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The effects of individuals' opinion and non-opinion characteristics on the organization of influence networks in the online domain

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Abstract: The opinion dynamics literature argues that the way people perceive social influence depends not only on the opinions of interacting individuals, but also on the individuals' non-opinion characteristics, such as age, education, gender, or place of residence. The current paper advances this line of research by studying longitudinal data that describe the opinion dynamics of a large sample (~30,000) of online social network users, all citizens of one city. Using these data, we systematically investigate the effects of users' demographic (age, gender) and structural (degree centrality, the number of common friends) properties on opinion formation processes. We revealed that females are less easily influenced than males. Next, we found that individuals that are characterized by similar ages have more chances to reach a consensus. Besides, we report that individuals who have many common peers find an agreement more often. We also demonstrated that the impacts of these effects are virtually the same, and despite being statistically significant, are far less strong than that of opinion-related features: knowing the current opinion of an individual and, what is even more important, the distance in opinions between this individual and the person that attempts to influence the individual is much more valuable. Next, after conducting a series of simulations with an agent-based model, we revealed that accounting for non-opinion characteristics may lead to not very sound but statistically significant changes in the macroscopic predictions of the populations of opinion camps, primarily among the agents with radical opinions ($\approx$ 3% of all votes). In turn, predictions for the populations of neutral individuals are virtually the same. Besides, we demonstrated that the accumulative effect of non-opinion features on opinion dynamics is seriously moderated by whether the underlying social network correlates with the agents' characteristics. After applying the procedure of random shuffling (in which the agents and their characteristics were randomly scattered over the network), the macroscopic predictions have changed by $\approx$ 9% of all votes. What is interesting, the population of neutral agents was again not affected by this intervention.

Keywords: opinion formation models; influence networks; online social networks; the effects of non-opinion characteristics; assimilative influence; bounded confidence

1. Introduction

Social influence is perhaps one of the most intriguing and fascinating phenomena that affects our daily lives. In so-called opinion formation models (aka social influence models), the social influence effects are captured by specific mathematical rules that outline how agents' opinions (operationalized as discrete or continuous quantities standing for agents' choices or subjective attitudes toward predefined controversial issues) are changed after being exposed to peers' opinions (Flache et al., 2017; Proskurnikov & Tempo, 2017). For example, in the classical DeGroot model, agents' opinions are represented on a continuous scale, and an agent's opinion at the next time model

$x_i(t + 1)$ is defined as a convex combination of their current opinion $x_i(t)$ and the opinions of the agent' peers at the previous time moment (DeGroot, 1974):

$$x_i(t + 1) = w_{i,i}x_i(t) + \sum_{j \in V_i} w_{i,j}x_j(t). \tag{1}$$

In (1), V_i is the list of i's peers, and $w_{i,j}$ represents how strong is the influence directed from j to i. In turn, $w_{i,i}$ outlines how stubborn (self-confident) agent i is. The quantities $w_{i,i}, \{w_{i,j}\}_{j \in V_i}$ are usually called the *influence weights*; the weight $w_{i,i}$ is sometimes referred to as the *self-weight*. The set of all influence weights defines the *influence network* – directed weighted graph whose edges represent how individuals influence each other and how individuals' trusts are distributed among their peers. Despite this terminology being usually applied within the framework of the DeGroot model (and other models that are extensions of the DeGroot model (Friedkin et al., 2016)), we will use the term "influence network" in a broader context—to describe how open individuals are to the influences from their peers and how strong are their attachments to their own opinions (without assuming that opinions evolve in accordance with the DeGroot model).

The influence network is a key ingredient without which we cannot predict the evolution of opinions in society. A large line of studies is dedicated to the extraction of the influence network from repeated measurements of individuals' opinions (Ravazzi et al., 2021). A different line of research investigates how influence weights are linked to the intrinsic characteristics of people. At the moment, we already know a lot about how individuals perceive their peers' opinions in information exchanges. For example, we know that individuals with radical opinions tend to be more stubborn (Kozitsin, 2023). In contrast, younger individuals are considered to be more vulnerable to social influence (Sears, 1986). Next, according to Refs. (Peshkovskaya et al., 2017, 2018, 2019) females cooperate better than males, and thus we should hypothesize that females are more easily influenced. However, such differences may stem from status inequalities (Eagly, 1983)—for example, according to empirical studies, males tend to have more friends and thus may perceive themselves as more valuable (Kozitsin et al., 2023). Further, we know that the perception of a message depends on how distant the message is from the focal individual in terms of the opinion space—too distant opinions may be less attractive (Moussaïd et al., 2013), a phenomenon referred to as *bounded confidence* (Deffuant et al., 2000; Hegselmann & Krause, 2002; Kurahashi-Nakamura et al., 2016). Next, empirical studies indicate that individuals that have common non-opinion features (such as age, place of residence, or culture) display more trust toward each other even if their opinions differ significantly (Balietti et al., 2021). Beside this, structural similarity, measured, for example, as the number of common friends, fosters the propagation of opinions and ideas (Aral & Walker, 2014).

Further, an individual's perception of external information and openness to influence may depend on how influential the individual's opinions were in previous discussions, even if these discussions were dedicated to completely different topics (the theory of *reflected appraisals*) (Friedkin, 2011). According to this theory, individuals whose opinions contributed most to previous conversations will reinforce their self-confidences in the next conversation and so on.

Despite our advantages in understanding the structure of trust in social networks, we still lack a systematic investigation and comparison of various factors affecting influence weights. In this paper, we attempt to challenge this problem by studying empirical longitudinal data derived from an online social network. In these data, detailed information on users' opinions, structural (social ties), and demographic (age and gender) attributes is provided. This gives us an opportunity to rigorously investigate and compare the effects of various, both opinion and non-opinion, factors on the organization of influence networks. To paraphrase, we will study how the influence weights depend on the nodal and structural characteristics of the networked social system.

The rest of the paper is organized as follows. Section 2 describes the empirical data. Section 3 outlines our notations and terminology. In Section 4, we apply regression analysis to the data. Section 5 conducts a series of simulation experiments to test the results of the empirical analysis from Section 4. Section 6 discusses the results and makes concluding remarks. In the Appendix, auxiliary information is provided.

2. Data

We investigate the dataset introduced for the first time in (Kozitsin et al., 2023). That dataset includes two snapshots of the online network VKontakte (VK), describing friendship-type connections and the opinions of a sample of $N = 29{,}248$ VK users, all citizens of the same city. The snapshots were made in March and September 2019. The information regarding users' ages and genders is also available. Users' opinions (on a political issue) were measured on the scale $[0,1]$ using the information regarding users' subscriptions to information sources (public pages and bloggers) with help of the methodology from (Kozitsin et al., 2020). It is worth noting that the sample was cleaned of any accounts that were employed in the opinion estimation procedure (to facilitate the independence of estimated opinions). The sample comprises adults (age > 17) with open VK accounts that were active no less than one time per month during the observation period. One more filter restricts users to having no less than 10 and no more than 200 followees (this ensures the highest accuracy of the opinion estimations). However, similarly to (Kozitsin et al., 2023), we focus on the giant connected component that includes ~95% of all vertices. As a result, we end up with a sample of $N = 27{,}861$ users. For more information regarding the dataset, we refer the reader to Ref. (Kozitsin et al., 2023) (Sections 4, 5, and Appendix B). Further, Figure C1 (Appendix C in the current manuscript) presents some histograms that help to understand the organization of the data.

3. Notations and Terminology

We denote the network snapshots by $G(t_1) = [V, E(t_1), x(t_1)]$ and $G(t_2) = [V, E(t_2), x(t_2)]$, where V represents the sample users and $E(t_1), E(t_2)$ stand for edges between them at times t_1 (March 2019) and t_2 (September 2019). Correspondingly, the vectors $x(t_1)$ and $x(t_2)$ outline estimated users' opinions. For a user i, their opinion is denoted by $x_i(t) \in [0,1]$, their age and gender are signified as $age_i \in \mathbb{N}$ and $gender_i \in \{1,2\}$ (1 – females, 2 – males), respectively. Throughout the paper, the set of natural numbers from 1 to $m \in \mathbb{N}$ is denoted by $[m]$. To denote the cardinal number of a set, we use the notation $\#\{...\}$. The number of the user i's friends at time t is $f_i(t) = \#\{j \mid (i,j) \in E(t)\}$. The number of peers users i and j have in common at time t is presented by $f_{i,j}(t) = \#\{k \mid (i,k) \in E(t), (j,k) \in E(t)\}$.

Following Ref. (Takács et al., 2016), we will say that a *positive* opinion shift is undertaken if it is directed toward the opinion of the influence source. If an opinion shift is directed oppositely, then it is *negative*.

If an individual j influences an individual i, then we will say that i is an influence object (focal individual) and j is an influence source.

4. Analysis of opinion dynamics

4.1. Map of opinion shifts

We first need to answer the following question: given the opinions of two befriended users at time t_1, can their opinions at time t_2 be predicted? To answer this question, we discretize the opinion scale $[0,1]$ into aggregated opinion values $\Xi_1 = \left[0, \frac{1}{m}\right], ... \Xi_m = \left[\frac{m-1}{m}, 1\right]$, and then the probabilities of all possible opinion changes $\Xi_s \rightarrow \Xi_k$ (including static ones $\Xi_s \rightarrow \Xi_s$) are computed across all possible influencing opinions Ξ_l. The resulting quantities $p_{s,l,k}$ (see Appendix A for details on their computation), where the low indices are synchronized with the indices of the fixed opinions Ξ_s, Ξ_l, and Ξ_k, can be grouped into m square row-stochastic matrices $P_1, ..., P_m$, where the matrix $P_s = \left[p_{s,l,k}\right]_{l,k \in [m]}$ showcases how users with opinion Ξ_s respond to peers' opinions (see Figure 1). Within such an encoding strategy, in matrix P_s, the s-th column contains the self-confidence rates of users with opinion Ξ_s across different values of the influence source opinion. From Figure 1 we conclude that:

- Individuals change their positions relatively rarely.

- Users with radical positions are more stubborn.

- Both positive and negative opinion shifts can happen, but positive shifts occur more often.

- Positive shifts tend to feature the *assimilative influence* mechanism, whereby more distant opinions induce positive responses with larger probabilities.

- Individuals with the right radical opinion Ξ_5 (see the matrix P_5 in Figure 1) display a tendency to distrust too distant opinions (aka *moderated bounded confidence*).

It is worth noting that all these observations are in line with the previous empirical studies on opinion dynamics (Carpentras et al., 2022; Friedkin et al., 2021; Kozitsin, 2022b, 2023; Moussaïd et al., 2013; Takács et al., 2016).
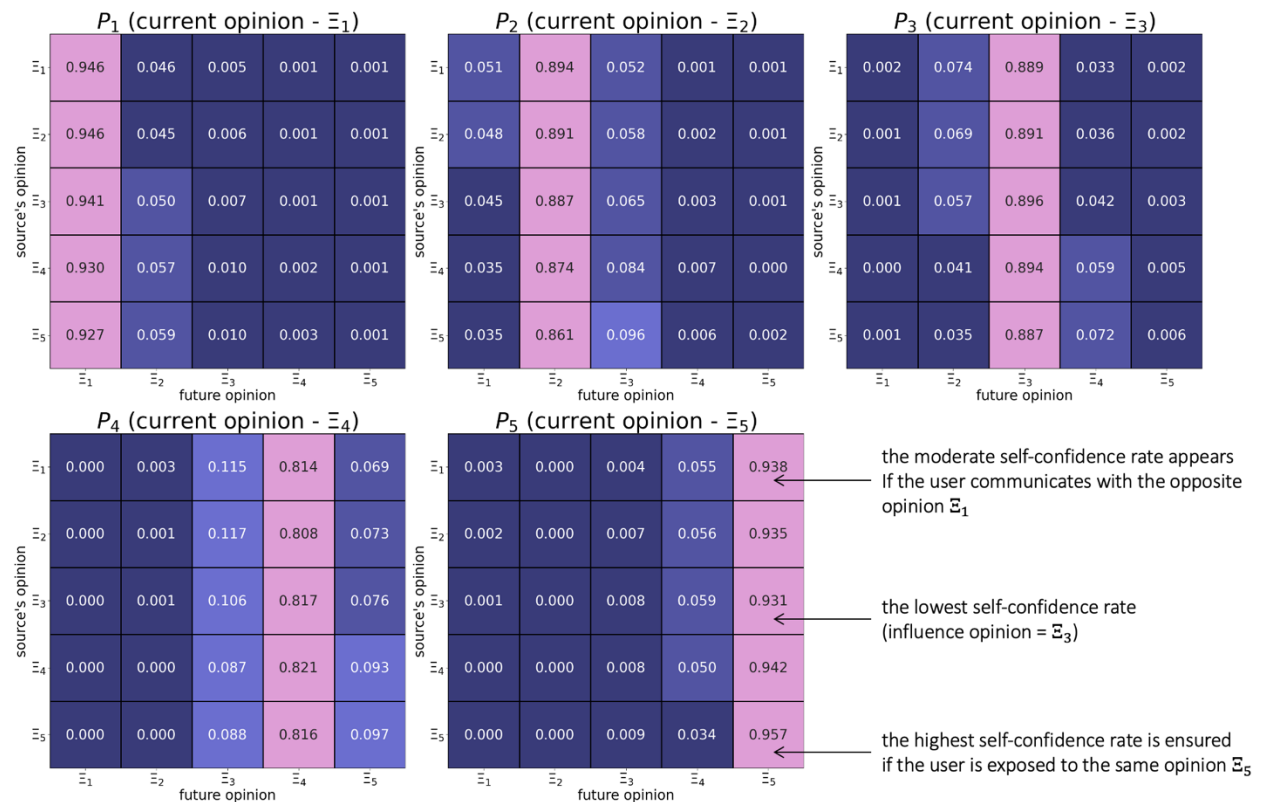

Figure 1. These heatmaps show how the probability of opinion shift depends on the opinions of the interacting agents. For this purpose, we discretize the opinion scale into five subintervals $\Xi_1 = [0, 0.2), \Xi_2 = [0.2, 0.4), \Xi_3 = [0.4, 0.6), \Xi_4 = [0.6, 0.8), \Xi_5 = [0.8, 1]$. The values are presented to three decimal places.

4.2. Effects of non-opinion characteristics on opinion shifts

In the previous analysis, we completely ignored the possible effects of non-opinion characteristics on opinion changes. As we said in Introduction, the way individuals perceive information could largely depend on the non-opinion characteristics of the interacting agents, such as age, gender, or the common number of friends. Let us now shed light on this issue. For this purpose, we employ the quantity

$$y_{i,j} = [x_i(t_2) - x_i(t_1)] * \text{sign}[x_j(t_1) - x_i(t_1)]$$

as a dependent variable. It measures the magnitude of an opinion shift $x_i(t_1) \to x_i(t_2)$ subject to its direction: if the shift is pointing towards the source's opinion $x_j(t_1)$, then the dependent variable is positive. Otherwise, $y_{i,j}$ is negative. By doing so, we want to find out what conditions facilitate the likelihood that the opinion stimuli will receive a positive response (will induce a positive opinion shift).

The list of independent variables is presented in Table 1. At the same place, we provide our intuition regarding the effects of these covariates on the dependent variable. Apart from the covariates that measure different sorts of *similarity* (structural one—as in the case of the common number of friends,—or demographic one—as in the case of the differences in age or gender), we also control for various characteristics of the focal node i (influence object). This allows us to discern any specific nodal-level effects.

Table 1. Independent variables (i – influence object, j – influence source)

Independent variable	Definition	Hypothesis
$\Delta x_{i,j} = \lvert x_j(t_1) - x_i(t_1) \rvert$	The absolute difference in opinions	$\Delta x_{i,j}$ should have a positive effect on the dependent variable—from Figure 1 it follows that more distant opinions tend to be more attractive.
$\Delta age_{i,j} = \lvert age_i - age_j \rvert$	The absolute difference in age	$\Delta age_{i,j}$ should have a negative effect on the dependent variable—a non-opinion similarity stimulates the decrease in opinion discrepancies (Balietti et al., 2021).
$\Delta gender_{i,j} = \lvert gender_i - gender_j \rvert \in \{0,1\}$	This variable demonstrates if two users have different genders ($gender_{i,j} = 1$) or not ($gender_{i,j} = 0$)	$\Delta gender_{i,j}$ should have a negative effect on the dependent variable—a non-opinion similarity stimulates the decrease in opinion discrepancies (Balietti et al., 2021).
f_i	The nodal degree of the influence object	f_i may have a negative effect on the dependent variable—we hypothesize that individuals that have many friends should perceive themselves as more valuable and having a higher social status and thus should be more attached to their own views (Eagly, 1983).

$f_{i,j}$	The number of common friends	$f_{i,j}$ should have a positive effect on the dependent variable—strong ties are more effective in conducting social influence (Aral & Walker, 2014).
$x_i(t_1)$	The opinion of the influence object	$x_i(t_1)$ should have a negative effect on the dependent variable—from Figure 1 it follows that users whose opinions are close to the right endpoint of the opinion spectrum are more stubborn.
$1_{gender_i=1}$	This dummy variable shows if the gender of i is female	$1_{gender_i=1}$ should have a positive effect on the dependent variable—according to Refs. (Peshkovskaya et al., 2017, 2018) females cooperate better than males.
age_i	The age of i	This covariate should have a negative effect on the dependent variable—younger individuals tend to be more sensitive to influence (Sears, 1986).

To develop a corpus of observations, we take each edge $(i,j) \in E$ and then calculate the quantities introduced above by considering first i as an influence object and j as an influence source and then reverse. As a result, each user i may potentially appear in $2f_i$ observations (due to the filters specified below, not all observations will participate in the further analysis). The weakness of such an approach is that each edge (i,j) is considered (twice) in isolation, thus ignoring potential influence from the rest of the peers of i and j. However, the influences of these peers are also added to the corpus as independent observations (we will return to this confounding factor in Section 6). As in the case of the computation of the probabilities of opinion changes presented in Figure 1, this approach silently assumes that during the observation period, each user was influenced by each of their friends strictly one time, with all these influences being independent from each other. In fact, such sort of interactions (aka one-to-one) is widely adopted in opinion formation models – see Refs. Deffuant et al., 2000; Mäs & Flache, 2013). However, the assumption that *each* pairwise interaction has happened is quite strict. We will return to this point in Section 6.

To facilitate the comparability of the covariates' effects, we standardize the data by making a zero mean and unit variance for each factor. Further, we exclude from our analysis those observations (i,j) that violate the following restrictions:

- $(i,j) \in E(t_2)$ (the tie should remain unchanged).

- $f_{i,j}(t_1) = f_{i,j}(t_2)$ (the number of common friends should be constant as it could have an effect on opinion dynamics).

- $|x_{\star}(t_2) - x_j(t_1)| < 0.05$ (the influence source's opinion should not undergo significant changes during the observation period—otherwise, we cannot precisely locate its value)[1].

As a result of such filtering, we end up with a corpus of 390,149 observations.

However, preliminary analysis (see Table 2) revealed that age is highly correlated with other covariates. On this basis, we decided to exclude it from the list of independent variables. Table 3 shows the results of OLS regression, and Figure 2 depicts the estimated values of the regression coefficients. We see that all the covariates, excepting the absolute difference in gender and the nodal degree appear to have significant effects on the dependent variable. Further, the effects of those covariates that were estimated to be significant (at the level of 0.05) coincide with our prior intuition (see Table 1). A surprising exception is that females appeared to be less easily influenced than males, other things being equal. From Figure 2, we conclude that the opinion-related covariates ($x_i(t_1)$ and Δx_{ij}) have the highest effects on the opinion formation processes (the highest effect is provided by Δx_{ij}). The contributions of other covariates are far less strong and, besides, roughly similar. The small values of the estimated coefficients stem largely from the fact that for most observations, the dependent variable is zero or small (see Figure C1 in Appendix C).

Table 2. VIF computed for the covariates in two cases: (1) the age covariate is accounted for (the upper row); (2) the age covariate is omitted (the bottom row)

Δx_{ij}	Δage_{ij}	$\Delta gender_{ij}$	f_i	$f_{i,j}$	$x_i(t_1)$	$1_{gender_i=1}$	age_i
2.508	1.857	1.448	1.874	1.483	3.432	1.901	5.346
2.247	1.556	1.422	1.853	1.45	2.948	1.701	–

Table 3. The results of OLS regression.

	Coefficient	Std error	t	P > |t|
Intercept	0.0027	8.53e-05	31.467	0.000***
Δx_{ij}	0.0022	8.63e-05	25.451	0.000***
Δage_{ij}	-0.0003	8.6e-05	-3.724	0.000***
$\Delta gender_{ij}$	-0.0002	8.57e-05	-1.826	0.068
f_i	-0.0002	9.06e-05	-1.911	0.056
$f_{i,j}$	0.0002	9.01e-05	2.018	0.044*
$x_i(t_1)$	-0.001	8.71e-05	-11.329	0.000***
$1_{gender_i=1}$	-0.0002	8.67e-05	-2.276	0.023*

Note. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 ' ' 1

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[1] In fact, if in a pair of connected vertices (i,j), one vertex (say, i) has changed its opinion for more than 0.05, then the inverse pair (j,i) will not appear in the corpus of observations. Further, if both the vertices have substantially modified their opinions, then the tie is completely ignored.
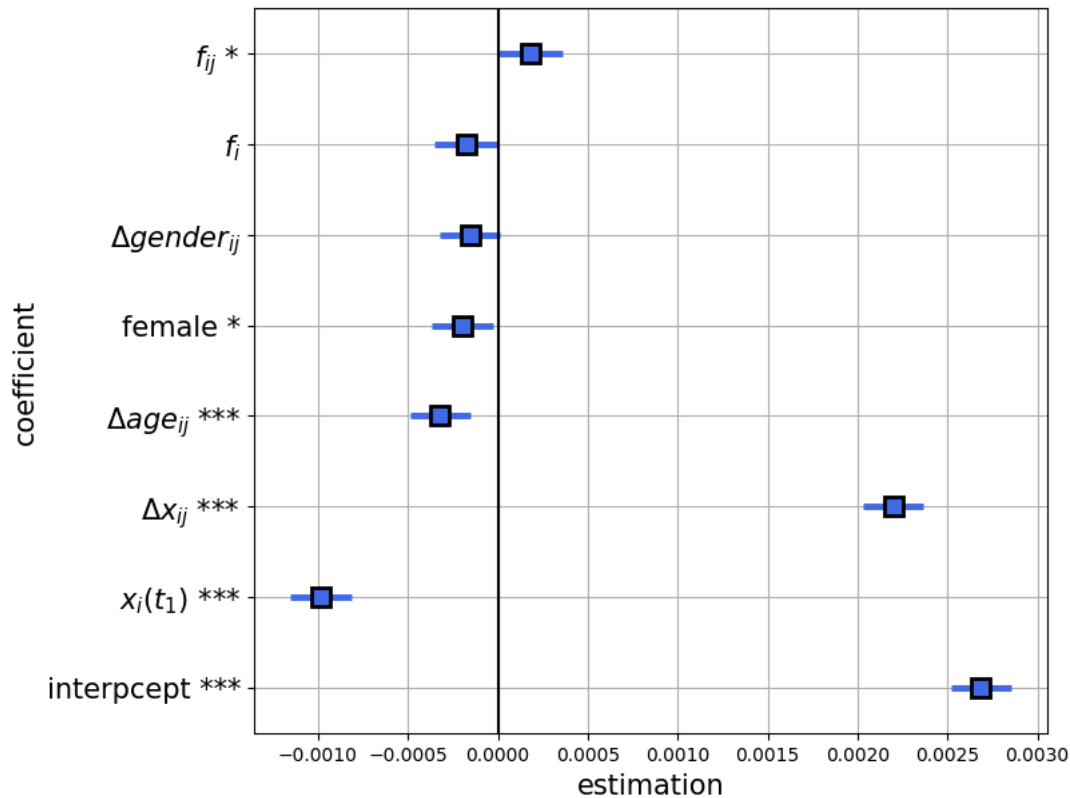
Figure 2. The values of the estimated OLS regression coefficients plotted with the corresponding confidence intervals.

5. Simulations

The results presented in the previous section indicate that despite some non-opinion features having significant effects on the way opinions change at the microscopic level, their impacts are not very sound. As such, the question arises if accounting for these features will change the macro-level behavior of the social system at stake. To answer this question, we perform auxiliary simulations with an agent-based opinion dynamics model using the empirical data from the dataset (see Section 2) to calibrate the model's parameters.

As a workhorse model, we employ the one from Ref. (Kozitsin, 2022a). That model was specially designed to investigate and simulate the patterns of opinion dynamics of empirical systems. In this model, agents connected by a social network are initially endowed with opinions from an abstract opinion alphabet $\Xi = \{\Xi_1, \dots, \Xi_m\}$. At each moment, a randomly chosen agent i communicates with one of their neighbors j (which is also chosen by chance). Let assume that the opinions of i and j are Ξ_s and Ξ_l respectively. As a result of the communication, the agent i's opinion stochastically updates according to the distribution $\{p_{s,l,1}, \dots, p_{s,l,m}\}$, in which the quantity $p_{s,l,k}$ stands for the probability that the opinion shift $\Xi_s \to \Xi_k$ will occur (the low indices are synchronized with the indices of the underlying opinions $\Xi_s, \Xi_l,$ and Ξ_k). The quantities $p_{s,l,k}$ form a 3D mathematical object $P = [p_{s,l,k}]_{s,l,k \in [m]}$ that is called the *transition matrix*. In some cases, it is convenient to represent the transition matrix as a list of 2D row-stochastic matrices $P_1, \dots, P_m$, where $P_s = [p_{s,l,k}]_{l,k \in [m]}$. In fact, previously, we have already worked with this kind of objects—see Figure 1. However, on that occasion, we used such a construction to investigate the *already existing* opinion dynamics. For now, we employ the transition matrix to develop our own opinion dynamics with the aim of predicting the further evolution of the empirical system at stake.

The macroscopic behavior of the model can be captured by the variables $Y_1(t), \dots, Y_m(t)$ that describe the populations of opinion camps $\Xi_1, \dots, \Xi_m$ at time t. Further, we will employ the normalized versions of these quantities: $y_s(t) = Y_s(t)/N$.

Below, the model introduced above will be referred to as the Basic Model.

However, in its current form, the Basic Model assumes that the outcome of an interaction depends on the interacting agents' opinions only, thus ignoring the effects of non-opinion covariates, which, as reported in Subsection 4.2, have some impact on opinion dynamics. To account for this issue, instead of applying a single transition matrix, we will use several ones, with each transition matrix dedicated to the description of its own specific combination of non-opinion characteristics of the interacting agents.

To be more specific, motivated by the results obtained in Subsection 4.2, we introduce two new features of agents (we use the same notations as in Subsection 2): (i) $age_i \in \mathbb{N}$ and (ii) $gender_i \in \{1,2\}$ (1 – females, 2 – males). Let us consider two interacting agents i (influence object) and j (influence source). For now, we assume that the outcome of this interaction depends on (i) how different the agents are in terms of age ($\Delta age_{i,j} = |age_i - age_j|$), (ii) the number of friends i and j have in common (denoted by $f_{i,j}$), and, finally, (iii) the gender of i. Depending on the values of these variables, each pair of interacting agents is assigned to one of the 8 possible types (see Table 4). For each type $f \in [8]$, a specific transition matrix P^f is recruited (which has the same properties as the transition matrix in the Basic Model). The resulting model is called the Advanced Model.

Table 4. Definition of the types of agent pairs.

Types of pairs	The values of the variable		
	$\Delta age_{i,j}$	$gender_i$	$f_{i,j}$
Type 1	≤ 5	$= 1$	$= 0$
Type 2	≤ 5	$= 2$	$= 0$
Type 3	≤ 5	$= 1$	≥ 1
Type 4	≤ 5	$= 2$	≥ 1
Type 5	> 5	$= 1$	$= 0$
Type 6	> 5	$= 2$	$= 0$
Type 7	> 5	$= 1$	≥ 1
Type 8	> 5	$= 2$	≥ 1

Note: the value of 5 that discretizes the range of $\Delta age_{i,j}$ was chosen as the mean of this variable (the 60th percentile)[2]. The threshold value 1 that separates the range of $f_{i,j}$ is the median.

Now we compare the macroscopic predictions (captured by variables $y_s(t)$) of the Basic and Advanced Models. We use the empirical data from the dataset to calibrate the models' parameters: (i) initial characteristics of agents, (ii) the social network, and (iii) the transition matrices. To project the opinion scale $[0,1]$ (on which the empirical opinions were estimated) to the opinion alphabet Ξ, we discretize the range $[0,1]$ into three subintervals $[0, 0.33\}, [0.33, 0.66), [0.66, 1]$ standing for a three-element opinion alphabet $\Xi = \{\Xi_1, \Xi_2, \Xi_3\}$ ($m = 3$). Next, we use the dataset snapshots to calibrate the transition matrices by replicating the algorithm presented in Appendix A. In the case of the Basic Model, non-opinion covariates are not accounted for, and we end up with one transition matrix (see Appendix B, Figure B1). For the Advanced Model, 8 transition matrices are constructed (see Appendix B, Figures B2–B9).

For each model, we conduct 20 independent simulations. Each simulation starts from the same state defined by the first snapshot of the dataset. The network structure and the agents' characteristics are delicately inherited from the empirical data. To isolate the effect of the correlations between the

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[2] Initially, we wanted to use the median value 3 to discretize the range of $\Delta age_{i,j}$, but we decided that this threshold is too small for being used as a separator between ages. However, the results remain virtually the same if using the threshold of 3.

network and agents' features (Kozitsin et al. (2023) revealed that the underlying networked system is assortative with respect to the opinion, age, and gender covariates), we also randomly shuffle the nodes of the network (keeping the nodes' characteristics fixed) so that all the correlations between the nodal characteristics and the network disappear[3]. As a result, we end up with four possible Scenarios (see Table 5). Each simulation lasts 4,000,000 iterations: pilots revealed that this time ensures that the system reaches equilibrium in terms of the populations of the opinion camps[4]. Figure 3 compares the aggregated results of simulations across Scenarios 1–4. We see that if ignoring the non-opinion covariates, then the shuffle procedure does not affect the macroscopic behavior of the model – in both cases, the system finds itself in the equilibrium state $y_1 = 0.33, y_2 = 0.46, y_3 = 0.2$. However, simulations with the Advanced Model revealed two important observations. First, we report that if not applying random shuffling (Scenario 3), then the Advanced Model stabilizes around the distribution $y_1 = 0.35, y_2 = 0.46, y_3 = 0.19$, which differs from the prediction of the Basic model by $\approx 1{,}000$ agents (3% of all votes). However, topologies with suppressed assortativity lead to even larger deviations: simulations within Scenario 4 tend to end up in the state $y_1 = 0.4, y_2 = 0.46, y_3 = 0.15$—the advantage of the leftists has increased by $\approx 9\%$ of all votes, if compared to Scenario 3. In all Scenarios, the population of the neutral opinion camp at the equilibrium remains virtually the same ($y_2 = 0.46$). Of course, one should keep in mind that all these differences in opinion distributions appear in the long run.

Table 5. Design of simulation scenarios.

	Agents' characteristics used in simulations		Random shuffle of nodes
	Opinion	Non-opinion characteristics	
Scenario 1	+	-	-
Scenario 2	+	-	+
Scenario 3	+	+	-
Scenario 4	+	+	+

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[3] It is worth noting that this procedure does not suppress the correlations at the nodal level – for example, even after applying the shuffling, younger agents will be biased towards the right opinion Ξ_3.

[4] To be more specific, equilibrium is reached at $t \approx 2{,}000{,}000$. To understand what this time span stands for, one should recall that in our case, one Monte-Carlo step (30,000 iterations) corresponds to the observational period (6 months). From this perspective, according to the model, the empirical social system should reach an equilibrium in ≈ 33.5 years. Of course, such estimations are unlikely applicable to the description of real-life processes because the underlying empirical system is not closed and is subject to external affairs that affect its development.
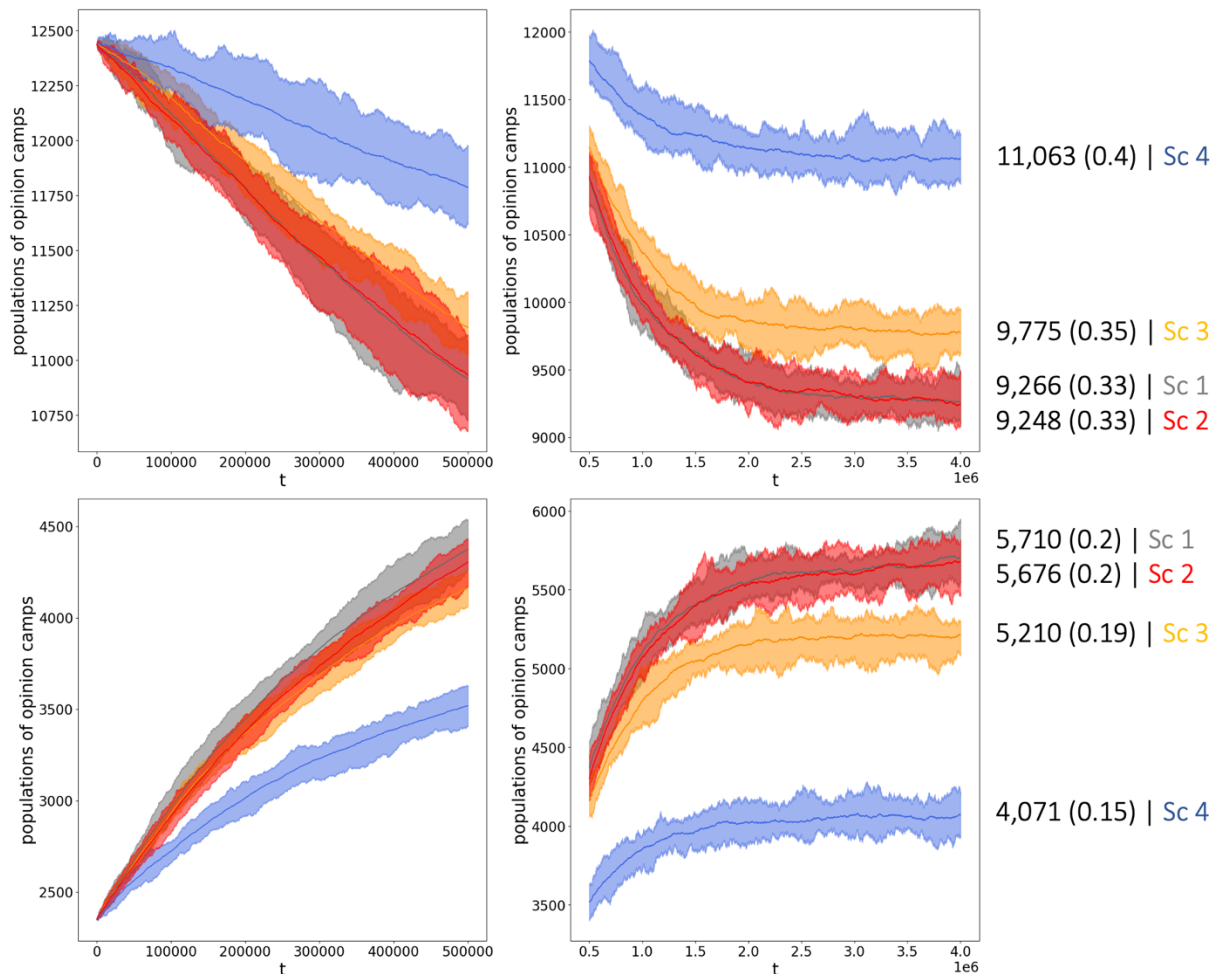
Figure 3. The figure demonstrates the averaged dynamics of the populations of leftists (upper panels) and rightists (bottom panels) across Scenarios 1–4. For each Scenario, the colored area is formed by the upper and lower contours of the corresponding simulations, and the curve represents the averaged trajectory. The left panels depict the time span $1 \leq t \leq 500,000$, the right panels investigate the range $500,000 \leq t \leq 4,000,000$.

6. Discussion and Conclusion

In this paper, using longitudinal data from an online social network, we systematically analyzed how individuals' opinion and non-opinion characteristics affect opinion dynamics. We revealed that females are harder to convince than males. Next, we found that individuals that are characterized by similar ages have more chances to reach a consensus. Finally, we report that individuals who have many common peers find agreement more often.

In general, these results align with the literature (perhaps, the effect of gender is somewhat novel). We believe that our contribution here is that we demonstrated that the impacts of these effects are virtually the same. Further, our analysis indicates that the effects of non-opinion characteristics, despite being statistically significant, are far less strong than those of opinion characteristics: knowing the current opinion of an individual and, what is even more important, the distance in opinions between this individual and the person that attempts to influence the individual is much more valuable than the information regarding their ages, genders, and the number of peers they have in common.

To gain a better understanding of this issue, we conducted a series of agent-based experiments using the underlying empirical data to calibrate the agents' characteristics and the way they interact with each other. We revealed that accounting for non-opinion characteristics lead to not very sound but statistically significant changes in the macroscopic predictions of the populations of opinion

camps in the long run, primarily among the agents with radical opinions ($\approx 3\%$ of all votes). In turn, predictions for the populations of neutral individuals are virtually the same. Besides, we demonstrated that the effect of non-opinion features is seriously moderated by whether the underlying social network correlates with the agents' characteristics. After applying the procedure of random shuffling (in which the agents and their characteristics were randomly scattered over the network), the macroscopic predictions have changed by $\approx 9\%$ of all votes. What is interesting, the population of neutral agents was not affected by this intervention.

The main disadvantage of our analysis is that it draws upon the data from the natural experiment, so we have no opportunity to control for many confounding factors, for example we completely dismiss external effects (Petrov et al., 2023). In fact, we do not know the history of users' interactions during the observational period. Likely not all users were active in promoting their views to their friends. Usually, individuals with radical opinions are those who translate their opinions more often (Preoţiuc-Pietro et al., 2017). In turn, our assumption was that each user influenced each of their friends. Further, we considered each pair of befriended users i and j as two independent observations, sequentially changing the roles of the agents (influence object and influence source). This approach is weakened by the following confounding factors: it ignores the possibility that the dynamics of the opinions of i and j may be subject to some external effects, such as opinions of the i's and j's peers (external stimuli). Despite this possibility being partially suppressed by the fact that we also considered the influences of i's and j's peers as independent observations, the assumption of independent observations is likely violated on this occasion, so our regression analysis, as well as our algorithm for the calibration of the transition matrices may lead to inaccurate estimations. In Refs. (Kozitsin, 2022b, 2023), this issue was controlled for to some extent because the influence directed on a user i was estimated as the mean of the opinions of the user i's friends . However, in our case, this approach is questionable because apart from opinions, we attempt to consider other users' characteristics. For a given user, the joint distribution of these characteristics among the user's friends may be quite complex and nontrivial, and simple averaging may suppress some important information.

At the end, we would like to highlight that in our analysis, we concentrated on the role of *observable* and *easily recoverable* user characteristics in opinion formation processes. Indeed, ages, genders, and the numbers of users' peers can be promptly retrieved from the Web using API facilities with a relatively small investment in resources. Of course, using more detailed information can lead to more precise predictions. For example, Bond et al. (2012) reported that the allocation of a user's trust is highly correlated with how intensively the user likes their peers, with more likes indicating more trust. However, this sort of information requires employing API facilities that was unavailable to us on this occasion. Nevertheless, it would be a promising direction for further research.

7. Data availability

All of the data and codes can be obtained upon a reasonable request.

8. Funding

9. Literature

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Appendix A

The quantities $p_{s,l,k}$ were computed via the following formula:

$$p_{s,l,k} = \frac{\#\{(i,j) \in E(t_1) \mid x_i(t_1) = \Xi_s, x_j(t_1) = \Xi_l, x_i(t_2) = \Xi_k\}}{\#\{(i,j) \in E(t_1) \mid x_i(t_1) = \Xi_s, x_j(t_1) = \Xi_l\}}.$$

It is worth noting that in the above formula, each edge (i,j) appears two times: (i) when i is an influence object and j is an influence source; (ii) when i is an influence source and j is an influence object[5]. Next, to control for the confounding factors conditioned by the dynamics of ties and possible changes in the opinion of the influence source, we discard those observations from our analysis that violate the following restrictions:

- $(i,j) \in E(t_2)$ (the focal tie should remain unchanged).

- $f_{i,j}(t_1) = f_{i,j}(t_2)$ (the number of common friends should be constant as it could have an effect on opinion dynamics).

- $|x_*(t_2) - x_j(t_1)| < 0.05$ (the influence source's opinion should not undergo significant changes during the observation period—otherwise, we cannot precisely locate its value).

The transition matrix for the Basic Model (see Figure B1 in Appendix B) is constructed using the same approach. The transition matrices for the Advanced Model are calculated in a similar fashion.

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[5] This approach silently assumes that during the observation period, each user was influenced by each of their friends strictly one time, with all these influences being independent from each other. In fact, such sort of interactions (aka one-to-one) is widely adopted in opinion formation models – see Refs. Deffuant et al., 2000; Mäs & Flache, 2013). However, the assumption that *each* pairwise interaction has happened is quite strict.

For example, the components of the transition matrix that describe interactions of type 1 (see Figure B2 in Appendix B) are defined as follows:

$$p_{s,l,k} =$$

$$= \frac{\#\{(i,j) \in E(t_1) \mid x_i(t_1) = \Xi_s, x_j(t_1) = \Xi_l, x_i(t_2) = \Xi_k, \Delta age_{i,j} \leq 5, gender_i = 1, f_{i,j} = 0\}}{\#\{(i,j) \in E(t_1) \mid x_i(t_1) = \Xi_s, x_j(t_1) = \Xi_l, \Delta age_{i,j} \leq 5, gender_i = 1, f_{i,j} = 0\}}.$$
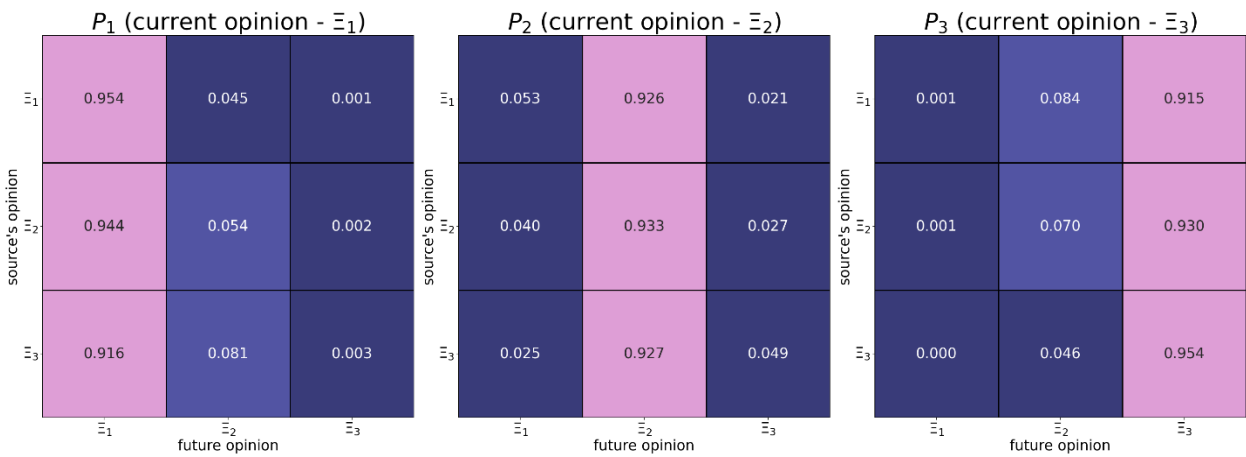
Appendix B

Figure B1. This transition matrix was estimated based on the empirical data (non-opinion covariates are ignored).
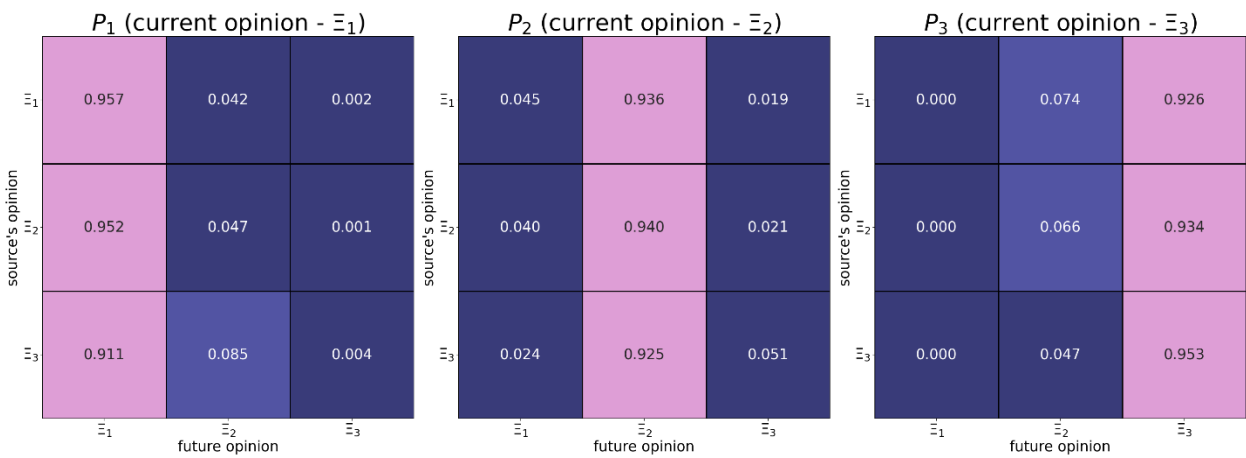
Figure B2. This transition matrix was estimated based on the empirical data (type 1 – see Table 4).
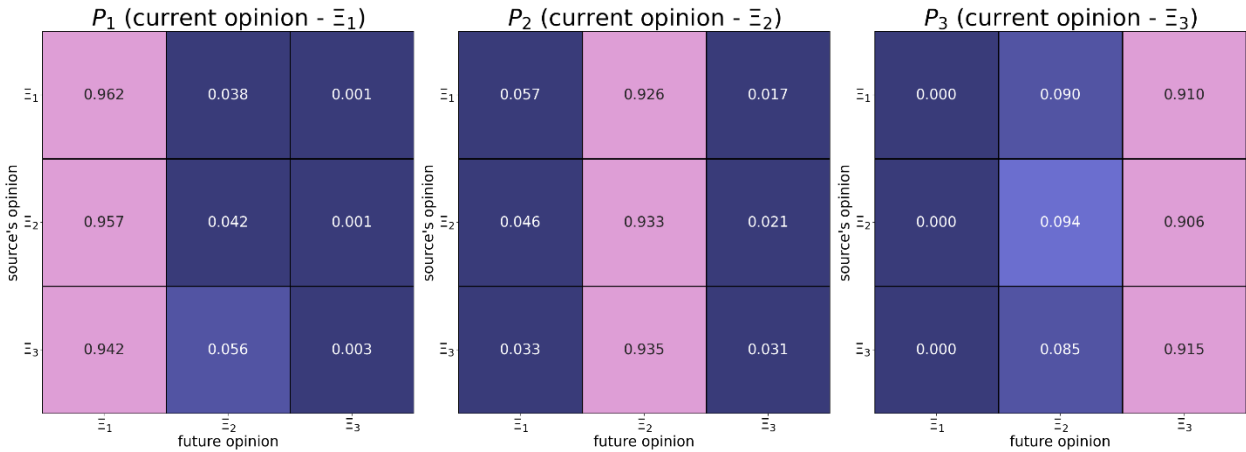
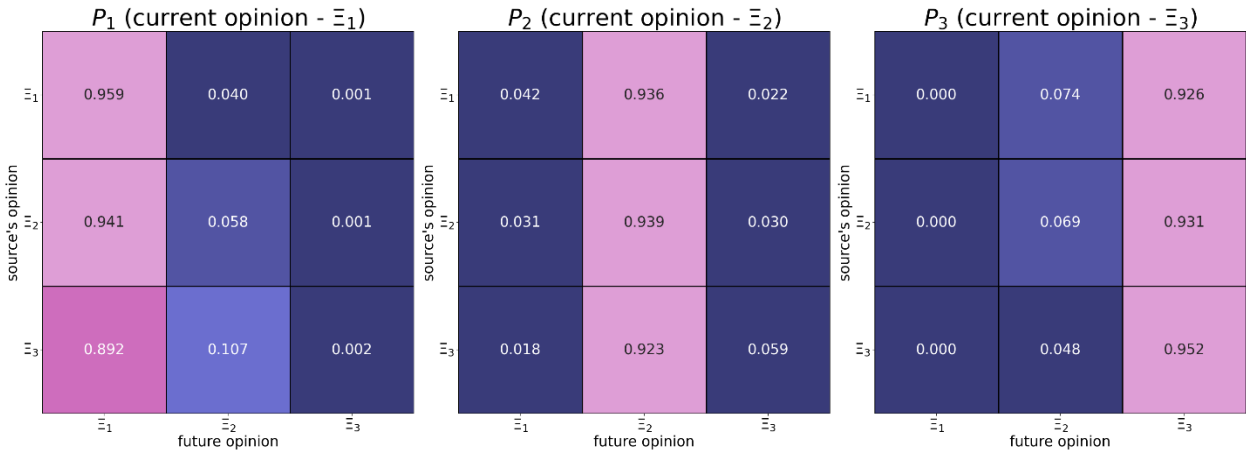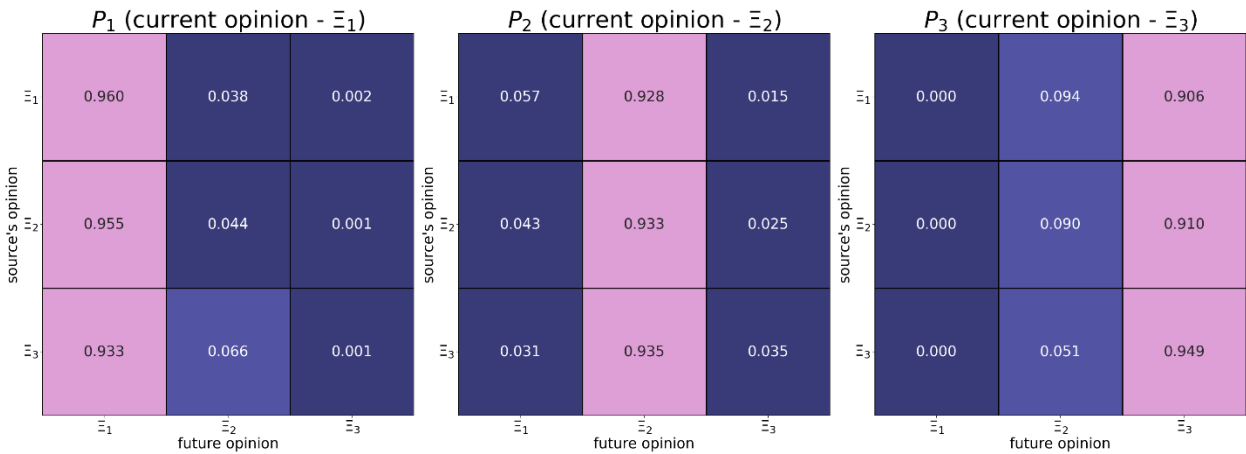*Figure B3.* This transition matrix was estimated based on the empirical data (type 2 – see Table 4).
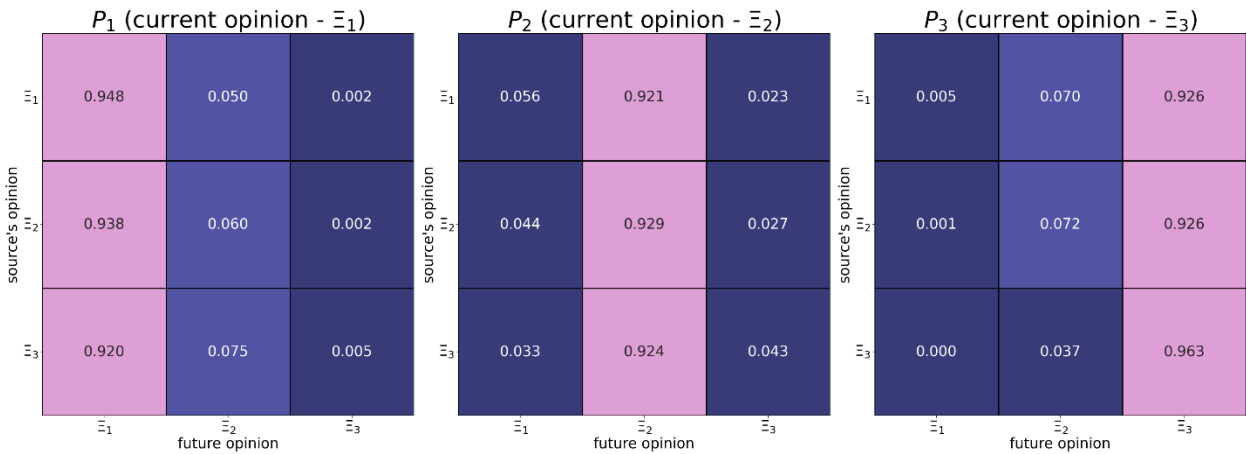
Figure B4. This transition matrix was estimated based on the empirical data (type 3 – see Table 4).
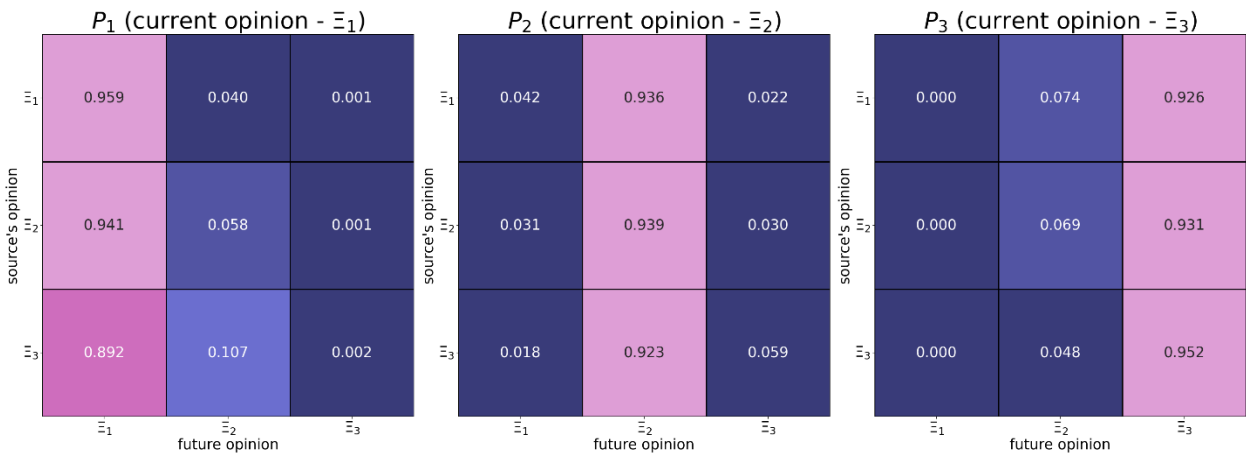
Figure B5. This transition matrix was estimated based on the empirical data (type 4 – see Table 4).
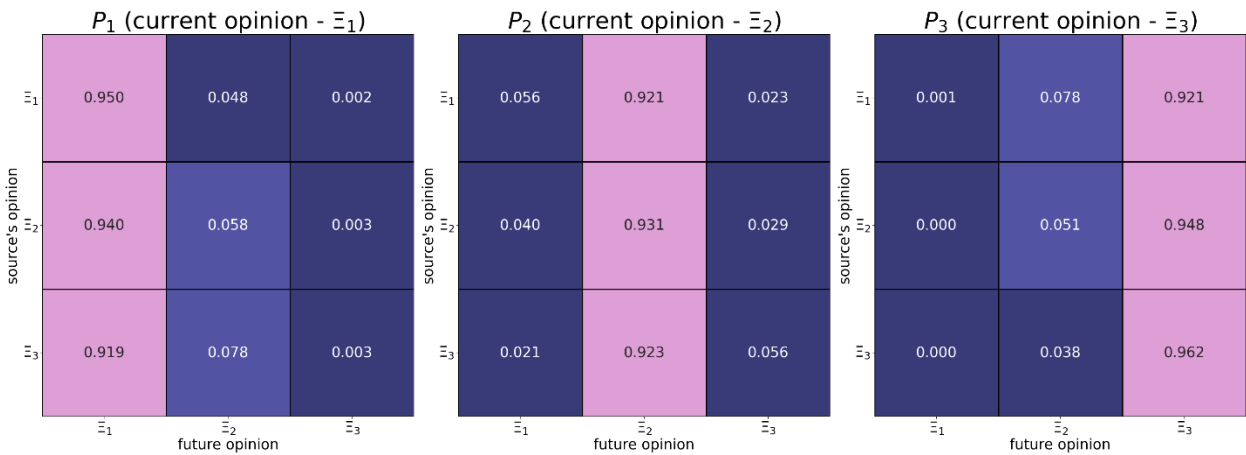
Figure B6. This transition matrix was estimated based on the empirical data (type 5 – see Table 4).

Figure B7. This transition matrix was estimated based on the empirical data (type 6 – see Table 4).

Figure B8. This transition matrix was estimated based on the empirical data (type 7 – see Table 4).
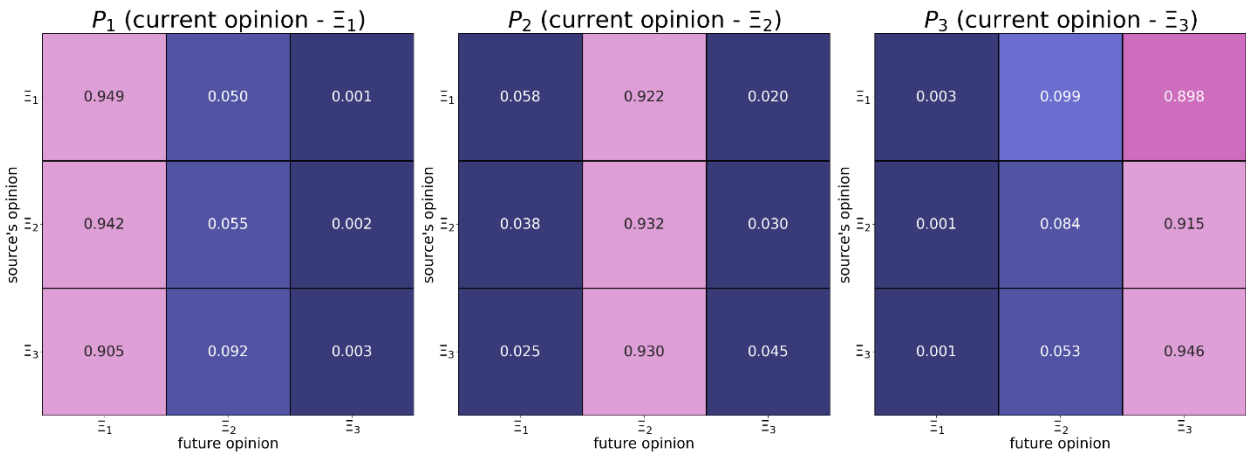
Figure B9. This transition matrix was estimated based on the empirical data (type 8 – see Table 4).
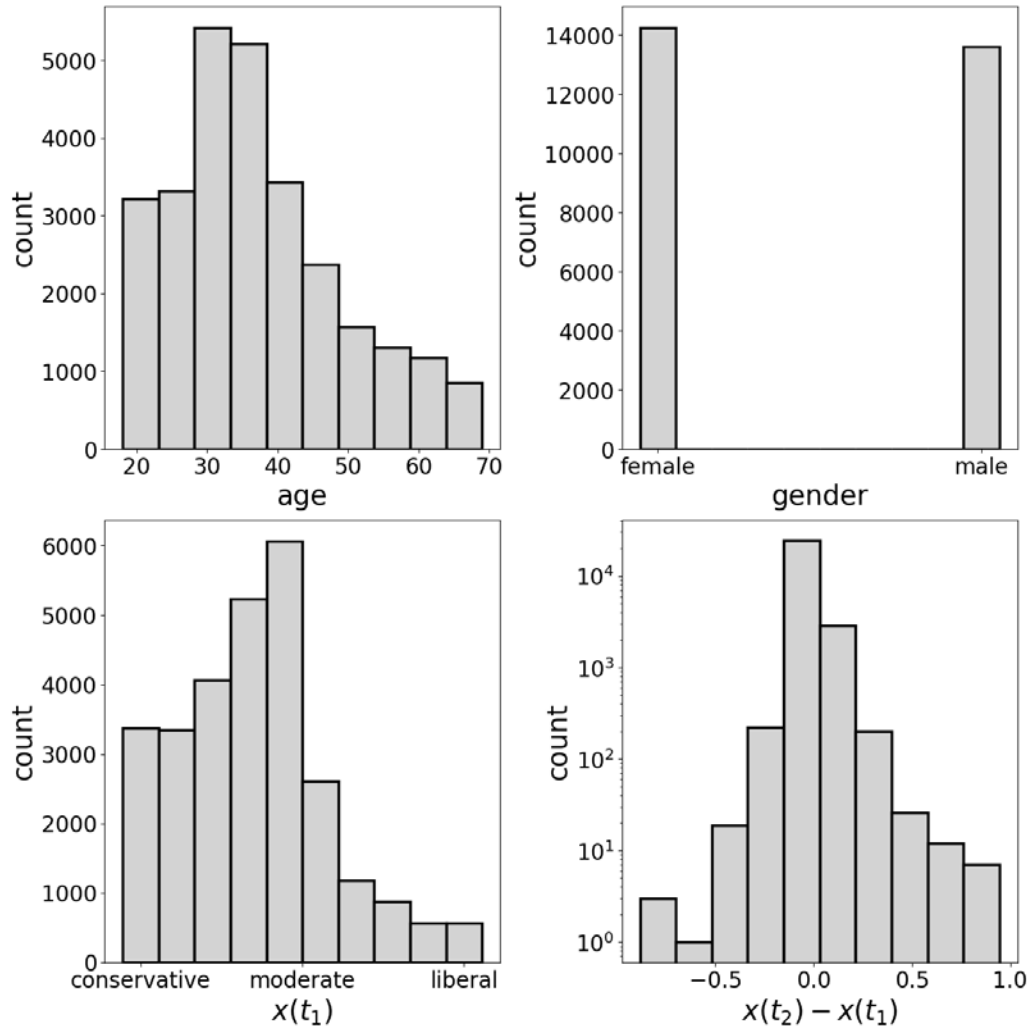
Appendix C

Figure C1. These histograms show the structure of the dataset. The histograms that represent the age, gender, and opinion distributions are borrowed from the Ref. (Kozitsin et al., 2023).