Homophily in opinion networks affects collective risk perception in heterogeneous populations

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ABSTRACT

Understanding how to accurately inform the population about the risks of disasters is key for the well-functioning of our societies. Risk communication is also an essential feature of the disaster cycle, fundamentally contributing to preparedness but also to management. Here, we use an agent-based model (ABM) to investigate such an important problem. Specifically, we study the emergent behavior of a population of individuals who revise their opinion on the risk of a certain event, based on information received from an institution, processed through individual sensitivity, and discussed with peers. Such a complex process may include several biases, e.g., due to heterogeneous risk perception across the population, and homophily, i.e., tendency of individuals to interact with like-minded people. Our ABM, which encapsulates these crucial features, allows us to perform a campaign of numerical simulations towards gaining mathematically-grounded insights into their impact on the emergent behavior of the population and, ultimately, on how accurately institutional information is received and processed by a population. Such insights can be useful to design empirical studies to test them and, in case of empirical support, to use them to design recommendations for policy decision makers.

Keywords

Agent-Based Model, Homophily, Opinion Dynamics, Risk Perception, Network

INTRODUCTION

Accurately informing the population about the risks connected to natural hazards, climate change, and men-made disasters is crucial. The importance of sharing accurate and useful information about risks is growing, together with the increase in the number of disaster events all over the world (*Global Assessment Report On Disaster Risk Reduction*, 2022). Effective risk communication means that citizens are correctly informed about what might happen, how they should prepare and what they should do to prevent, mitigate or adapt to the consequences. In a way, risk communication is crucial for response and management (Mamuji & Etkin, 2019), but its effects are present also in the recovery and mitigation phase. However, effective risk communication is extremely hard to achieve, and its effectiveness can depend on several factors (Bradley et al., 2014).

One major challenge comes from the fact that the same message can be interpreted in different ways, but also that the process of sharing information can lead to a final outcome, in terms of content and its spread, that is impossible to predict. The social amplification of risk framework (SARF), first proposed by Kasperson et al., 1988, was intended as a way to explain how risks can be amplified in social interactions. Its purpose is to show the multiple interactions between psychological, social and cultural factors that can heighten or attenuate public perceptions of risk and related risk behaviours. The SARF has been applied to many different situations and hazards, ranging from wildfire risks (Brenkert-Smith et al., 2012) to chemical accidents (de Souza Porto & de Freitas, 1996), and to nuclear energy generation in Europe (Bearth & Siegrist, 2021). However, several decades after the introduction of the SARF, there are open issues that are still puzzling researchers and practitioners (Kasperson et al., 2022): social media, uncertainty, risk communication and integrated analysis. In this work, we focus on risk communication and systemic risk (which is referred to as integrated analysis by (Kasperson et al., 2022)) and we aim to contribute to understanding how collective risk perception emerges from artificial agents' beliefs, but also how it changes and evolves over time.

Agent-based modeling offers the opportunity to explore the factors impacting the spread of reassuring or worrying messages (Onggo et al., 2014)), then contributing to identify possible pathways for the social amplification of risk (Busby et al., 2016). A parallel but unrelated strand of research about the spread of beliefs in a population is opinion dynamics, a well-known sub-field of complex systems and agent-based modeling which aims to model the determinants of opinion spreading in a population, and predict its emergent behavior, which can span from the emergence of consensus among individuals, to steady disagreement andpolarization (Deffuant et al., 2000; Hegselmann & Krause, 2002; Proskurnikov & Tempo, 2017; Sen & Chakrabarti, 2014).

An early attempt to combine an opinion-dynamical model with a model of collective risk perception (Giardini & Vilone, 2021) has provided interesting insights about the impact of trust in institutional communication, trust in peers and varying level of agents' individual risk sensitivity. This model of collective risk perception based on opinion dynamics shows that, even if the agents receive the same initial information about the likelihood of the hazard, their perception of the actual risks is modified by individual traits and by the resulting social influence process. For different parameter configurations, overestimating risks (with regard to the initial state and the information received) is a likely outcome, but the system never reaches full consensus. This suggests that, regardless of the content of the message, individual risk perception and belief revision processes will lead the population to hold different beliefs about how risky a certain situation is. Even if the message has the same content, heterogeneous agents will perceive and transmit it according to their individual features, meaning that collective risk perception can be feebly linked to the original message. Another interesting but rather counter-intuitive result of that model is that different network structures (including regular structure, random topologies, and real-world structures) had negligible effects on the final opinion distribution, even on two empirically calibrated network topologies. This result is at odds with empirical studies (Becker et al., 2017) and simulation models of opinion spreading on networks (Flache et al., 2017), which suggest that network structure plays an important role in opinion formation and change. In order to better understand the interplay between network structure and collective risk perception, we designed a model in which information about risk is spread on the basis of the similarity across agents, i.e., their homophily. Homophily, *the observed tendency of like to associate with like* (Kossinets & Watts, 2009), is one of the most recurrent empirical regularities of social life (McPherson et al., 2001). Friends, romantic partners, colleagues, and other kinds of associates all tend to be more similar to each other than randomly chosen members of the same population with respect to a variety of dimensions (race, age, gender, socioeconomic status, habits, education, hobbies). Homophily can foster the spread of healthy behaviors in social networks (Nunner et al., 2022), but it can also contribute to the formation of echo chambers and polarization (Bessi et al., 2016). It is worth noting that, to the best of our knowledge, homophily in disaster risk perception has not been previously addressed. In the risk and decision making literature some attention has been devoted to risks related to different health treatments (Berry et al., 2018), and infectious disease outbreak (Kadelka & McCombs, 2021), but we are not aware of any work focusing on the relationship between homophily in risk perception and risk communication.

In order to fill in this gap, we explore the effect of homophily-based communication in an opinion dynamic model of collective risk perception. Building upon the work of (Giardini & Vilone, 2021), we designed an agent-based model (ABM) in which agents receive information about the likelihood of a disaster from an institutional source (broadcast), revise this information according to their own individual traits (risk perception), and then share the information with other agents (risk communication) on the basis of their homophily.In our model, agents interact in pairs, thus resembling an interpersonal discussion on risk, which is an important means through which individuals gather information and make sense of uncertain situations (Perlstein, 2023). Binder and colleagues in their study (Binder et al., 2010) using data from a public opinion survey on a new and potentially risky facility in the US found empirical support for the hypothesis that people are more likely to engage in interpersonal conversations with interaction partners who are expected to share their 'discussion valence', i.e., like minded individuals. This is in line with studies on political communication that reported that it is relatively common for people to find themselves in discussion networks with people sharing similar opinions (Huckfeldt & Sprague, 1987). Homophilous ties can also be established on the basis of other characteristics, for instance shared political views or trust in institutions, but in this study we are interested in understanding whether and how preferentially interacting with others who have similar levels of risk perception might lead to consensus on risk perception in the population. In an extension of the model (in preparation) we plan to add homophily in trust in institutions and trust in the media as additional conditions to explore whether being homophilous in different dimensions has an effect on the final distribution of risk perception in the population.

Inspired by similar approaches in mathematical modeling of epidemic spreading (Frieswijk et al., 2023), we encapsulate homophily into the risk communication step of the ABM. Specifically, we include an additional parameter that captures the level of homophily of the population, which shapes the network formation process through which agents share information with others, favoring interactions among agents with the same risk sensitivity. Ultimately, our goal is to employ the ABM to understand whether homophily leads to highly clustered and polarized risk perceptions, and whether this varies depending on the levels of perceived risk.

MODEL DESCRIPTION

In our ABM, we consider a population of L agents, indexed by positive integer numbers $\mathcal{V} = \{1, \dots, L\}$. Each agent $i \in \mathcal{V}$ is characterized by an opinion $O_i \in [0, 1]$, which represents their evaluation of the risk. We shall refer to this variable as the *opinion* of agent i, consistent with the opinion dynamics literature. Specifically, $O_i = 0$ represents the scenario in which agent i's evaluation is of minimum risk, whereas $O_i = 1$ means that i gives the maximum evaluation of the risk. For the sake of simplicity, we model opinions as the subjective probability that the disaster will actually take place, regardless of the magnitude of the possible consequences. We acknowledge that this is an important issue and we will tackle this in future work. Agents' opinions are updated on the bases of the interplay between internal characteristics of the agents and two different sources of influence: i) elaboration of institutional information, and ii) interaction among peers.

The elementary dynamics is set as follows: at the beginning of each discrete time step, the institution communicates to each and every agent the value of the risk I, which is a continuous value in the range $I \in [0, 1]$ with the same convention that $I = 0$ means minimum risk and $I = 1$ means maximum risk. Here, we assume that the institutional information I is kept constant throughout the iterations. The agents elaborate the information received. Then, they share their updated opinions among each other, and further elaborate their opinion on the base of such interaction with peers. The mathematical details of such opinion revision process are described in the following section.

Elaboration of Institutional Information

Once received the value I of risk assessment by the institution, each agent i modifies their opinion on risk o_i according to the Deffuant's model (Deffuant et al., 2000). Specifically, the current opinion (O_i^o) is revised to the new opinion (O_i) as

$$O_i^o \longrightarrow O_i = O_i^o + T_i(I - O_i^o) \ , \tag{1}$$

where $T_i \in [0, 1]$ is a parameter that captures individual's trust in the institution: the larger such parameter, the larger the impact of the information provided by the institution in agent's i opinion formation process.

Then, the updated opinion O_i is further processed according to internal characteristics of the agent. Specifically, we introduce a parameter $R_i \in \{-1, 0, +1\}$ that captures i's risk sensitivity. When $R_1 = -1$, agent i has low risk sensitivity, and is thus inclined to underestimate the risk; when $R_1 = +1$, agent i is highly sensitive to risk, tending to overestimate it; while $R_i = 0$ captures risk-neutral agents who do not distort the information received. Such a further process based on risk sensitivity is captured by the following update rule:

$$O_i \longrightarrow \begin{cases} \frac{1}{2}(1 + O_i) & \text{if} \quad R_i = +1 \\ O_i & \text{if} \quad R_i = 0 \\ \frac{1}{2} O_i & \text{if} \quad R_i = -1 \ . \end{cases} \tag{2}$$

In plain words, the presence of (positive or negative) risk sensitivity induces a bias affecting how individuals process the information received from the institution. This is consistent with what observed in the social psychology literature (see, e.g., Popovic et al., 2020; Richard Eiser et al., 2012).

Table 1. Variables and Parameters of the Model

Symbol	*Values*	*Meaning*
L	Integer	Number of agents in the network
O_i	$[0, 1]$	Evaluation of the risk (opinion) of agent i
I	$[0, 1]$	Risk assessment communicated by the institution
T_i	$[0, 1]$	Trust in the institution of agent i
R_i	$\{-1, 0, +1\}$	Risk sensitivity of agent i
P_i	$[0, 1]$	Trust in peers of agent i
H	$[0, 1]$	Level of homophily in the network

Interaction Among Peers

Once the agents have received and processed the institutional information I, they exchange their opinions with peers on a social influence network, consistent with Scherer and Cho, 2003. More precisely, for each time step, we pick up L couples of agents (i, j), sampled uniformly at random. Each of these couples is a candidate interaction that can take place. Once the pair (i, j) is selected, we randomly assign an order to the two agents that form the edge, say i and j. Let us define j as the "speaker" and i as the "listener" (the symmetrical interaction where i is the speaker and j the listener will take place in the same way).

At this stage, we incorporate homophily in the model as the possibility that individuals may prefer to interact with akin peers than strangers. This assumption is based on the homophily principle, which means that we assume that agents with the same risk sensitivity interact more often (McPherson et al., 2001). Homophily is modeled as follows. For each one of the L couples of agents (i, j) sampled at random, i and j actually interact according to a probabilistic rule. Specifically, the interaction always takes place if the two agents i and j have the same risk sensitivity. Otherwise, the interactions takes place only with probability equal to $1 - H$, while with probability equal to H the "listener" refuses to receive information from the sender, and thus link (i, j) is discarded. In other words, if $H = 0$ there is no homophily in the population, and everyone interacts indifferently with everyone else; at the opposite of the spectrum, if $H = 1$, agents avoid completely interactions with peers not belonging to the same class. Clearly, such a mechanism ultimately generates a time-varying network of social contacts, whose pattern is shaped by homophily. In fact, for $H = 0$, at each discrete time step individuals interacts on an instance of an Erdos-Renyi random graph with L links (Newman, 2010); as H increases, the network starts displaying a clustered structure, which will ultimately impact the emergent behavior of the system, as we shall see in the following section.

Finally, if the interaction between a speaker j and a listener i takes place, then the listener revises their opinion. Specifically, let O_i and O_j be their opinions before such interaction takes place, respectively. Then, agent i will change their own opinion according to the Deffuant's rule described in Deffuant et al., 2000:

$$O_i \longrightarrow O_i' = O_i + P_i(O_j - O_i) \,, \tag{3}$$

where $P_i \in [0, 1]$ is a parameter that captures agent i's trust in peers. In this work, we set $P_i \equiv 1 - T_i$, which yields

$$O_i \longrightarrow O_i' = O_i + (1 - T_i)(O_j - O_i) \,. \tag{4}$$

On the other hand, the speaker does not revise their opinion. Finally, the listener elaborates again its opinion according to the rule in Eq. (2). All the variables and parameters of the model are summarized in Table 1.

Simulation Setting

In this work, we perform a campaign of numerical simulation on the model described in the above, in order to explore the role of homophily on the collective risk perception. To this aim, we generate Monte Carlo simulations of the ABM, and we estimate the quantity of interest (i.e., the final average opinion of the population), by averaging the result obtained over an ensemble of 2,000 independent realizations (*i.e., runs*).

In each run, we consider $L = 1,000$ agents and we initialize agents' initial opinions and trust in institution uniformly at random in the domain $[0, 1]$, each agent independently of the others. The risk sensitivity is assigned as follows: each agent has a probability $p = 0.5$ to have risk sensitivity equal to zero (neutral agent), a probability $\rho/2$ to have $R_i = +1$ (risk-averse agent) and $(1 - \rho)/2$ to have $R_i = -1$ (risk-prone agent), where $\rho \in [0, 1]$ captures the average bias of the population: $\rho < 0.5$ means that there are more risk-prone agent than risk-averse agent, while $\rho > 0.5$ represents the opposite scenario.

Every run is performed for a sufficiently large number of iterations in order to achieve a final steady state, *i.e.*, a configuration where the dynamics has become constant and the global configuration of the system is stable, that is, the state of the system does not change anymore.

RESULTS

In this section, we describe the results of our numerical simulations. Specifically, we perform two sets of numerical simulations. In the first one, we consider the scenario with no homophily ($H = 0$). In this scenario, we consider populations with different characteristics in terms of risk sensitivity (captured by the parameter ρ). Specifically, we consider a balanced scenario ($\rho = 0.5$), and two biased scenarios (with $\rho = 0.15$ and $\rho = 0.85$, respectively). In all scenarios, we consider different values of the risk assessment communicated by the institution I, and we study how the opinion revision process shapes the collective risk perception.

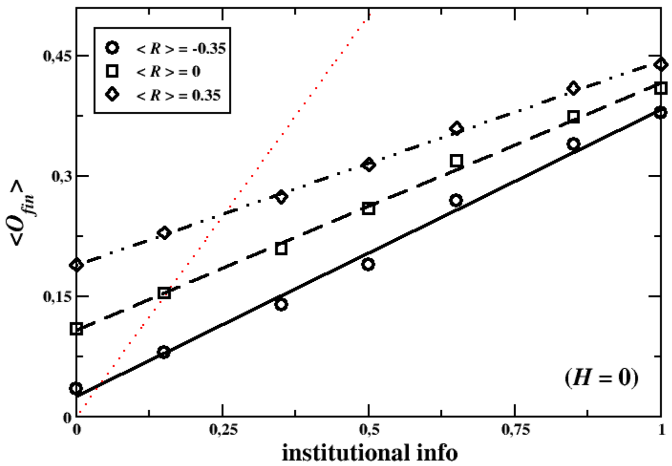

Figure 1. Monte Carlo estimation of the average final opinion $\langle O_{fin} \rangle$ as a function of the institutional information I for a system of $L = 1,000$ agents and a population with initial opinions and trust towards institution randomly assigned with uniform distributions, for different values of risk sensitivity. Lines represent linear fits of numerical data, red-dotted one is the bisector of the first orthant.

Specifically, Figure 1 shows the final average opinion, that is, the average evaluation of the risk in the population, in a completely balanced system, that is, when $\rho = 0.5$, yielding a balance between the number of agents with high and low risk sensitivity (on average). In general, our results are consistent with those described in Giardini and Vilone, 2021: the population tends on average to overestimate the risk for low-risk situations (that is, small values of I), and underestimate it in the opposite case. Interestingly, the value of I for which the population starts to underestimate the risk is lower than $I = 0.5$. The same study is reproduced also in the case of non-balanced populations, that is, for populations with lower and higher risk sensitivity. Overall, the emergent behavior is qualitatively similar. Unsurprisingly, the collective risk perception is higher for the population that is more sensitive to risk. However, it is worth noticing that even in the scenario in which $\rho = 0.85$ (yielding an average risk sensitivity of 0.35), the population starts underestimating the risk even for values of institutional information lower than $I = 0.5$. These observations are consistent with the conclusions of previous research, which highlighted how the nontrivial way through which people elaborate information received from the institution may lead to a biased collective risk perception; in particular, with an underestimation of severe risks (Giardini & Vilone, 2021).

In the second set of simulations, whose results are illustrated in Figure 2, we consider a scenario in which homophily is present. Specifically, we investigate how increasing the value of homophily shapes the final average opinion of the population. To this aim, we consider the basis balanced scenario presented in Figure 1 (with $\rho = 0$), and we estimate the average final opinion for different values on H. Our results suggest that increasing the homophily can lead to an overestimation of the risk, whereby the echo chambers formed by the network formation process seem to amplify the risk perception, with potentially harmful consequences to the society.

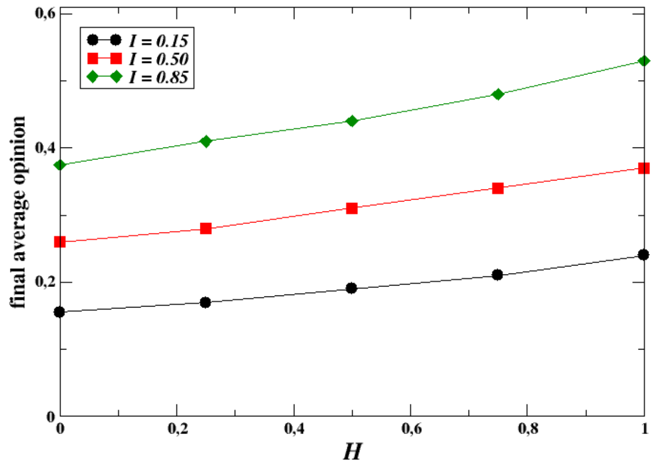

Figure 2. Monte Carlo estimation of the average final opinion $\langle O_{fin} \rangle$ as a function of the homophily H for different values of the institutional information. The system has $L = 1,000$ agents with fully balanced parameters: initial opinions, trust towards institution, and risk sensitivity randomly assigned with uniform distributions.

CONCLUSION AND ONGOING RESEARCH

In this work, we used agent-based modeling to explore the role of homophily on the collective risk perception in heterogeneous populations. Specifically, building on an ABM proposed in Giardini and Vilone, 2021, we have incorporated a mechanism that captures the tendency of individuals to interact more with like-minded people. Then, we have performed a campaigns of Monte Carlo simulations to unveil the impact of such behavioral mechanism on the emergent behavior of the system, showing how it could lead to biases in how institutional information is received and processed by a population.

The results discussed in the previous section offer us a preliminary understanding of the interplay between risk communication, individual biases and homophily in information spreading. When agents interact preferentially with similar agents this results in a widespread amplification of the risk perception, which can have several undesired outcomes. This finding is in line with research on homophily in the spreading of desirable and undesirable behaviors (Brechwald & Prinstein, 2011), paving the way for different lines of further research toward extending the existing findings, deriving analytical results to support them, and validating the model on real-worlds case studies. We are aware of the multiple limitations of this work in progress, including lack of validation of the model, limited exploration of the parameter space and a quite simplistic description of the homophily principle.

To address some of these limitations, we are currently working along three main avenues in order to further develop the model.

First, the numerical simulations presented in this paper are being extended along several directions. One relevant direction is to embed the model on a nontrivial network structure, restricting social interactions to those between neighbors on the network. This approach, already used in Giardini and Vilone, 2021 for the simpler model without homophily, can be readily extended to incorporate homophily toward investigating the interplay between such behavioral mechanisms and the complexity of real-world networks of social interactions. Moreover, more realistic implementations of homophily should be considered and incorporated into the model.

A second research direction that we are currently exploring is the possibility to establish rigorous analytical results for the model of collective risk perception formation described in this paper. Concerning this research direction, the key step consists in re-formulating the opinion formation process described in Eqs. (1)–(4) using the system-theoretic formalism of opinion dynamics models [See, e.g., Proskurnikov and Tempo, 2017] Using this formalism, under some assumptions, it is possible to gain analytical insights into the emergent behavior of the population, and derive closed-form expressions for the final average opinion, as function of the different parameters of interest. Some promising preliminary steps towards achieving such a goal can be found in Zino et al., 2024. This procedure will allow us to corroborate the findings of our numerical simulations with rigorous analytical observations.

Third, we are working towards validating the ABM in real-world scenarios, using survey and experimental data to calibrate the model. A recent review paper (Bradley et al., 2014) pointed out that natural disaster preparedness interventions, which authorities might wish to target at a whole population, mainly involved interpersonal communication, but their effectiveness is limited. The insights gathered thanks to ABM can be used to shape theories and data collection on the factors driving an heterogeneous population to form its collective risk perception about a certain event. This can be done starting from survey data, such as the study in Salvati et al., 2014, which collects data on risk perception concerning floods and landslides in different Italian regions, and how such collective opinion evolves over time. Using this data, we are currently working towards calibrating the model to provide an empirical validation that supports our ABM. We also plan to extend the model in order to design opinions about hazards differing in terms of impact.

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