



The casual effect of relational mobility on integration of social networks: An agent-based modeling approach

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Abstract

Despite converging evidence for the importance of relational mobility on shaping people's social experiences, previous work suggested mixed findings for its influence on the structure of sociocentric networks, which lays the basis for the development of all types of social relationships. Additionally, as it is timely and economically intractable to administer such longitudinal experiments in real-life settings, most previous work mainly relied on cross-sectional correlation analyses and provided limited causal evidence. The current research used an agent-based modeling approach to examine whether higher relational mobility (i.e., the number of opportunities to meet new people) would promote integration among social networks over time. Using parameters derived from survey data, we simulated how the integration of sociocentric social networks evolves under different levels of relational mobility. Based on the data of three network structural indicators, including modularity, global efficiency, and standard deviation of nodal betweenness, we obtained causal evidence supporting that higher relational mobility promotes greater network integration. These findings highlight the power of socioecological demands on our social experiences.

Keywords Relational mobility · Social network · Social network integration · Socioecological approach · Agent-based modeling

Social relationship experiences have been extensively examined in social and cross-cultural psychological research (e.g., for a review, Kim et al., 2008). However, surprisingly only a few psychological studies (Igarashi et al., 2008; Na et al., 2015) were conducted to closely explore the influence of socioecological contexts on the evolution of social network structure, which can bring unique and important perspectives as compared with other social relationship research (e.g., studies on perceived social support or dyadic relationships) (Smith & Christakis, 2008).

Social network structure reflects not only an individual's social experiences but also complex interactions among all members, which can facilitate our understanding of how intragroup and intergroup relationships, as a whole, evolve

over time (Williams et al., 2018). Second, the structure of social networks substantially shapes people's responses in different types of social relationships due to their interconnected nature (Felmlee, 2001). In other words, understanding the change in social network structure can deepen our understanding of the development of all types of social relationships simultaneously. Finally, social network structure is found to affect how social influence takes place, including social norm maintenance (Muthukrishna & Schaller, 2020) and contagion of (un)healthy practice (Smith & Christakis, 2008). Thus, investigating the influence of socioecological factors on social networks, the structure in particular, can bring insights into how socioecological factors shape collective processes.

To advance our understanding of the evolution of social network structure, the present research employed an agent-based modeling approach to examine the role of relational mobility, which is an important socioecological factor that reflects the degree of freedom of forming new social relationships and abandoning undesirable social relationships afforded by a given social ecology (Yuki et al., 2007), on

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the integration of social networks among members in an environment.

Relational Mobility and Social Relationships

In the past decades, a surging amount of research (for a review, Yuki & Schug, 2020) was conducted to investigate the consequences of relational mobility, a socioecological factor referring to the number of opportunities that allow people to meet new people for forming new relationships or to leave the undesirable ones (Yuki et al., 2007). As an important socioecological factor, relational mobility explains both individual variations and cross-cultural variations in social experiences (e.g., Schug et al., 2010). High relational mobility in an environment creates a “free market” of social relationships, in which people voluntarily form new relationships and leave undesirable ones based on their personal preferences (Schug et al., 2009). In contrast, low mobility in an environment creates a relatively “closed market” for social relationships, which encourages people to maintain their existing stable social relationships (e.g., Li et al., 2015; Lou & Li, 2017). Generally, relational mobility substantially shapes our strategies used in different types of social relationships, including friendships, romantic relationships, and enemyships (e.g., Kito et al., 2017; Li et al., 2015, 2018; Schug et al., 2009), as well as other social behaviors (Thomson et al., 2018) and responses to public health issues (e.g., Salvador et al., 2020) across societies.

However, one important question has not been answered yet: how does societal-level relational mobility affect social networks? The structure of social networks creates the basis for how different social relationships, such as friendships and romantic relationships, develop and interconnect (Felmlee, 2001), making it crucial to understand the influence of relational mobility on social network structure.

Given the conceptual frameworks of relational mobility (Yuki & Schug, 2012), we speculated that more opportunities of meeting new people and leaving the existing ones in highly mobile environments may make people less constrained by specific social contexts but freer to express personal preferences (Schug et al., 2009; Yuki et al., 2007), which may give them greater freedom to connect social networks formed in different contexts and finally result in greater integration among social networks.

However, some limited existing findings suggested inconclusive expectations for the influence of relational mobility on social network integration. Igarashi and colleagues (2008) studied the extent to which people integrated their cliques of friends in three Western countries (i.e., Australia, Germany, and the United Kingdom) and two East Asian countries (i.e., Japan and Korea). Supporting our speculation, they found that people were more likely to integrate

their social networks in the Western cultures than in the Eastern cultures, with the former ones having higher levels of relational mobility (Li et al., 2018). These findings suggested that high relational mobility would promote greater integration of social networks. In contrast, some studies did not support our speculation. Lun et al. (2013) found that an activated residential mobility mindset (vs. an activated residential stability mindset) made people more likely to adopt friendship compartmentalization, in which they would keep social networks separated for different activities if they sought social support. A study by Na et al. (2015) suggested that social network integration would be lower in cultures emphasizing the uniqueness of personal goals, which would be more likely to happen in environments with unstable social relationships. These findings suggested that less mobile social environments would promote greater integration of social networks.

Taken together, different patterns for the influence of relational mobility on social network integration were suggested: Igarashi et al.’s study (2008) suggested that people from high-relational-mobility societies would report greater social network integration, while the studies of Lun et al. (2013) and Na et al. (2015) suggested that people from high-relational-mobility societies would report lower social network integration. Some limitations identified in previous studies might attribute to this inconsistency. First, previous studies mostly examined individuals’ personal networks, which primarily focused on the direct relationships between the respondent and each of their network members but ignored the indirect relationships among the network members. Therefore, personal networks do not fully capture the global perspective of the whole social networks in a given environment and thus fail to provide a comprehensive picture of social network structure. The sociocentric networks, in contrast, capture all possible relationships among each network member (Smith & Christakis, 2008) and can provide a more global view of the network structure. Second, most previous studies on the effect of socioecological factors mainly provided correlational cross-sectional evidence. Direct evidence for the causal effect of macro-level socioecological factors on the evolution of social networks was lacking, though some insights could be drawn from longitudinal studies that examined the influence of changes in the personal social environment on the structure of personal networks (e.g., McCarty, 2002). These longitudinal studies revealed that people’s personal networks evolved over time as a function of changes in their personal social environments associated with moving, education, employment, or marriage (e.g., Bidart & Lavenue, 2005; Bidart et al., 2018; Lubbers et al., 2010). Thus, it is likely that the macro-level socioecological environment can substantially shape the evolution of sociocentric social networks over time. However, since social networks may take a long time to develop,

stabilize, and integrate, temporarily manipulating relational mobility in an environment, which is a chronic socioecological factor, may be hard to induce a salient immediate effect in changing people's social network structure. Thus, it would be challenging to capture the changes in sociocentric network structures over time (Williams et al., 2018), which made obtaining causal evidence for the relationship between socioecological factors and real-life sociocentric networks intractable.

Agent-based Modeling Approach

In this paper, we proposed to use the agent-based modeling approach to investigate the effect of relational mobility on the structure of sociocentric networks. The agent-based modeling approach establishes a computational multi-agent system, where each agent represents an individual and is programmed with a series of behavioral rules to simulate real-world interactions with other individuals or/and the virtual environment (Schelling, 1971). With each agent behaving accordingly, collective patterns driven by individual behaviors may gradually emerge. The agent-based modeling approach thus offers a way to observe and examine how individual behaviors accumulate among populations over time to affect the emergence and development of social phenomena.

Compared with traditional psychological experimental methods, agent-based modeling possesses several unique advantages (Jackson et al., 2017; Lewandowsky, 1993; Smith & Conrey, 2007). First, with multi-agent systems running through simulations on computers, the agent-based modeling approach enables researchers to carry out large social-contextual experiments that are unaffordable in the real world due to the limitations of finance, time, and/or ethics. In particular, the scale of the experiments can be directly parameterized in the agent-based models (e.g., the number of agents and the number of days in simulations), large samples can be conveniently obtained, which adds to the statistical power of the experimental results. Second, compared with traditional approaches that mostly embedded linear assumptions, the agent-based modeling approach allows simulations of non-linearity in the dynamics of social phenomena by encoding individual behaviors into the autonomous rules of agents and letting the effect of rules unfold and accumulate over time. Last but not least, the agent-based modeling approach allows us to better examine causal relationships. By manipulating only the factors in concern and keeping other factors constant, the agent-based modeling approach facilitates isolation from potential confounders. Additionally, the agent-based modeling approach is, by definition, a longitudinal experimental method. Taken the above advantages together, the agent-based modeling approach helps shed light on the causal effect of individual

behaviors of psychological phenomena in the social context, which is often difficult or even impossible while using natural samples.

Due to the above advantages, the agent-based modeling approach has received increasing attention in the field of social psychology (Muthukrishna & Schaller, 2020; Nowak et al., 2016). In particular, a few pioneering studies have implemented different agent-based models to study how individual behaviors could shape social relationships. For instance, Oishi and Kesebir (2012) modeled the cost–benefit tradeoff of friendships at different levels of societal residential mobility and economic status, exploring how the two factors affect the utility of individual social networking choices. The simulation results showed that regardless of the economic condition, having a broad, shallow social network is more advantageous in a residentially mobile environment, whilst narrow, deep social ties are more beneficial in a residentially stable society. Gray and colleagues (2014) used the agent-based modeling approach to study group genesis in a homogeneous population, showing that groups could be formed without identity if only individuals possessed the characteristics of reciprocity and transitivity during interactions.

As for this study, the agent-based modeling approach was chosen to investigate the question of how relational mobility can influence the structure of social networks for two reasons. First, our research question targeted at the influence of macro-level socioecological factors on the overall social network structure, which was clearly unaffordable by laboratory-based paradigms or field studies. Second, considering the complex dynamics underlying the multiple interactions occurring over the entire network, the advantages of the agent-based modeling approach in non-linearity tolerance and casual implications may also benefit our study.

Overview of the Current Research

To overcome the methodological challenges of previous studies and systematically evaluate the influence of relational mobility on social network structure over time, we conducted a computational study and attempted to seek causal evidence for the influence of relational mobility on sociocentric network integration. To enhance the external validity of the agent-based model, we first conducted a survey study to obtain data for identifying and estimating potential parameters included in our simulations, which were detailed in the next section. Next, we ran simulations of the agent-based model to examine how the integration of sociocentric social networks evolves under different levels of relational mobility. For investigating the casual influence of relational mobility on the change of network structure over time, following the recommendation of previous work

(Hill & Dunbar, 2003), the proposed agent-based model was examined under two network sizes (small: $N=150$ vs. large: $N=1500$) for a sufficiently long period of time ($D=1000$).

Methods

General Analytic Approach

Our agent-based model generated a small-world network of N nodes to simulate a sociocentric social network of N agents and assigned each pair of agents an adjustable weight to indicate their closeness. As suggested by previous findings (e.g., Burt, 2001, 2002), we assumed that the weight was a continuous value related to the amount of interaction time, dynamically reflecting the closeness between agents from strangers (minimum) to intimate friends (maximum). The closeness between agents was further summarized into two relational types: stable (e.g., acquaintances and friends) and unstable (e.g., strangers and non-acquaintances), namely *stable connected pairs* (SCPs) and *unstable connected pairs* (UCPs). As in the real world, our model did not define a crisp boundary over the weight to distinguish the two relational types. Contrarily, the mapping between weights and relational types was fuzzy (Fig. 1), with larger weights indicating a higher chance of SCPs but smaller weights for a higher chance of UCPs. These N agents then interacted daily regarding the following three rules derived from the real-world behaviors. First, for each agent, the total number of interactions allowed on each day was limited (Robert & Dunbar, 2011). Second, each agent randomly chose their interaction targets based on the weight distribution. Larger weights (higher closeness) signified a greater interaction opportunity. Third, the weight (closeness) between two agents slowly decayed over time, but interaction behaviors could increase the weight (Burt, 2000, 2002; Oswald et al., 2005). It is thus possible that two agents, who were once strangers, develop into acquaintances due to frequent

interactions (the increasing rate of the weight outruns its decay rate, raising it to the level of acquaintances), or vice versa (viz., acquaintances degenerate into strangers due to lack of interactions). After repeating the daily interactions among agents until the total number of simulation days (denoted by D) was reached, the resulting social network was submitted for further analyses.

Besides the two environmental parameters, viz., N (number of agents) and D (number of simulation days), the above agent-based model required the following control parameters: the initial number of stable social relationships per agent (K), the initial weights between agents (w), the number of daily interactions per agent (I), the amount of time per interaction (T), and the decay rate of weights (ρ). To increase the external validity of the above model, we first conducted a survey study to acquire data for determining these control parameters and identifying which parameters were correlated with relational mobility. By setting the correlated parameters according to the level of relational mobility and keeping the rest configurations constant, we could realize precise manipulation of relational mobility in the agent-based model.

Using Dunbar's number (Hill & Dunbar, 2003) as the baseline for network size, the agent-based model was examined under two scales (small: $N=150$ vs. large: $N=1500$) for a sufficiently long period of time ($D=1000$). That is, the agent-based model established an initial social network of N agents. The same initial network was then evolved for D days under the conditions of high and low relational mobility, respectively. To avoid bias induced by randomness in the agent-based model, we initialized 20 networks for each setting of N and repeated the simulation of each network under each mobility condition for 10 times. These settings were determined in advance to ensure a sufficient sample size for subsequent analyses to achieve 80% statistical power at least at a medium effect size using G*Power (Faul et al., 2009). Figure 2 shows the schematic diagram for the overall simulation design. Detailed implementations are introduced in the next section.

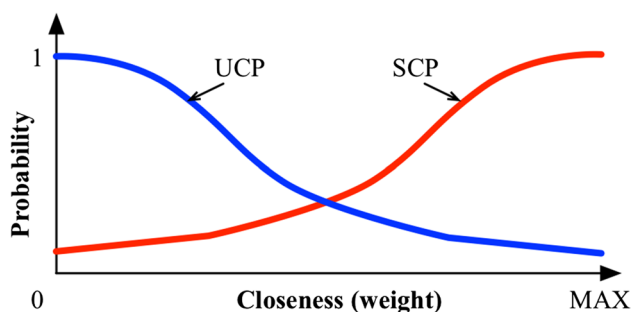


Fig. 1 Mapping from closeness (weight) between agents to the probability of having a specific relational type. SCP: stable connected pair; UCP: unstable connected pair

Materials and Procedure

Survey Study

This study was approved by the Institutional Review Board in the Department of Psychology of Sun Yat-sen University, and informed consent was acquired from all participants before the survey. The items used in our survey study can be found in the online supplementary material. Considering the effect size, we recruited a total of 140 students from a university in China to answer the survey. The data of 31 students were excluded because they did not complete the survey or follow the instructions, leaving the data of 109

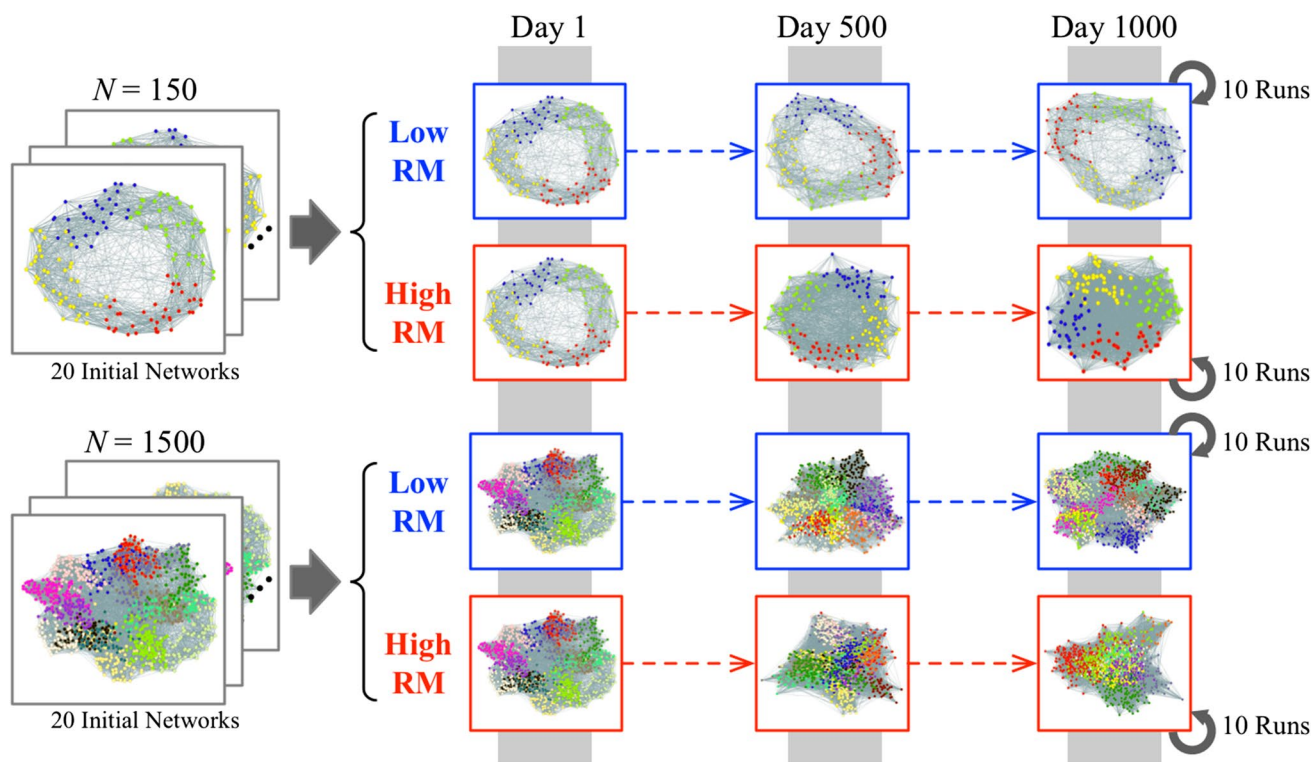


Fig. 2 Schematic diagram for the simulation design of the agent-based model. N : number of agents; RM: relational mobility

students (33 males, age = 19.67 ± 1.50). For each item, we further excluded outliers beyond three standard deviations. The final sample size was still adequate to detect correlations with a medium effect size with 80% power according to G*Power (Faul et al., 2009).

In the survey, participants first answered questions related to the frequency and duration of social interactions unrelated to work or study ($Q1.1$ to $Q1.3$, six items in total). Herein, the interactions related to work and study were excluded for minimizing the confounds associated with different natures of diverse social relationships, as previous studies have found that interactions in task-oriented relationships (e.g., friendships in the workplace) may be on more formal and involuntary bases than those in other social relationships (Pillemer & Rothbard, 2018). Based on the answer data, three of the model control parameters (viz., K , I , and T) mentioned in the previous part could be directly acquired, whilst the rest two (viz., w and ρ) were needed deduction. As in our survey, the settings of I and T were distinguished between SCPs and UCPs (namely, I^{SCP} , I^{UCP} , T^{SCP} , and T^{UCP}) considering the distinctive interaction behaviors of these two relational types. The setting of w was also distinguished between SCP and UCP (namely, w^{SCP} and w^{UCP}) since its deduction involved the data corresponding to I . Notably, the settings of all the parameters related to the agents' interaction behaviors (i.e., w , I , T) were subject to

Gaussian distributions with means and standard deviations derived from our survey data. Considering the large number of agents and interaction behaviors, the Gaussian assumption was reasonable according to the central limit theorem. Moreover, by doing so, we managed to simulate the random fluctuations that would probably occur for each individual and at each time of interaction. The closeness decay rate (ρ) was set as a constant as we considered it relatively stable in homogeneous social networks. Its value was deducted from the answer data based on previous findings that the decay tended to be a power function of time (Burt, 2000, 2002). Refer to the Appendix for the detailed procedure of setting these control parameters.

We also asked the participants to answer questions about their relational mobility using items modified from the 12-item Relational Mobility Scale (Yuki et al., 2007) on a 6-point scale (1: strongly disagree; 6: strongly agree). A sample item includes, "It is common for me to have a conversation with someone I have never met before."

Correlations were then computed between the participants' relational mobility scores and their answers regarding the interaction experiences with the two relational types. The model control parameters were considered by whether their sourced items had significant correlations with relational mobility. For the parameters related to the significantly correlated items, we recalculated their settings under the

high and low mobility conditions in the same way as in the Appendix but replacing the answers of all participants with those of the participants with the top and the bottom 25% of relational mobility scores, respectively. By parameterizing the model simulation under different conditions with different settings, we thus achieved the manipulation of high versus low relational mobility.

Agent-based Model

As shown by the flowchart in Fig. 3, the agent-based model was built based on the following steps.

Step 1: Synthetic Sociocentric Social Network Initialization The small-world nature of real-world social networks has been widely acknowledged (Kleinberg, 2000). To match this property, we employed the Watts-Strogatz model to generate complex networks as the initial sociocentric social networks of our agent-based model. The Watts-Strogatz model is a classic generation method for small-world networks (Watts & Strogatz, 1998) and has been widely applied in social network studies (Bellerose et al., 2021; Nowak et al., 2016; Rolfe, 2014). It requires three parameters: the network size, average degree, and rewiring probability. In this study, the network size was set as N (number of agents), the average degree was set by K (i.e., the rounded mean of the average number of stably connected counterparts per agent), and the wiring probability was set at 0.1 for achieving sufficient small-worldness (Watts & Strogatz, 1998). In this way, the connected agents were considered as SCPs (people with stable social connections) whilst the disconnected agents were considered as UCPs (people with unstable social connections). The initial weights between connected

and disconnected agent pairs were generated based on the average interaction time, respectively, as explained in the Appendix.

Step 2: Daily Interactions Between Agents On every simulation day d ($d = 1, 2, \dots, D$), interactions randomly occurred between SCPs and UCPs in the synthetic sociocentric social network. For the SCP interactions of each agent i ($i = 1, 2, \dots, N$), the interaction quota was determined by the control parameter I^{SCP} . For UCP interactions, considering its scarcity in real life (as shown in the Results section), the interaction quota was either zero or one, with the probability of being one set by the control parameter I^{UCP} . After deciding the interaction quotas, each agent i used the roulette wheel selection approach (Michalewica, 1992) to determine the SCP and the UCP interaction targets based on the weight distributions over agents connected and disconnected to i , respectively. The amount of interaction time between agent i and each selected target j was set by the control parameter T^{SCP} or T^{UCP} , depending on whether i and j were connected. Note that interactions were bidirectional in our model. Once an interaction occurred, the quotas of both involved agents would be consumed by one. Agents with zero quota would not interact with others any further. Additionally, to further increase the external validity of the simulations, all the parameter values used at this step were probabilistically derived from their respective distributions, as shown in Table 1.

Step 3: Daily Update of Closeness and Social Connections As in the real world, our model had the weights (closeness) between agents change with daily interactions. On each day d ($d = 1, 2, \dots, D$), the update of weights comprised the following two parts. First, based on previous findings that

Fig. 3 Flowchart of the simulation procedure for the proposed agent-based model

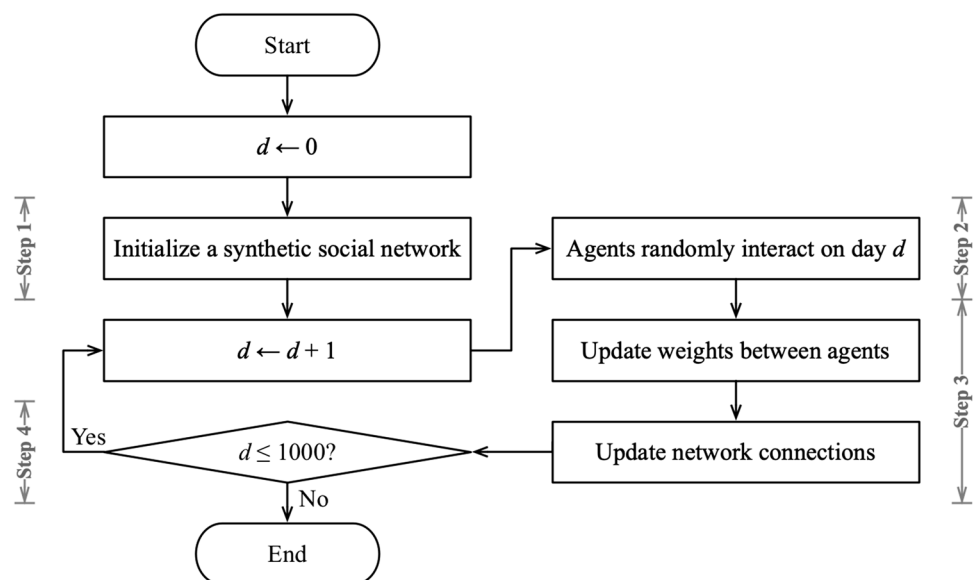


Table 1 Parameter settings of the agent-based model

Parameters	Condition	Settings
D : number of simulation days		1000
N : network size		150 1500
K : initial number of people with stable connections		30
I^{SCP} : number of daily interactions between SCPs		$\mathfrak{N}(5.26, 2.85)$
T^{SCP} : amount of interaction time between SCPs		$\mathfrak{N}(1.01, 0.93)$
w^{SCP} : initial weight between SCPs		$\mathfrak{N}(0.17, 0.16)$
I^{UCP} : number of daily interactions between UCPs	High RM	$\mathfrak{N}(0.38, 0.43)$
	Low RM	$\mathfrak{N}(0.13, 0.18)$
T^{UCP} : amount of interaction time between UCPs	High RM	$\mathfrak{N}(1.06, 1.14)$
	Low RM	$\mathfrak{N}(0.39, 0.32)$
w^{UCP} : initial weight between UCPs	High RM	$\mathfrak{N}(3 \times 10^{-3}, 4 \times 10^{-3})$ $\mathfrak{N}(2 \times 10^{-4}, 3 \times 10^{-4})$
	Low RM	$\mathfrak{N}(4 \times 10^{-4}, 3 \times 10^{-4})$ $\mathfrak{N}(3 \times 10^{-5}, 3 \times 10^{-5})$
ρ : daily decay rate of closeness	High RM	0.989 0.982
	Low RM	0.982 0.976

RM , relational mobility; $\mathfrak{N}(\mu, \sigma)$, Gaussian distribution with the mean μ and the standard deviation σ , truncated at $[\max(\mu - \sigma, 0), \mu + \sigma]$; the settings of all the parameters were identical across different network sizes except for w^{UCP} and ρ , because only these two parameters involved the network size in their calculation (see Appendix for details)

social relationships tend to decay as a power function of time (Burt, 2000, 2002), the closeness between every agent pair would decrease by the preset decay rate ρ . Second, considering that interactions benefit the maintenance and improvement of social relationships (Hays, 1984; Oswald et al., 2005; Roburts & Dunbar, 2011), the weights would increase proportionally to their updated average interaction time if two agents interacted on day d , which was also consistent with our assumption that closeness was related to interaction time. Mathematically, the updating formula of the weight $w_{ij}^{(d)}$ between agents i and j on day d was

$$w_{ij}^{(d)} = \rho w_{ij}^{(d-1)} + \delta_{ij}^{(d)}(1 - \rho)t_{ij}^{(d)}, \quad (1)$$

where $\delta_{ij}^{(d)} \in \{0, 1\}$ was the indicator for whether i and j interacted on day d and $t_{ij}^{(d)}$ was the average daily interaction time between i and j since the simulation began, viz.,

$$t_{ij}^{(d)} = \frac{1}{d} \left[(d-1)t_{ij}^{(d-1)} + T_{ij}^{(d)} \right], \quad (2)$$

$T_{ij}^{(d)}$ was the interaction time between i and j on day d , $i, j = 1, 2, \dots, N$, and $i \neq j$. Taken the two parts together, the above updating rule enabled a nonlinear evolving trend of closeness, which was more likely the real case than linear increase or decrease. The change in closeness might cause new connections to emerge or old connections to dissolve, and thus bring further alternations to the social network structure. In detail, based on the central limit theorem, we assumed that the weight distributions over SCPs and UCPs in the current network were also subject to the Gaussian assumption. Two Gaussian distributions $\mathfrak{N}_{\text{SCP}}$ and $\mathfrak{N}_{\text{UCP}}$ were

then established using the means and standard deviations derived from the current network. For a UCP between i and j , the probability of connecting them was computed as $P(0 \leq x \leq w_{ij}^{(d)}) / P(x \geq 0)$ with x subject to $\mathfrak{N}_{\text{SCP}}$. That is, if the closeness between i and j was already a relatively large value among the closeness of the current SCPs, they were likely to establish a stable connection. Similarly, for a SCP between u and v , the probability of disconnecting them was computed as $P(x \geq w_{ij}^{(d)}) / P(x \geq 0)$ with x subject to $\mathfrak{N}_{\text{UCP}}$. That is, if the closeness between agents u and v was relatively low even among the closeness of the current UCPs, the two agents have a larger chance to disconnect. All the social connections were updated as above.

Step 4: Termination Check The simulation repeated Steps 2 and 3 until the number of simulation days reached 1000.

The above agent-based model was implemented using our in-house MATLAB code (https://osf.io/nq8v3/?view_only=7ac3003e73ab4d8dae9fa0a2b2922a60).

Graphical and Statistical Analyses

Three indicators from the graph theory were employed to measure the integration level of the synthetic networks. The first indicator was modularity, with a high score indicating a stronger modular structure. That is, nodes in the same module are much more densely connected than nodes from different modules do, implying a lower integration level of the networks. The second indicator was the network global efficiency, which is calculated as the reciprocal of

the average shortest-path length between every two nodes. Higher global efficiency thus reflects higher integration of the networks. The last indicator was the standard deviation of nodal betweenness. The betweenness centrality of a node indicates its frequency of belonging to the shortest paths in the network. Nodes with higher betweenness thus play a more important role in network communication. A large standard deviation of the nodal betweenness indicates that the importance of the nodes in communication varies extensively, implying the emergence of a few hub nodes and thus a less integrated network structure. All these three indicators have been widely used for analyses of complex network topology (Costa et al., 2007). Refer to the online supplementary material for detailed computation and implementation.

The three indicators were calculated over each synthetic network along with the entire simulation procedure at a step of 100 days. Using each indicator as the dependent variable, we performed the two-way (mobility condition \times time) repeated measures analysis of variance (ANOVA) to examine how relational mobility and time interact in predicting the integration level of small and large networks ($N=150$ or 1500), respectively. Furthermore, the independent two-sample t-test was employed to examine the effect of relational mobility on the network integration level at different time points.

Results

Settings of the Agent-Based Model

The correlation analyses showed that the number ($r=0.222$, $p=0.023$) and duration ($r=0.324$, $p=0.001$) of interactions between UCPs were positively associated with relational mobility (Figure S1). Therefore, the control parameters directly acquired from the two items, viz., I^{UCP} (number of interactions per day with unstable connected people) and T^{UCP} (daily interaction time with unstable connected people), were considered for manipulating the level of relational mobility in the agent-based model. Further, the control parameters w^{UCP} (initial weight between UCPs) and ρ (decay rate of closeness) were also involved as the manipulation criteria, as their deductions utilized the answers to the above information (refer to the Appendix for details). The values of the above four manipulation criteria for the high and low levels of relational mobility were calculated, respectively, from the first and the fourth quarters of the participants sorted by their relational mobility scores, while the other control parameters, viz., K , w^{SCP} , I^{SCP} , T^{SCP} , were set constant according to the answers to the respective items. Refer to Table 1 for detailed settings of all the parameters used by our agent-based model.

Effect of Relational Mobility on Social Network Integration

To visually compare the structural change in social networks under different levels of relational mobility, for each network size ($N=150$ or 1500), we randomly chose one simulation of the 20 initial networks as an exemplar to visualize its structure under the two levels of relational mobility at $d=0$, 300, and 1000 (Figs. 4 and 5) using the Pajek software package (<http://vlado.fmf.uni-lj.si/pub/networks/pajek/>). The networks were presented in such a way that closer locations implied stronger connections (for more details, refer to the online supplementary material). As shown in Fig. 4, the initial network with 150 agents was composed of four well-separated modules. The agents in the same module tended to connect more densely than the agents across different modules, making the number of edges within modules (E_{intra}) much larger than that between modules (E_{inter}). After about a year ($d=300$), the synthetic network evolved under low relational mobility generally maintained the initial structure, although some modules began to overlap to a small extent and the number of inter-module connections slightly increased. In contrast, the synthetic network evolved under high relational mobility exhibited notable changes in terms of integration, as reflected by enlarging overlap between modules and heavily increased inter-modules connections. In the later period ($d=301 \sim 1000$), the two networks continued the previous evolutionary patterns. That is, the network under low relational mobility still preserved the initial modular structure, whilst the network under high relational mobility had the inter-module overlap and connections further increased, suggesting a trend for continuous integration. The evolutionary patterns of the synthetic networks with 1500 agents under the two conditions of relational mobility were similar as the above, except that the layout was more complex due to the larger number of nodes and edges. Taken together, the visualization of the evolutionary procedures further supported our hypothesis that higher relational mobility promotes the integration of social networks.

Figure 6 plots the change in the three indicators for network integration over time under different levels of relational mobility in the small ($N=150$) and large ($N=1500$) networks. The figure shows that, regardless of the network scale, the network evolved in low and high mobile contexts became distinct on all the three indicators since the early stage of the simulations, and the difference became more salient over time. More specifically, the networks under high mobility had lower modularity and smaller standard deviations of nodal betweenness but achieved higher global efficiency, suggesting a more integral topological structure. We then performed the two-way repeated-measures ANOVA with the Greenhouse–Geisser correction (Greenhouse & Geisser, 1995) to examine the effects of time and

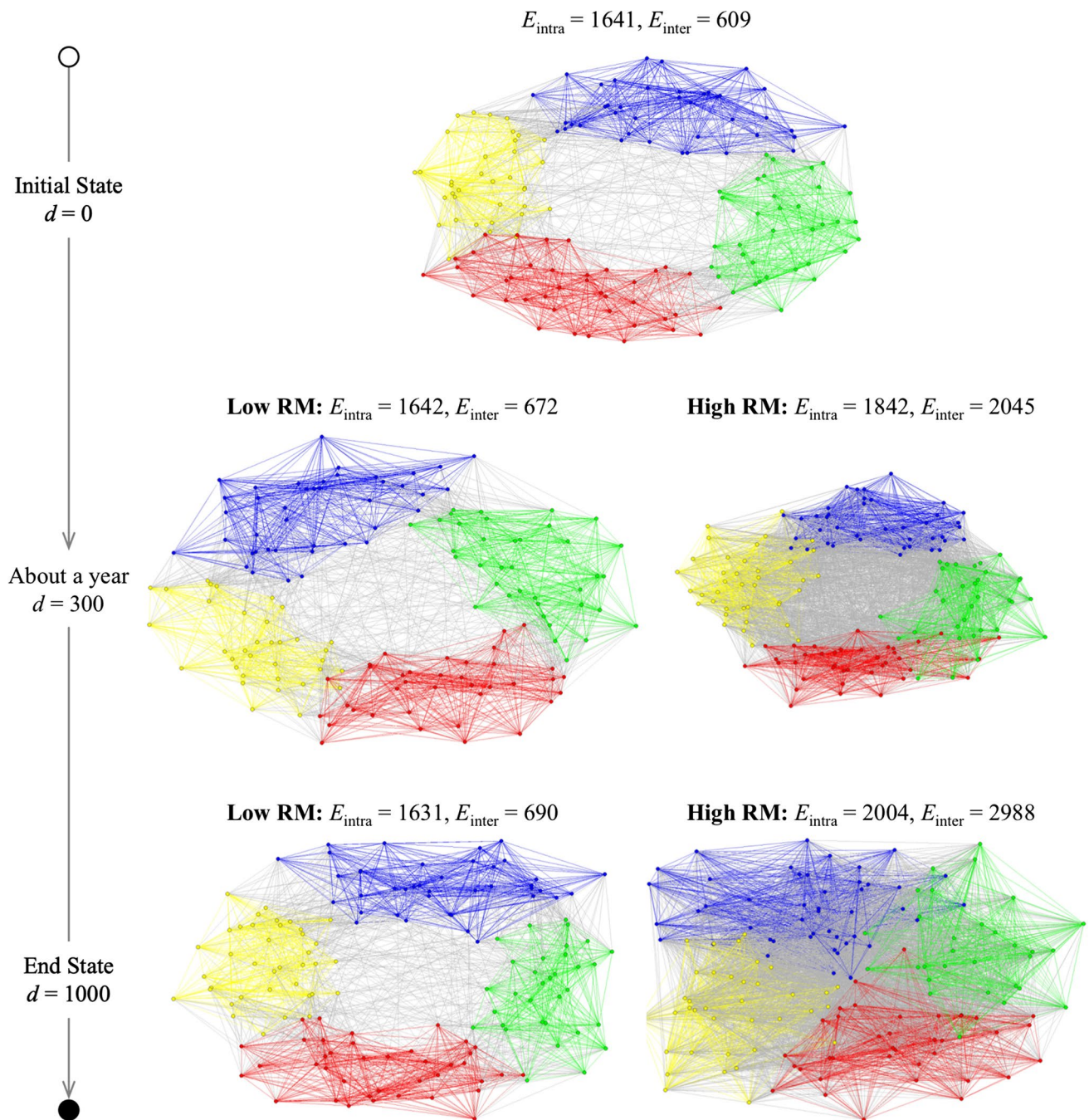


Fig. 4 Visualization of the evolutionary procedures for a synthetic network with 150 agents. Note. Visualization of the evolutionary procedures for a synthetic network with 150 agents under different levels of relational mobility. The network was partitioned into modules using Newman's algorithm (Newman, 2006). Nodes (agents)

and edges (stable connections between agents) in one module were colored the same, whilst edges between modules were colored in gray. RM: relational mobility; d : simulation days; E_{intra} : number of edges within modules; E_{inter} : number of edges across modules

relational mobility on each of the three indicators. Table 2 summarizes the results across all the 40 synthetic networks. We found that the main effects of relational mobility and time were both significant. The interaction effect of time and relational mobility was also significant. As shown by the post-hoc t-test in Table 3, since the first time of comparison

($d = 100$), the differences between the two networks under different mobility levels were significant in all the three indicators. Also, consistent with the visualization in Figs. 4 and 5, Fig. 6 shows that the network topological structure under low relational mobility changed only initially and stabilized more quickly as compared with the network topological

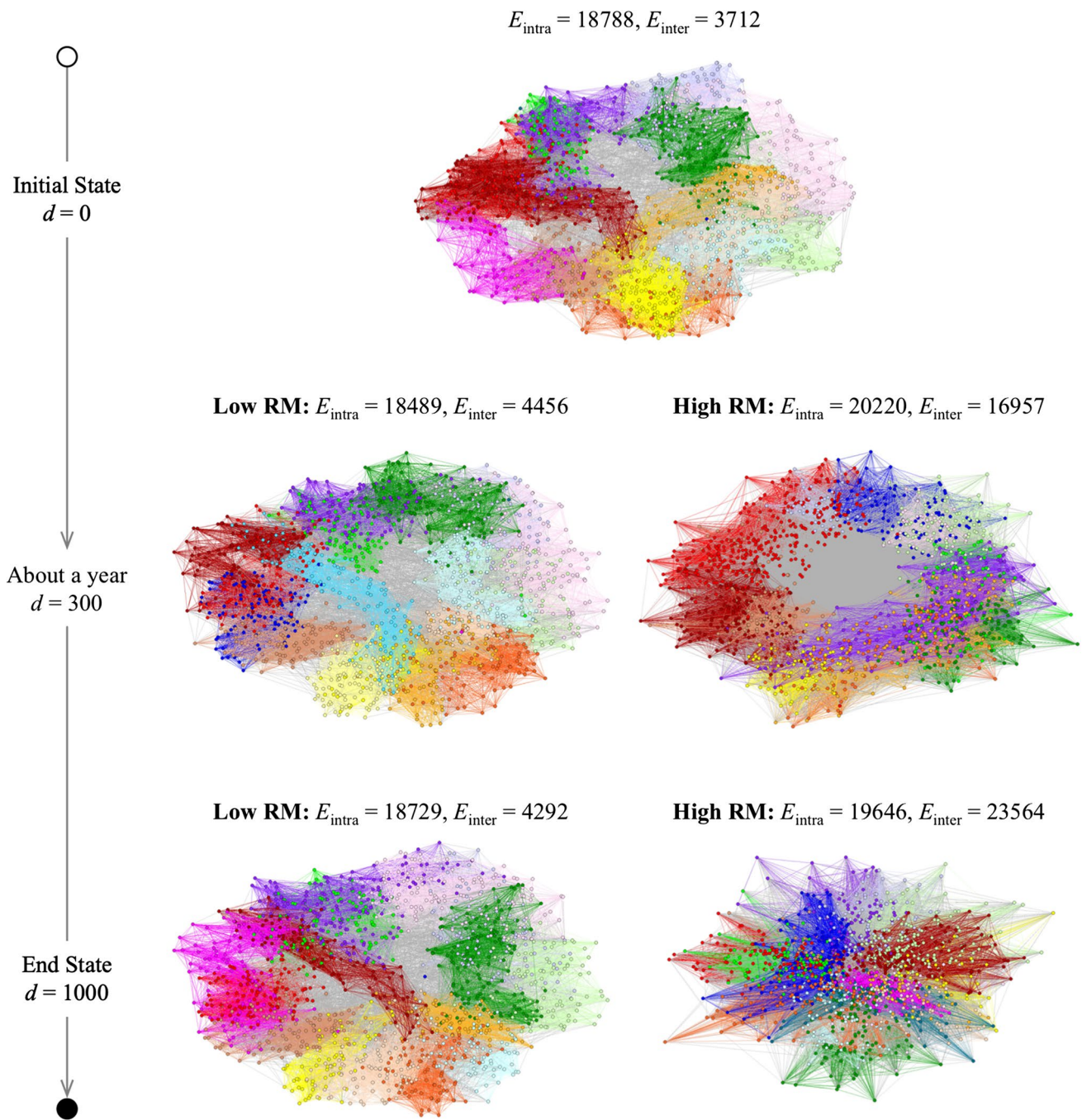


Fig. 5 Visualization of the evolutionary procedures for a synthetic network with 1,500 agents. Note. Visualization of the evolutionary procedures for a synthetic network with 1,500 agents under different levels of relational mobility. The network was partitioned into modules using Newman’s algorithm (Newman, 2006). Nodes (agents)

and edges (stable connections between agents) in one module were colored the same, whilst edges between modules were colored in gray. RM: relational mobility; d : simulation days; E_{intra} : number of edges within modules; E_{inter} : number of edges across modules

structure under high relational mobility. These results supported our hypothesis that higher relational mobility promoted greater social network integration.

Discussion

Previous work using correlational data suggested contradictory patterns for the relationship between relational mobility and integration of social networks (e.g., Igarashi

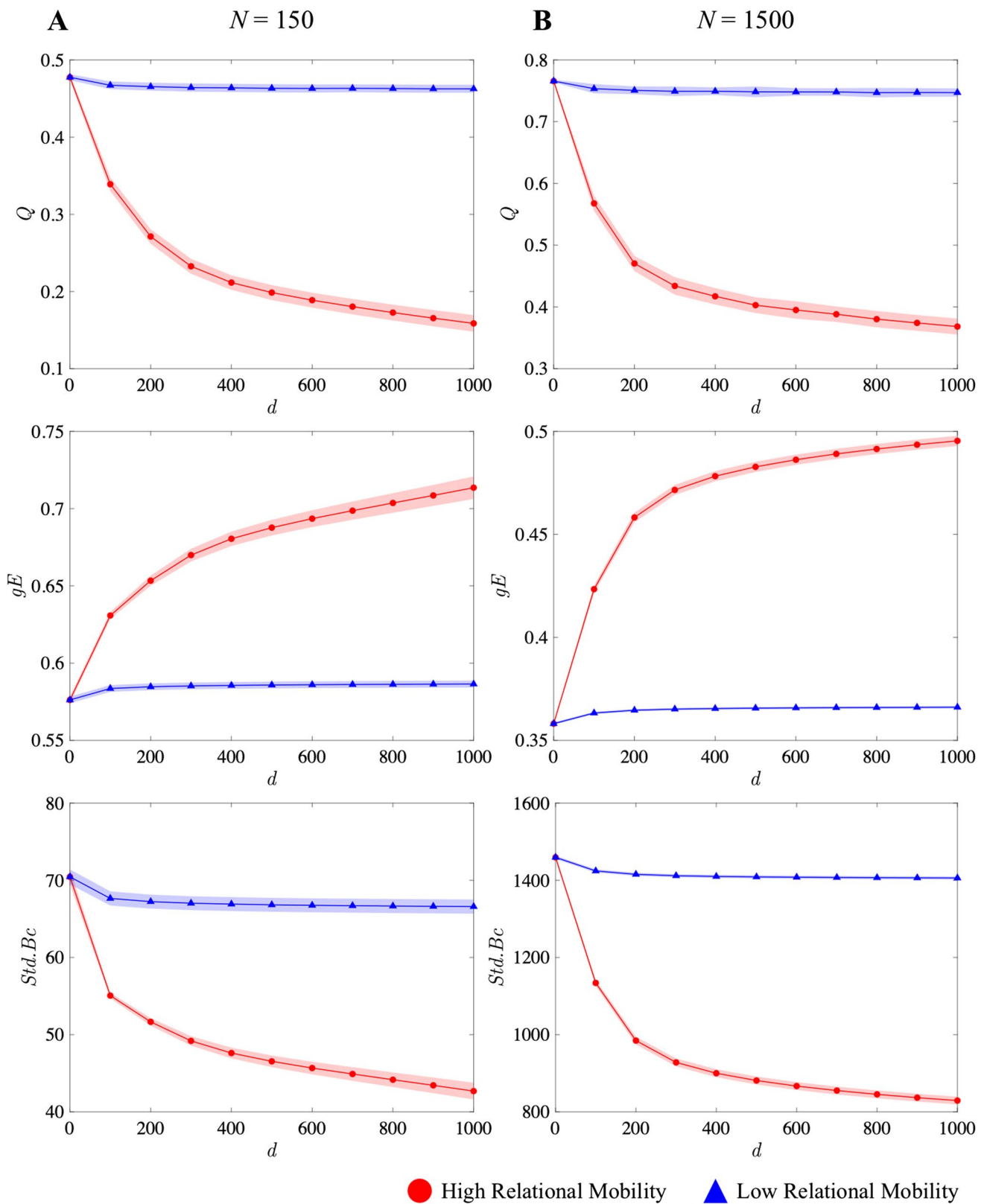


Fig. 6 Evolutionary curves of the three indicators for integration of (A) small ($N=150$) and (B) large ($N=1500$) networks. Note. The solid markers denote the mean values of the indicators across different initial networks and different runs, whilst the shade indicates the

corresponding standard deviation. The color and the shape of markers and shade are distinguished regarding the level of relational mobility. Q : modularity; gE : global efficiency; $Std.Bc$: standard deviation of nodal betweenness; d : simulation day

Table 2 Results of the two-way repeated measures ANOVA on the three network integration indicators

<i>N</i>	Indicator	Effect	<i>df</i>	<i>F</i>	η^2
150	<i>Q</i>	RM	[1, 18]	[3460.3, 28,648.7]	[0.995, 0.999]
		Time	[2.0, 73.5]	[2908.5, 8730.1]	[0.994, 0.998]
		RM×Time	[2.0, 79.8]	[2462.0, 7930.8]	[0.993, 0.998]
	<i>gE</i>	RM	[1, 18]	[2157.0, 20,477.1]	[0.992, 0.999]
		Time	[1.1, 36.2]	[2111.3, 9972.9]	[0.992, 0.998]
		RM×Time	[1.1, 36.2]	[1597.3, 7470.8]	[0.989, 0.998]
	<i>Std.Bc</i>	RM	[1, 18]	[951.4, 4015.0]	[0.981, 0.996]
		Time	[2.3, 69.0]	[841.9, 1939.6]	[0.979, 0.991]
		RM×Time	[2.3, 69.0]	[506.7, 1132.1]	[0.966, 0.984]
1500	<i>Q</i>	RM	[1, 18]	[10542.3, 43559]	[0.998, 1]
		Time	[3.8, 104.0]	[559.5, 1677.9]	[0.969, 0.989]
		RM×Time	[3.8, 104.0]	[460.0, 1428.2]	[0.962, 0.988]
	<i>gE</i>	RM	[1.1, 41.9]	[13745.5, 124,632.9]	[0.999, 1]
		Time	[1.1, 41.9]	[20336.5, 118,414.1]	[0.999, 1]
		RM×Time	[1, 18]	[16341.5, 94,270.3]	[0.999, 1]
	<i>Std.Bc</i>	RM	[1, 18]	[16918.8, 46,626.0]	[0.999, 1]
		Time	[1.9, 58.6]	[14534.5, 32,364.0]	0.999
		RM×Time	[1.9, 58.6]	[8270.5, 19,311.3]	[0.998, 0.999]

N, network size; *Q*, network modularity; *gE*, network global efficiency; *Std.Bc*, standard deviation of nodal betweenness; *RM*, relational mobility; *df*, degree of freedom; *F*, *F* statistics; η^2 , effect size. The values of *df*, *F*, and η^2 were summarized over the 20 initial networks of the corresponding network size

Table 3 T-test results on the difference in the three network integration indicators between the two levels of relational mobility

<i>N</i>	<i>d</i>	<i>Q</i>		<i>gE</i>		<i>Std.Bc</i>	
		<i>df</i>	<i>t</i>	<i>df</i>	<i>t</i>	<i>df</i>	<i>t</i>
150	100	[9.7, 18]	[-106.9, -33.7]	[12.5, 18]	[43.1, 101.2]	[11.6, 18]	[-36.8, -19.6]
	200	[9.9, 18]	[-115.4, -39.4]	[11.5, 18]	[44.1, 117.7]	[10.4, 18]	[-44.4, -28.0]
	300	[9.9, 18]	[-123.2, -53.0]	[10.6, 18]	[49.6, 130.6]	[10.5, 18]	[-53.9, -29.2]
	400	[9.7, 18]	[-137.3, -59.6]	[10.2, 18]	[52.0, 135.4]	[10.0, 18]	[-51.7, -30.1]
	500	[9.5, 18]	[-143.3, -61.5]	[9.9, 18]	[51.0, 149.6]	[10.3, 18]	[-55.6, -29.9]
	600	[9.5, 18]	[-184.6, -58.6]	[9.7, 18]	[48.1, 151.9]	[10.0, 18]	[-59.7, -30.7]
	700	[9.5, 18]	[-166.5, -61.7]	[9.7, 18]	[44.8, 136.8]	[9.7, 18]	[-58.8, -32.2]
	800	[9.7, 18]	[-159.3, -56.2]	[9.7, 18]	[43.5, 124.4]	[9.9, 18]	[-63.1, -31.4]
	900	[9.6, 18]	[-186.1, -58.9]	[9.5, 18]	[42.1, 124.7]	[9.8, 16]	[-65.7, -30.9]
	1000	[9.6, 18]	[-189.7, -62.2]	[9.4, 18]	[41.5, 114.9]	[9.9, 18]	[-65.0, -30.9]
1500	100	[9.6, 18]	[-102.2, -26.6]	[9.2, 18]	[72.2, 208.0]	[13.1, 18]	[-169.3, -79.1]
	200	[9.3, 18]	[-167.9, -48.4]	[9.1, 18]	[92.2, 267.6]	[12.0, 18]	[-189.9, -108.8]
	300	[9.2, 18]	[-123.4, -48.4]	[9.1, 18]	[102.6, 320.6]	[11.0, 18]	[-219.0, -119.8]
	400	[9.2, 18]	[-115.5, -43.0]	[9.1, 18]	[111.3, 345.1]	[11.1, 18]	[-222.8, -122.1]
	500	[9.4, 18]	[-122.2, -41.4]	[9.1, 18]	[119.0, 371.3]	[11.5, 18]	[-227.6, -126.4]
	600	[9.5, 18]	[-130.7, -31.8]	[9.2, 18]	[124.9, 372.8]	[10.5, 18]	[-214.1, -129.0]
	700	[9.4, 18]	[-144.9, -59.5]	[9.2, 18]	[129.2, 376.1]	[10.2, 18]	[-205.1, -129.9]
	800	[9.3, 18]	[-145.3, -58.2]	[9.2, 18]	[133.5, 378.5]	[11.0, 18]	[-207.6, -136.0]
	900	[9.2, 18]	[-133.7, -69.2]	[9.2, 18]	[137.0, 385.6]	[10.9, 18]	[-211.0, -135.7]
	1000	[9.4, 18]	[-197.8, -58.8]	[9.2, 18]	[139.1, 379.9]	[11.0, 18]	[-210.8, -132.5]

N, network size; *d*, simulation days; *Q*, network modularity; *gE*, network global efficiency; *Std.Bc*, standard deviation of nodal betweenness; *df*, degree of freedom; *t*, *t* statistics. The values of *df* and *t* were summarized over the 20 initial networks of the corresponding size

et al., 2008; Lun et al., 2013; Na et al., 2015). Adopting the agent-based modeling approach, we found supportive causal evidence for our hypothesis. Specifically, the results on the three indicators for network integration, including the modularity index, global efficiency, and standard deviation of nodal betweenness, showed that higher relational mobility promoted greater integration of social networks. On the one hand, the difference in network integration between the two levels of relational mobility became stronger over time. On the other hand, the network structure under low relational mobility stabilized more quickly than that under high relational mobility. Prior work provided accumulative evidence for the effect of relational mobility on our interpersonal relationship experiences (e.g., Li et al., 2015; Schug et al., 2009). Extending previous work, we provided causal evidence for the influence of relational mobility on social network structure, which lays the basis for developing all different types of social relationships (Felmlee, 2001).

By revealing the effect of relational mobility on social network structure, the present findings may further advance our understanding of the influence of social ecologies on the development of social relationships. It was suggested that people from social ecologies with low relational mobility put greater emphasis on relationship maintenance (Li et al., 2015; Sato et al., 2014). Our findings of lower integration and greater stability of social networks since the early stage of simulations under low relational mobility may provide strong rationales for the aforementioned tendencies. The quickly stabilized network structural characteristics under low relational mobility may create a strong basis for cultivating fixed belief in social relationships (Lou & Li, 2017), which results in stronger sensitivity toward negative signals in social relationships (Lou & Li, 2017; Sato et al., 2014).

The present study also brings implications for cross-cultural research. The theoretical framework in cross-cultural research mainly focused on the relationship between self and other people (e.g., Markus & Kitayama, 1991) and the relationship between ingroups and outgroups (e.g., Yuki et al., 2005). We provided causal evidence for how socio-cultural factors affect social network structure. The examination of the evolution of social network structure may further enhance our understanding of different collective processes. Although we did not test the downstream consequences of the generated social networks in the present study, it is relatively straightforward to anticipate that, without other restrictions, there will be a faster speed of information dissemination or a faster speed of disease infection to all members in high-relational-mobility societies given the visualized social networks and the three integration indicators presented in the results section. This speculation is consistent with the positive relationship between higher relational mobility and the faster spread of COVID-19 observed in a previous study (Salvador et al., 2020). Muthukrishna and

Schaller (2020) modeled different social network structures and the level of vulnerability to social influences (viz., the level of collectivism). They found that both factors predicted the speed of consolidating majority opinions and disseminating unpopular beliefs. These results suggested that socio-ecological factors (e.g., the social network structure) and cultural heritage (e.g., collectivism) may take independent roles in shaping collective processes. Similar findings were also observed in previous studies (e.g., Li et al., 2016). Future research may use computational models to causally examine the interplay of socioecological factors (e.g., relational mobility or economic development) and cultural values (e.g., individualism-collectivism) for further enhancing our understanding of collective processes. It is worth noting that the abovementioned discussion relies on the assumption that the existence of structural connections in social networks indicates successful information transmission. This assumption is consistent with the work of Coleman (1990) and Burt (1992) that focused on the topological properties of social networks. Given the distinct influences of different perspectives on social capital and processing (Borgatti & Foster, 2003), we acknowledged that the present study did not consider the quality and the content of connections in social networks, which are essential for understanding the success of obtaining social resources in social networks following the connectionist perspectives of social capital (e.g., Lin, 2001).

The present study also brings implications for social network research. We examined the effect of relational mobility, which refers to the opportunities for people to freely form new relationships and terminate existing relationships (Yuki & Schug, 2012). The results showed that higher relational mobility led to higher integration for sociocentric networks. In contrast, previous research on geographical mobility, which captures individuals' personal residential moving, demonstrated different patterns in the structure of personal networks. It was found that people with moving experiences, such as immigrants or college students who moved to a new place for work or study, often reported a lower degree of social network integration (e.g., Cachia & Maya-Jariego, 2018; Grossetti, 2005; Maya-Jariego & Holgado, 2015), as they tended to keep their geographically diverse social networks separated. The discrepancies in the effects between relational mobility and geographic mobility might be because previous work on geographical mobility focused on personal networks while the present study on relational mobility focused on sociocentric networks, which may produce different results in social network integration (Smith & Christakis, 2008). Alternatively, it could also be possible that different types of mobility exert distinct influences on social network structure. Some findings showed that relational and geographical aspects associated with moving have different influences on individuals' perceived disposability

of social relationships (Gillath & Keefer, 2016), which may suggest diverse effects of relational and geographical mobility on social network structure. Future studies need to explore this possibility.

The present study had some limitations. First, using the agent-based modeling approach, we obtained supportive evidence that higher relational mobility promoted greater social network integration. Although the assumptions for our agent-based models were made based on reasonable abstraction of reality and statistical rules, and the related parameters were derived from survey data for enhancing external validity, it was unclear to what extent the results could reflect the complex real-life situations. Future studies should examine and refine the assumptions based on large natural samples. Relatedly, our survey data were from young Chinese college students studying in a metropolitan city, whose pattern may reflect a stronger interdependent orientation (Markus & Kitayama, 1991) or strong effects of young age (e.g., Cornwell, 2011) and urban regions (e.g., Korte, 1980). The resulted social networks might also ignore the effect of gender, in which previous studies suggested that different compositions of social networks between male and female respondents may implicate different levels of social capital to each gender (e.g., Lin, 2000). Although our post-hoc analyses found non-significant effects of gender and socioeconomic status on the parameters, future work needs to evaluate the generalizability of the present findings to real life as well as to other groups of participants with different demographic characteristics (e.g., cultural background, age, and living regions). Second, given that social relationships in the workplace contexts were found to be more formal and mostly involuntary (Pillemer & Rothbard, 2018), the present study measured social relationships unrelated to study or work to reduce potential confounds associated with different natures of various social relationships. Relatedly, the present study did not differentiate the roles of different types of social relationships (e.g., relationships with friends, family members, acquaintances) and the quality of these social relationships, which can be essential in affecting social network structure (e.g., Lin, 2001). To understand the potential role of the social relationship type in shaping the effect of relational mobility on network integration, future studies should consider measuring respondents' experiences in distinct types of social relationships and examining how their interactions with relational mobility may shape social network structure over time. Third, we primarily focused on the influence of socioecological factors on social network structure. More complex pictures for the evolution of social networks may be generated when we consider the interplay between socioecological factors and individual factors, such as personality traits (Ishiguro, 2016) or individual moving experiences (Cachia & Maya-Jariego, 2018; Grossetti, 2005; Maya-Jariego & Holgado, 2015). Finally, future studies

may explore the consequences of resulted social networks in different socioecological environments. For instance, as social network structures have a strong effect on different collective processes (e.g., Muthukrishna & Schaller, 2020; Smith & Christakis, 2008), future studies may explore the consequences associated with the social networks evolving under high versus low relational mobility for better understanding of the extensive influence of relational mobility. Additionally, the greater integration of social networks may help understand the positive relationship between societal-level relational mobility and generalized trust (Thomson et al., 2018).

Using a computational approach with parameters derived from the real-life survey data, we provided causal evidence supporting that higher relational mobility promotes greater integration of multiple social networks. The present study highlights the power of socioecological factors on people's social experiences (Oishi, 2014).

Appendix

Let $data_{id}$ denote the related response data to the item indexed by id in the survey shown as the online supplement material. The control parameters of the proposed agent-based model were set as follows:

- K : number of stable connections per person, set as a truncated Gaussian distribution with the mean μ and the standard deviation σ calculated from $data_{1,1}$ and the truncated range set as $[\max(\mu - \sigma, 0), \mu + \sigma]$.
- I^{SCP} : number of interactions per day between SCPs, set as a truncated Gaussian distribution with the mean μ and the standard deviation σ calculated from $data_{1,2,1}$ and the truncated range set as $[\max(\mu - \sigma, 0), \mu + \sigma]$.
- I^{UCP} : number of interactions per day between UCPs, set as a truncated Gaussian distribution with the mean μ and the standard deviation σ calculated from $data_{1,2,3}/30$ and the truncated range set as $[\max(\mu - \sigma, 0), \mu + \sigma]$.
- T^{SCP} : amount of time per interaction between SCPs (unit: hours), set as a truncated Gaussian distribution with the mean μ and the standard deviation σ calculated from $data_{1,2,2}$ and the truncated range set as $[\max(\mu - \sigma, 0), \mu + \sigma]$.
- T^{UCP} : amount of time per interaction with between UCPs (unit: hours), set as a truncated Gaussian distribution with the mean μ and the standard deviation σ calculated from $data_{1,2,4}$ and the truncated range set as $[\max(\mu - \sigma, 0), \mu + \sigma]$.
- w^{SCP} : initial weight between SCPs, set as a truncated Gaussian distribution with the mean μ and the variance σ^2 calculated as

and the truncated range set as $[\max(\mu - \sigma, 0), \mu + \sigma]$.

$$\mu = \frac{\text{Mean}(\text{data}_{1.2.1})}{\text{Mean}(\text{data}_{1.1})} \text{Mean}(\text{data}_{1.2.2})$$

$$\sigma^2 = \frac{\text{Mean}(\text{data}_{1.2.1})}{\text{Mean}(\text{data}_{1.1})} \text{Dev}(\text{data}_{1.2.2})$$

- w^{UCP} : initial weight between UCP, set as a truncated Gaussian distribution with the mean μ and the variance σ^2 calculated as

and the truncated range set as $[\max(\mu - \sigma, 0), \mu + \sigma]$.

$$\mu = \frac{\text{Mean}(\text{data}_{1.2.3})/30}{N - \text{Mean}(\text{data}_{1.1})} \text{Mean}(\text{data}_{1.2.4})$$

$$\sigma^2 = \frac{\text{Mean}(\text{data}_{1.2.3})/30}{N - \text{Mean}(\text{data}_{1.1})} \text{Dev}(\text{data}_{1.2.4})$$

- ρ : decay rate of closeness (weight), set as a constant value derived as follows:

$$\rho = \left[\frac{\text{Mean}(w^{\text{UCP}})}{\text{Mean}(w^{\text{SCP}})} \right]^{1/\text{Mean}(\text{data}_{1.3})}$$

Note: For the control parameters set as random distributions, their exact values used by each agent in the simulations were derived at random from the respective distributions.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s12144-022-03130-x>.

Author Contribution L. Li and Y. Lin conceived the present idea and designed the experiments. Y. Lin and S. Wang performed the experiments and analyzed the data. All the authors participated in the result discussion and contributed to the final paper.

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Data Availability The data and code of this study are available for peer review in the Open Science Framework (OSF) at https://osf.io/nq8v3/?view_only=7ac3003e73ab4d8dae9fa0a2b2922a60 and can be made publicly available after published.

Declarations

Ethics Approval and Consent This study was approved by the Institutional Review Board in the Department of Psychology of Sun Yat-sen

University, and informed consent was acquired from all participants in advance.

Conflicts of Interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

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