule effects [34], [35], social network topology rewiring [36]–[38], and the inherent imprecision in interpersonal communication, have been considered individually in numerous studies.

To facilitate the analysis of opinion dynamics in complex multi-agent networks, rumors can simplistically be interpreted as objective descriptions of preceding incidents or events. Such information can, in general, be categorized into opposing polarities—for instance, factually correct or incorrect, subjectively positive or negative, and agreeing or opposing to a certain status quo. Rumor propagation can then be studied with this binary categorization, interlinked closely with linguistic characteristics; while the underlying interaction mechanisms have received much attention [39]–[42], the potential polarization of information during the propagation process and its dynamical effects on social networks have been largely neglected. Cumulatively, information polarization may yield significant quantitative effects, including the division of the population into segregated groups each of like opinions, or the mass evolution of the population towards a specific polarity. The effects of information polarization have indeed been assessed as significant factors in the political and governance mechanics of democracies [43], social stability and welfare [44], [45], and the behavior of open economies [46], [47], especially amidst volatility.

In the present study, we investigate the progressive polarization of information in the process of dissemination and its potential implications, via an information-entropic complex topology framework greatly extended from our previous study [48]. In addition to the comprehensive model, we present the full diversity of behavioral regimes in the framework and elucidate the mechanisms underlying the different outcomes, thereby providing an understanding of the combined dynamics of polarization, distortion, and propagation.

II. MODEL

In this section, we present a rumor propagation framework based on information entropy. The formalism is extended from our previous study [48], with key additions on imperfect memory and communication, and stochastic bias when conveying information. These are important features to enable more realistic modeling of complex socio-physical phenomena encompassing information distortion and polarization, as is the focus of this paper.

In the current model, individuals are modeled as nodes in a Barabási-Albert (BA) scale-free [49], [50] network G of size N, with the links between nodes representing a social connection between agents. The spread of information is considered as occurring in three consecutive phases—information spreading, information acceptance, and information consolidation. We first detail the relevant mathematical preliminaries and definitions, followed by a description of the three-phase propagation of information adopted in our model. A summary of model parameters is given in Table 1. Though beyond the scope of the present study, plausible methods of characterizing these parameters for application to real-world networks are also discussed in Section IV.

TABLE 1. List of parameters of the information propagation and polarization model. Of the six parameters, the first three (N, s and L) define the size and the per-agent characteristics of the network, and the last three (K, β and γ) define the interaction behavior between agents.

Parameter	Definition
N	Number of agents in network
s	Length of information strings
L	Memory length of agents
K	Conservation factor
β	Confidence factor
γ	Polarization bias factor

A. MODEL PRELIMINARIES

To begin, we define the information representation in our model (Section II-A.1) and the characteristic behaviors of the human agents in the network (Section II-A.2–II-A.4).

1) INFORMATION POLARIZATION REPRESENTATION

For simplicity, each packet of information is considered to be a binary string of length s. For instance, for $s = 5$, a candidate binary string might be 11011. In such a binary representation, there are 2^s distinct subtypes of information, where each subtype is labeled with an integer $0 \leq i \leq 2^{s-1}$. These binary strings can be taken to encode any type of real-world data, including, for instance, opinions being propagated through social platforms, pieces of news, or potentially distorted or inaccurate facts.

The binary magnitudes of the information strings are taken as a measure of the associated degree of polarization. In particular, it is taken that the smaller the value, the more negative the information is perceived to be; conversely, the larger the value, the more positive the perception is. Information characterized by 00000 and 11111 bit strings, therefore, correspond to the two extreme polarization states (most negative and most positive). In the present model, we take s to be time-invariant and homogeneous throughout the network, thus reflecting the propagation and polarization of a single information type.

2) MEMORY CAPACITY

Realistically, the human agents involved in the propagation of information possess some ability to remember and reproduce previously-encountered information. We assume that every individual has the same memory capacity, denoted L, such that they can remember up to L pieces of information each.

3) ENTROPY-DEPENDENT INFORMATION DISTORTION

It is known that there is inherent imprecision in social communication. When information and rumors spread, states of strong emotional response, in combination with failures in cognition and transmission, may cause the propagated information to be distorted. Individuals realistically do not have perfect control over the reproduction and distribution of information—a phenomenon termed the "trembling hand" effect [51]. It is therefore important to model the potential distortion of propagated information pieces within our information-entropic framework.

In our proposed model, the propensity for each agent to distort information is taken to be related to the entropy of the information stored in their memory. The greater the information entropy, the more uncertain their memory is, and the more prone they are to errors in recalling and reproducing information. Such a relation can be heuristically justified by noting that information entropy is, in most cases, a measure of the complexity of the represented content; higher entropy may thus reasonably be associated with tendencies of confusion or inaccurate reproduction.

We let H_n denote the classical Shannon information entropy for individual $\mathcal{A}_n \in V(G)$, defined as

$$H_n = -\sum_i f_i \log_2 f_i, \tag{1}$$

where f_i is the frequency of occurrence of the i^{th} subtype of information within the memory of $\mathcal{A}_n$. The average information entropy of the population $\overline{H}$, reflecting the level of information noise in the entire social network, can be written as

$$\overline{H} = \frac{1}{N}\sum_{n=1}^{N} H_n. \tag{2}$$

The probability of information distortion by individual $\mathcal{A}_n$ can now be defined as

$$P_n = \left[\exp\left(\frac{H_{\max} - H_n}{H_{\max}} \cdot K\right) + 1\right]^{-1}, \tag{3}$$

where K, termed the conservation factor, represents an antagonizing control force against information distortion, and $H_{\max}$ is the maximum possible information entropy, reached when $f_i = 1/2^s$. The larger K is, the stronger the ability of the individual to mitigate information distortion. Such may be presumed to be the result of, say, a more conservative social culture, or a more well-informed populace. Information distortion is taken to occur through a bit-wise mechanism, where a random bit in the information string is flipped, and the distorted information persists within the memory of the individual.

4) INFORMATION ACCEPTANCE

Human agents are, in general, not entirely trusting of one another, especially in large networks. When an individual $\mathcal{A}_m \in G$ receives a piece of information from another individual $\mathcal{A}_n \in G$, individual $\mathcal{A}_m$ will not always believe the information received. Rather, acceptance of information depends on how trustworthy individual $\mathcal{A}_m$ considers individual $\mathcal{A}_n$, which is taken to be related to the relative social status (as measured by number of connections) of $\mathcal{A}_m$ among the neighbors of $\mathcal{A}_n$. The more trustworthy $\mathcal{A}_n$ is, the higher the probability η_{mn} that individual $\mathcal{A}_m$ will accept the information, as given by

$$\eta_{mn} = \frac{k_n^\beta}{\max_{l \in \text{nbd}(m)} k_l^\beta}, \tag{4}$$

in which nbd(m) denotes the neighbor set of $\mathcal{A}_m$, k_n denotes the degree of node $\mathcal{A}_n$ (in other words, the number of social connections that person $\mathcal{A}_n$ has with other individuals), k_l denotes the degree of each neighbor $\mathcal{A}_l$, and β is a parameter termed the confidence factor. A range of $\beta > 0$ indicates that individuals will tend to trust neighbors of a greater network degree, and vice versa for $\beta < 0$. In the former case, information conveyed by individuals of a greater number of social followers is preferentially accepted over competing counterparts, reflecting a bandwagon-like social behavior tendency in individuals, whereas the latter case reflects an opposite tendency of preferentially accepting information from low-profile social associates. The special case of $\beta = 0$ reflects equivalent trust amongst all neighbors.

B. THREE-PHASE INFORMATION PROPAGATION

The three consecutive phases of information propagation in our model—spreading (Section II-B.1), acceptance (Section II-B.2), and updating (Section II-B.3)—can now be defined.

1) SPREADING PHASE

All individuals $\mathcal{A}_n \in G$ begin to disseminate information. Out of all the pieces of information currently remembered by each individual, the most salient subtype (the subtype i that occurs with the highest frequency f_i within the memory of $\mathcal{A}_n$) is selected for transmission, with random selection should there be two or more subtypes of information with maximum saliency. This piece of information, potentially distorted due to imperfect memory integrity, is spread to all neighbors of $\mathcal{A}_n$. In addition, we introduce a probability of polarization ξ, describing the information polarization tendencies by individuals during communication. With probability ξ, individuals distort rumors by applying an increment operation (adding a binary value of 00001) on the most salient binary information string; and with probability $(1 - \xi)$, individuals apply a decrement operation (subtracting a binary value of 00001) to the most salient information string. When the information strings have reached the minimum or maximum extreme states of polarization (00000 and 11111 respectively), no further distortion occurs.

The probability of positive polarization ξ_m by individual $\mathcal{A}_m$ may be defined as

$$\xi_m = \frac{k_m^{\gamma}}{\max_{j\in\{1,2,\ldots,N\}} k_j^{\gamma}}, \tag{5}$$

where γ is termed the polarization bias factor, and k_m and k_j are the degree of node $\mathcal{A}_m$ and node $\mathcal{A}_j$ respectively. With $\gamma < 0$, individuals with few social connections (small-degree nodes) tends to be positively polarizing, distorting information towards the positive extreme, and individuals with a large number of social connections (large-degree nodes) tends to be negatively polarizing, distorting information towards the negative extreme. Conversely, with $\gamma > 0$, small-degree nodes tend to be negatively polarizing, and large-degree nodes tend to be positively polarizing. In the real-world, these types of polarization behavior may manifest as a result of intentional hyperbole, for political reasons or otherwise, or unintentional bias when communicating.

2) ACCEPTANCE PHASE

Upon the receipt of a piece of information from one of their neighbors, each agent decides on whether to accept the information and commit it to memory, as detailed in Section II-A.4.

3) UPDATING PHASE

The finite memory bank of each individual is modeled as a first-in-first-out (FIFO) queue, with newly accepted pieces of information displacing the oldest pieces within memory once the maximum capacity has been reached. Memory updates are taken to be synchronous across the network—at every time-step t of the process, all individuals attempt to spread the most salient subtype of information currently known to their neighbors, following which all individuals decide on information acceptance, and their memories are updated to reflect a new set of values at time $t+1$. The information propagation cycle then repeats.

III. RESULTS

To provide a sufficient diversity of information subtypes, the length of the binary information strings was set to $s = 5$, giving $2^5 = 32$ subtypes in total. Barabási-Albert (BA) scale-free networks of size $N = 3000$ were randomly generated, on which simulations of the presented information propagation model were run. The simulation model assumes a memory capacity of $L = 320$.

The intrinsic relationship between polarization probability ξ and the bias factor γ is first explored in Section III-A, thereby providing a basis to facilitate the qualitative understanding of the various phenomena emergent from the propagation model. Information polarization phenomena are then described in Section III-B, with emphasis on the effects of the confidence factor β and the bias factor γ on propagation dynamics and polarization behavior in the network.

A. DISTRIBUTION OF POLARIZATION PROBABILITY ξ

Figure 1 presents the relationship between the propensity of individuals to information distortion, encoded in the polarization probability ξ, and the bias factor γ. The mean value and variance of ξ are denoted $E(\xi)$ and $D(\xi)$ respectively.

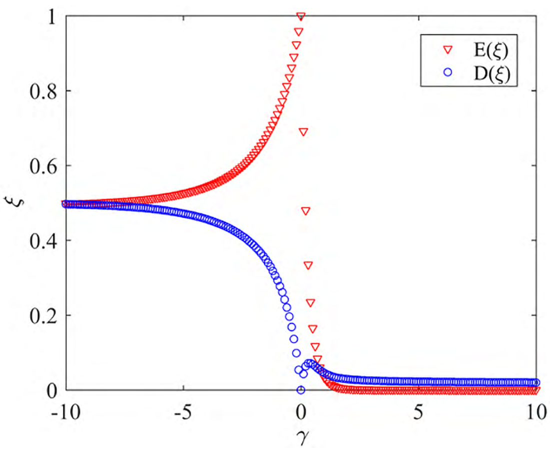

FIGURE 1. Relationship between the propensity of individuals to information distortion, encoded in the polarization probability ξ, and the bias factor γ. $E(\xi)$ and $D(\xi)$ denote the mean value and variance of ξ respectively.

In the range $-10 \leq \gamma \leq 0$, it is observed that an increase in γ yields a gradual increase in ξ from an initial value of approximately $1/2$, representing a balanced probability of polarization towards either extremum, simultaneously accompanied by a decrease in variance of ξ. This indicates that a large number of small-degree nodes in the population has clustered into a $\xi > 1/2$ positively-polarizing group, with a small number of large-degree nodes clustering into a $\xi < 1/2$ negatively-polarizing group. Increases in γ lead to expansions in the size of the positively-polarizing cluster, due to the continued addition of new nodes aligned with $\xi > 1/2$; simultaneously, the average ξ within the cluster also increases. At $\gamma = 0$, all individuals within the population has $\xi = 1$, in effect skewed towards positive polarization with absolute certainty.

When $\gamma > 0$, the average ξ within the population decreases as γ increases, accompanied by a largely decreasing trend in ξ variance. This reflects that the probability of negative polarization in small-degree nodes is increasing, leaving behind very few remaining nodes with a positive polarization tendency.

B. INFORMATION POLARIZATION

To start the simulation, a node from the network is randomly selected as the information source, and one piece of information is set in its memory. This source information string was taken to be 01110, and the memories of all other nodes in the network were initialized to be empty. Simulations of the presented model are then run, to investigate the information propagation dynamics and emergent polarization patterns.

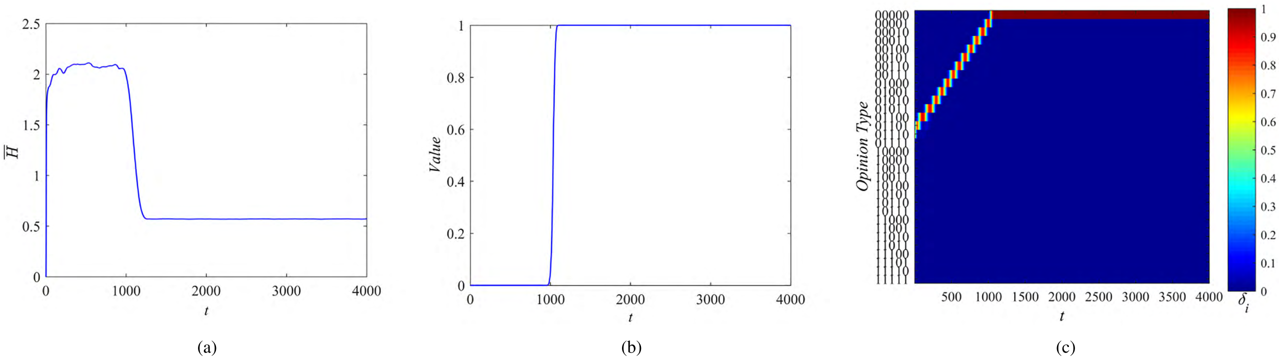

FIGURE 2. Evolution charts for $\beta = 1$, $\gamma = -4$ and $K = 0.1$, showing (a) the dynamics of information entropy $\overline{H}$, (b) the dynamics of δ_0, and (c) the dynamics of δ_i where the x-axis denotes time and the y-axis denotes opinion subtype, and the value of δ_i is represented by color.

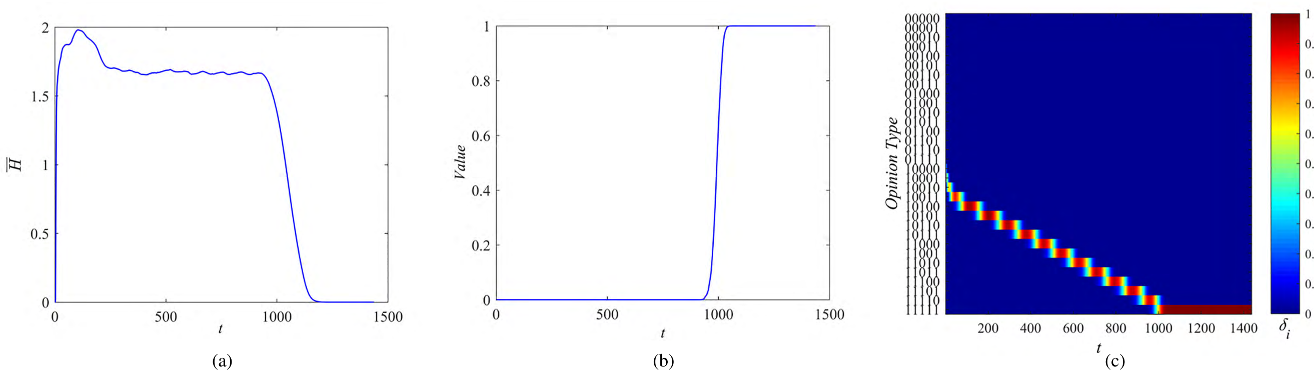

FIGURE 3. Evolution charts for $\beta = 1$, $\gamma = 0$ and $K = 0.1$, showing (a) the dynamics of information entropy $\overline{H}$, (b) the dynamics of δ_{31}, and (c) the dynamics of δ_i where the x-axis denotes time and the y-axis denotes opinion subtype, and the value of δ_i is represented by color.

We consider an individual to hold the opinion i if the most salient piece of information in their memory, that is, the piece of information with maximal f_i is of subtype i. Let D_i be the total number of individuals with opinion i. Then we can define

$$\delta_i = D_i/N, \quad i \in \{0, 1, \ldots, 31\}, \tag{6}$$

as the proportion of individuals who hold the opinion i. By analyzing how δ_i changes for each opinion over time, we can study the effects of information polarization across the population.

1) CONFIDENCE FACTOR $\beta = 1$

Figure 2 presents the simulation results obtained, with confidence factor $\beta = 1$ and bias factor $\gamma = -4$. A cross-examination with Figure 1 reflects that at $\gamma = -4$, the positively-polarizing cluster comprises primarily of small-degree nodes and is small in size, and the population average of the polarizing probability ξ is slightly above 0.5. Such a result suggests that the distortion driving force towards a positive polarization extremum of 11111 is weak. At the same time, due to the negative bias factor, the large-degree nodes tend towards negative polarization; and with $\beta = 1$, individuals have comparatively greater trust in these large-degree nodes, thus creating a strong driving force towards a negative polarization of 00000 within the population. Under the competition of these antagonistic factors, negative polarization tendencies overwhelm the influence of the small positively-polarizing clusters, and the final polarization state of the population is therefore expected to be a negative 00000, as indeed observed in the presented simulation.

Next, Figure 3 presents a set of simulation results for $\gamma = 0$. This is an extreme case, in that all nodes are characterized by a perfect polarizing probability of $\xi = 1$, analytically deductible from Eq. (5). There is no antagonistic factor present towards positive polarization, and the final polarization state is therefore 11111, as can be clearly observed.

Figure 4 presents simulation results for $\gamma = -0.5$. In combination with Figure 1, it is observed that at $\gamma = -0.5$, the positive cluster formed by small-degree nodes is significant, and the population average of polarization probability ξ is also large, therefore resulting in the presence of a strong driving force towards the positive polarization state of 11111. At the same time, large-degree nodes tend towards negative polarization, and the preferential trust amongst the population towards these individuals result in the emergence of a negative polarization driving force. Under the competition of these two forces, a division of the population between negative 00000 and positive 11111 polarization

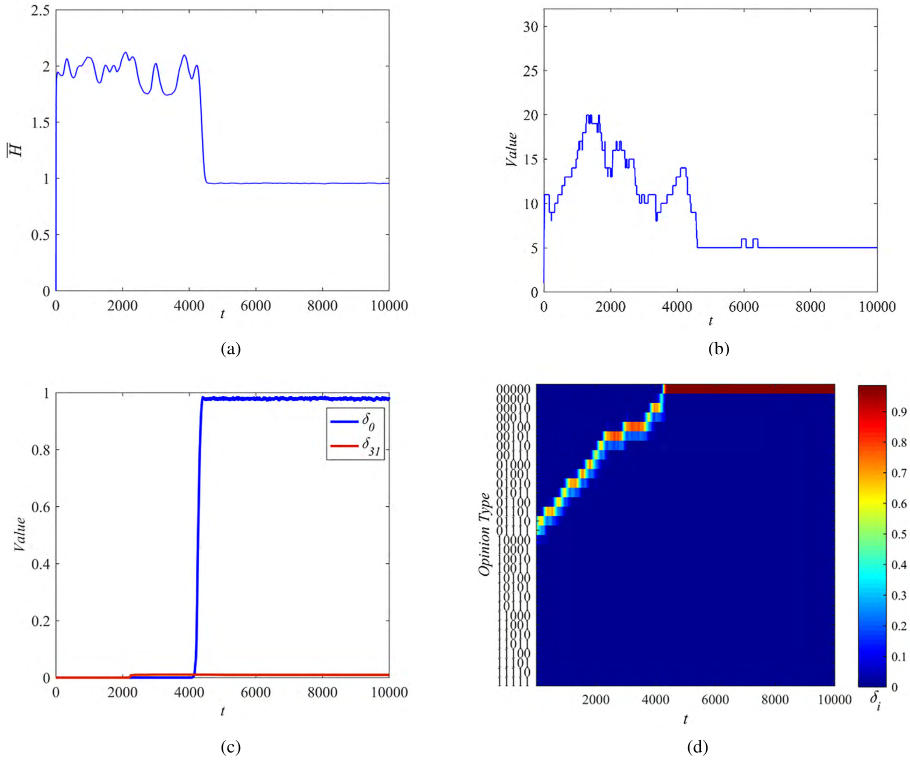

FIGURE 4. Evolution charts for $\beta = 1$, $\gamma = -0.5$ and $K = 0.1$, showing (a) the dynamics of information entropy $\overline{H}$, (b) the dynamics of the number of information subtypes in the network, (c) the dynamics of δ_0 and δ_{31}, and (d) the dynamics of δ_i.

states is observed. The proportion of the 11111 state remains significantly smaller than that of the 00000 state, indicating that the status-dependent acceptance of information plays a key role in controlling the spread of rumors.

A contrasting set of results is presented in Figure 5, for a bias factor of $\gamma = 0.5$. In such a scenario, the population average of ξ is small, reflecting that a large number of small-degree nodes have positive polarization probabilities close to zero. These small-degree nodes form a large number of negatively polarizing clusters, resulting in a driving force towards the 00000 negative polarization state. Simultaneously, the positive polarization probability ξ amongst large-degree nodes is relatively large, and $\beta = 1$ creates a preferential trust towards these individuals, resulting in a strong positive driving force. Similar to the $\gamma = -0.5$ scenario, a co-existence of negative 00000 and positive 11111 polarization states is observed, but here the proportion of the latter is significantly greater than the former.

2) CONFIDENCE FACTOR $\beta = -3$

We now examine scenarios with the confidence factor set to $\beta = -3$. Figure 6 presents a set of simulation results with $\gamma = -1$. Examined in conjunction with Figure 1, it is deduced that in such a configuration, the size of the positive cluster formed by small-degree nodes is relatively large, with a large average polarization probability ξ within the population. The population is hence driven towards the positive polarization state 11111. The low confidence factor of $\beta = -3$ creates preferential trust towards small-degree nodes, further aiding the propagation of positively-polarized information, therefore resulting in a final state of positive 11111 polarization as is indeed observed in the simulation results.

In Figure 7, the bias factor is set to $\gamma = 0.5$, and the mean ξ within the population is small, indicating that a large number of small-degree nodes tend to be negatively polarizing. This creates a driving force towards the 00000 negative polarization state. The confidence factor of $\beta = -3$ reflects preferential trust towards small-degree nodes, aiding the propagation of the negatively-polarized information from the small-degree nodes and resulting in a final state of 00000 polarization, as is observed.

3) FINAL POLARIZATION DISTRIBUTIONS IN β–γ SPACE

The simulation results presented in Sections III-B.1 and III-B.2 indicate that the bias factor γ and confidence factor β influence the propagation of polarized information profoundly. In this subsection, we examine the terminal probability distributions of the two extreme polarization states (δ_0 and δ_{31}) in β–γ parameter space, for a spectrum of differing conservation factors K.

The simulation results are presented in Figures 8(a)–(h). In these figures, we present the terminal probability distributions of the two extreme polarization states within the populations, for differing values of the conservation factor K.

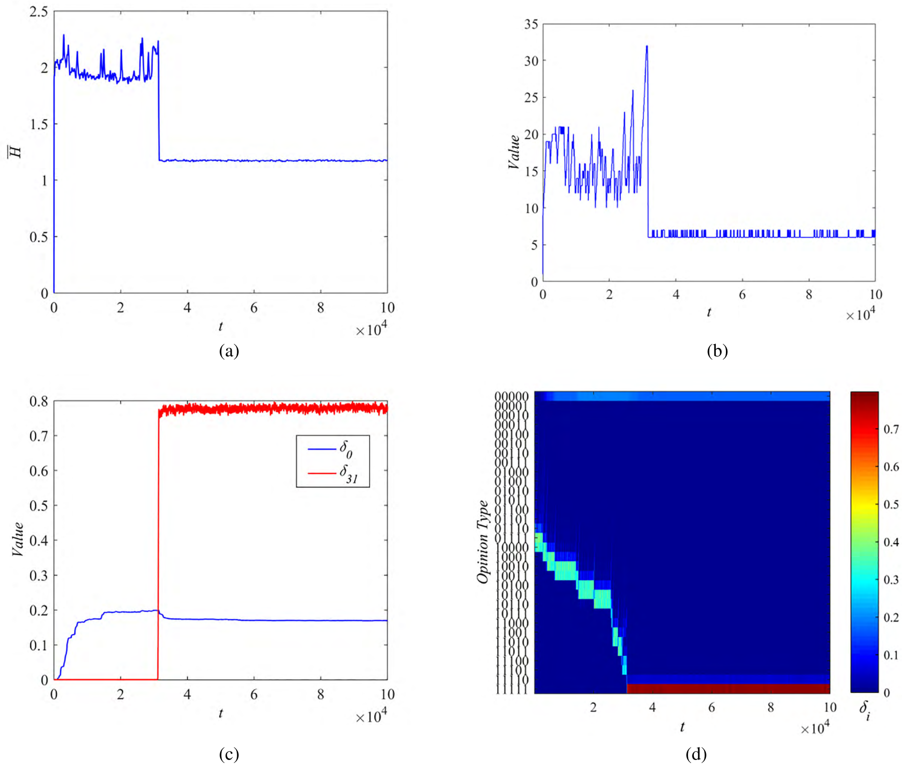

FIGURE 5. Evolution charts for $\beta = 1$, $\gamma = 0.5$ and $K = 0.1$, showing (a) the dynamics of information entropy $\overline{H}$, (b) the dynamics of the number of information subtypes in the network, (c) the dynamics of δ_0 and δ_{31}, and (d) the dynamics of δ_i.

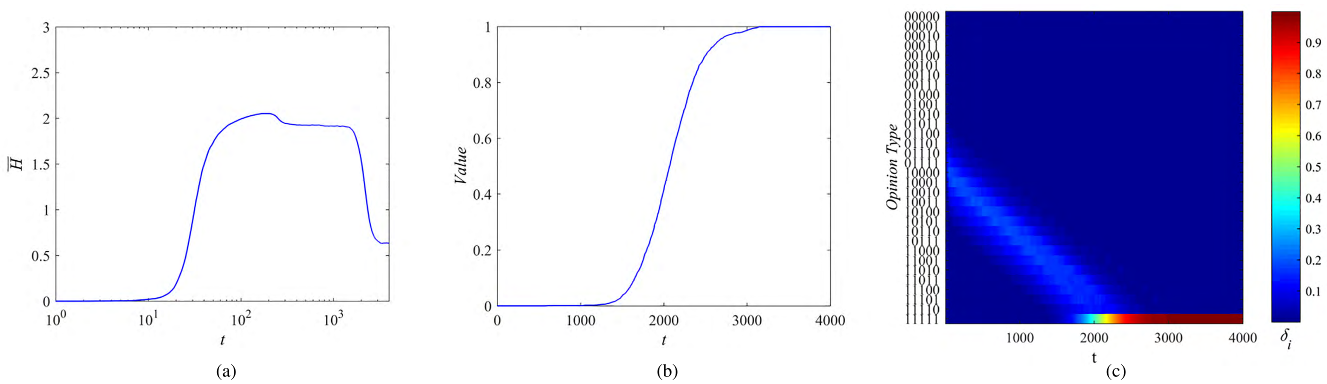

FIGURE 6. Evolution charts for $\beta = -3$, $\gamma = -1$ and $K = 0.1$, showing the dynamics of (a) information entropy $\overline{H}$, (b) frequency δ_{31}, and (c) frequency δ_i.

It can be observed that with a low conservation factor K, the propagated information can be polarized into the negative 00000 state; the conditions for this to occur can be divided into two regimes. The first regime is of confidence factor $\beta > 0$ and bias factor $\gamma < 0$; the second regime is of confidence factor $\beta < 0$ and bias factor $\gamma > 0$. The qualitative principles for these conditions can be deduced. In the first regime, $\beta > 0$ and $\gamma < 0$ reflects preferential trust and negatively-polarizing tendency on large-degree nodes respectively, and these circumstances are clearly synergistic in driving negative polarization throughout the population; and in the second regime, $\beta < 0$ and $\gamma > 0$ reflects preferential trust and negatively-polarizing tendency on small-degree nodes respectively, again conducive for the spread of negatively-polarized information.

In contrast, the necessary conditions for the propagated information to be polarized into the positive 11111 state is encompassed within a narrow strip in β–γ parameter space, primarily in proximity around $\gamma = 0$. In very limited regions of $\gamma < 0$ and $\beta < 0$, and $\gamma > 0$ and $\beta > 0$, positive polarization of the majority of the population is possible, via means of an analogous synergistic mechanism responsible for the

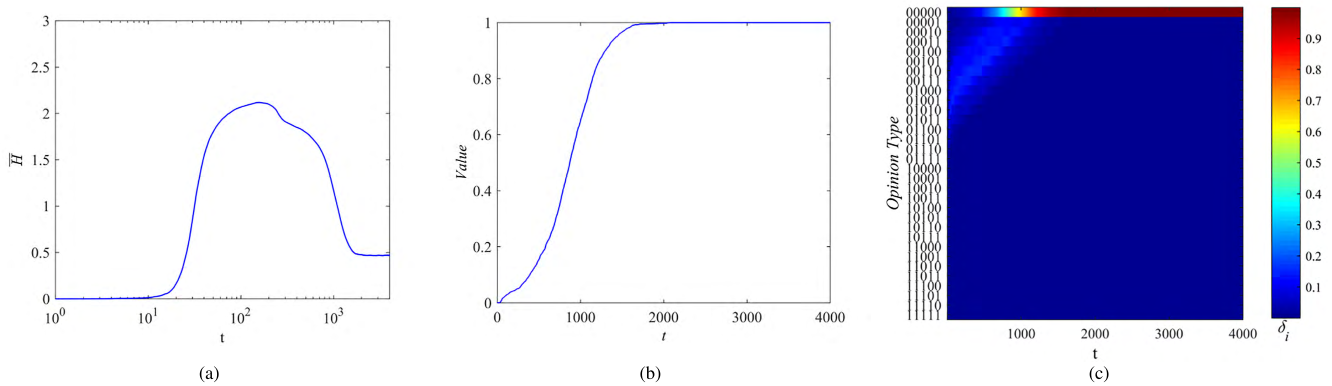

FIGURE 7. Evolution charts for $\beta = -3$, $\gamma = 0.5$ and $K = 0.1$, showing the dynamics of (a) information entropy $\overline{H}$, (b) frequency δ_0, and (c) frequency δ_i.

previously-discussed negative polarization phenomenon; but outside of these narrow regions, there is essentially negligible polarization.

It is also observed that mass polarization of the population becomes increasingly difficult as the conservation factor K increases. This is fully expected, as K suppresses information distortion in individuals (Section II-A.3).

IV. DISCUSSION

In the present study, the semantics of propagated information is taken to be categorizable into binary opposing extrema, in particular, a negative polarization extreme represented as an information bit string of minimal value, and a positive polarization extreme represented as one of maximal value. The mapping of propagated data as information strings enables much generality—the strings may, for instance, represent opinions shared on social media or news pieces. A bias factor γ has been introduced to characterize relations between the degree size of a node, analogously the size of an individual's social circle, and its polarizing tendencies. The mechanics of information acceptance are also considered, which are assumed to be dependent on the social standing of the information source in our model; a confidence factor β characterizes such aspects. In this manner, the dynamics of information propagation and polarization have been analyzed.

A diversity of phenomena have been observed in our proposed model. At a low conservation factor of $K = 0.1$, numerous behavioral regimes may be observed. Firstly, when there is preferential trust towards large-degree nodes ($\beta = 1$) and the bias factor is low ($\gamma = -4$), the entire population is swayed towards the negative polarization extremum due to the strong influence of large-degree nodes. In contrast, an intermediate bias factor of $-0.5 \leq \gamma \leq 0.5$ in general divides into clusters of differing polarizations, resulting in a long-term co-existence of both polarization extrema. Secondly, when there is preferential trust towards small-degree nodes ($\beta = -3$), the large number of small-degree nodes within the population become overwhelmingly important in the dissemination of information. As such, when $\gamma = -1$, the positive polarizing tendencies of the small-degree nodes drive the entire population towards the 11111 polarization state; and when $\gamma = 0.5$, their negative polarizing tendencies drive the population towards the 00000 state. These cases illustrate the antagonistic, competitive nature of information sources in driving polarization, and the synergistic mechanism between polarization tendencies and preferential trust in aiding the propagation of polarized information.

In light of the profound effects of the confidence factor β and bias factor γ on information polarization phenomena, the terminal polarization distributions had been investigated in β–γ parameter space, across a spectrum of conservation factor K values. The population exhibits mass negative polarization in two regimes, of $\beta > 0, \gamma < 0$, and $\beta < 0, \gamma > 0$; in contrast, mass positive polarization is only observed within a narrow strip of β–γ space close to $\gamma = 0$, with either $\beta > 0, \gamma > 0$ or $\beta < 0, \gamma < 0$. In the remaining regions, polarization effects are insignificant. In addition, the polarization of information is suppressed when K increases. When $K > 10$, the system no longer exhibits appreciable polarization phenomena. These presented results span the range of realizable phenomena in the model comprehensively, and model sensitivity to remaining parameters has been found to be weak.

While the presented model differs from existing statistical mechanics-based approaches, for instance the Sznajd model and generalizations [5], [30]–[32], certain important similarities in results are observed. In the Sznajd model and its generalizations to higher-dimensional topologies, agents are typically assumed to be arranged in lattices; whereas in the current model, more realistic scale-free network topologies are used [52], [53]. Furthermore, in the generalized Sznajd and contagion models [28], interactions between agents are typically very simplified, in contrast to the current modeling incorporating effects of agent memory, varying confidence towards other agents, and information distortion tendencies. Yet, the special-case phenomenon of the eventual division of a populace into distinct sectors of opposing opinions is observed in both these models and in the current study, and the mechanism for reaching these outcomes, in which small 'seed' regions expand and compete with neighboring domains for influence, are likewise qualitatively similar. This suggests a sort of universal behavior across topologies and

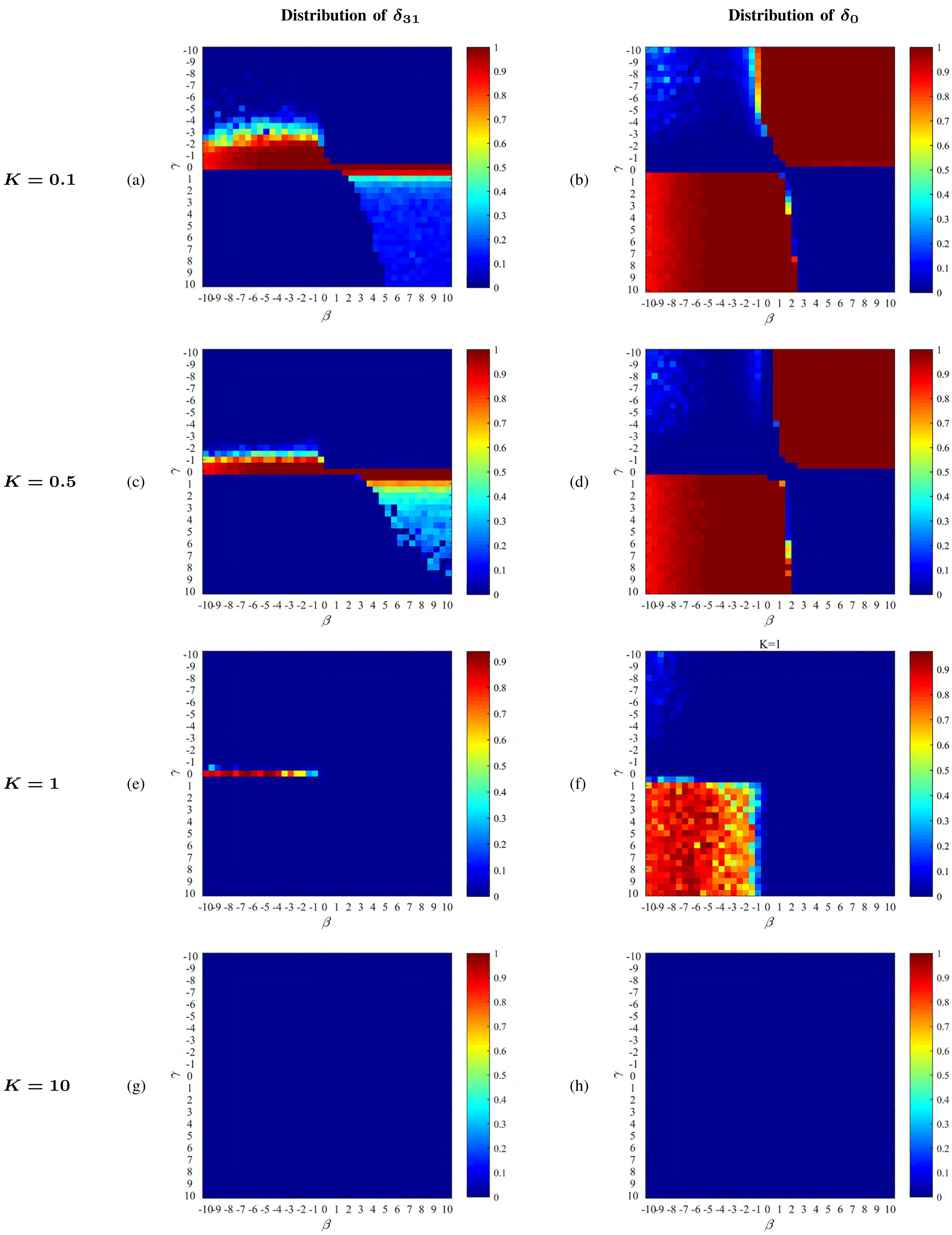

FIGURE 8. **Final probability distributions of positive and negative extreme polarization states for different values of K in β–γ parameter space.**

varying degrees of model complexity, and also serves as a form of validation for the presented model. Outside of this common regime, model behavior diverges between these various works, as is expected from the fundamentally different degrees of freedom conferred.

The behavioral regimes of the current model may be linked with corresponding analogues in the real world. In particular, in contexts where sources of a large social connectivity are preferentially trusted by the public, the accuracy and agency of information spread by them become of vital importance. Such sources may typically include news agencies and celebrities, the latter encompassing both professional artistes and 'self-made' counterparts on social media, or individuals with highly-rated personas on trust-driven forum platforms such as *Stack Overflow* [54] or *Reddit*. On the other hand, in situations where small-degree connectivity is preferentially trusted, the chain propagation of distorted information can lead to the eventual polarization of a majority of the population. Balanced influence between large-degree and small-degree connectivities carry elevated risks of population division between different opinions. Relevance of the model to the real-world is hence established, with a wide variety of scenarios encompassed within the present framework.

To enable the application of the presented framework on real-world networks, it is imperative that the various independent model parameters (summarized in Table 1) be measurable. Here, we provide a plausible methodology. N can be straightforwardly determined from the size of the examined network, s can be taken as the average size of messages exchanged, and L can either be adapted from well-established human cognition studies [55]–[58] or characterized from the shift of trends in the history of exchanged messages. The remaining conservation factor K, confidence factor β, and polarization bias factor γ are most easily characterized by calibration on the examined system, with appropriate β and γ determined by regression over node degree, and K determined by regression over all agents. The characterization of these parameters then allows the model to be used to predict the future evolution of the social system, or to be applied to another network reasonably assumed to be described by similar parameter values.

This study represents a significant development over the previously reported information-entropic model for rumor propagation, in which polarization effects were not examined. The structure of the proposed information-entropic framework is intrinsically conducive for the addition of polarization effects, with natural means of modeling the imprecision of human-to-human communication, polarization evolution, memory depth, and the probabilistic tendencies for individuals to reject information based on subjective confidence. The proposed model provides a realistic, generalizable framework for research into propagative and polarization dynamics in networked information systems, with the fundamental mechanisms and the emergent dynamics being of potential relevance to social platform design, policy-making, and sociophysics.

V. METHODS & MATERIALS

The proposed information-entropic model had been programmatically implemented, and all presented results were obtained from the implemented numerical simulations. The simulation process begins with the construction of a Barabási-Albert (BA) scale-free network [49], [50] modeling the inter-agent connectivity, with the polarization bias factor γ and confidence factor β specified. The agent characteristics in the information spreading and information acceptance phases (Sections II-B.1 and II-B.2) are then calculated, in particular the agent-specific constants ξ_m and η_{mn}. The propagation of information can then be initiated at time $t = 0$—a random node is picked and seeded with a specified source information string. A synchronous three-phrase information propagation process (Section II-B), entailing information spreading, information acceptance, and memory updating in order, is then iteratively executed, incrementing t each cycle. In each iteration, the entropy-dependent probability of information distortion P_n is computed for each individual, and the distortion outcome is stochastic, implemented programmatically via a pseudorandom number generator. Individuals not yet exposed to information from adjacent neighbors are taken to be idle and do not partake in the propagation process, until first exposure occurs. Statistical indicators such as δ_i (Section III-B) are also evaluated at each iteration to aid in data visualization.

COMPETING INTERESTS

The authors declare that they have no competing interests.

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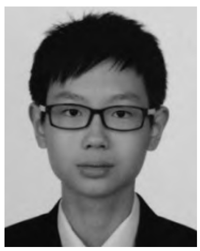

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