Network Footprints: A Laboratory Experiment on Brokerage and Information Diffusion

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Abstract

The idea that network brokers play a pivotal role for the dissemination of non-risky and non-controversial information reflects an analogy from mathematical models of contagion: information would spread by mere social contact like any infectious disease. Instead of an effortless spread of infection, it is more plausible that information sharing between individuals encounters frictions, due to various social contingencies or personal traits. This implies that network brokers could be the most effective spreaders only if they would have a greater inclination to overcome such frictions than individuals in other network positions. As brokers regulate non-redundant information flows across otherwise disconnected groups, their network experience may have led them to develop a more comprehensive understanding of the potentially positive outcomes from information diffusion. Here, we present an original laboratory experiment with a sample of university students in Italy where we tested the hypothesis that subjects with experience as network brokers in their social life behave differently when exposed to an information diffusion task within an artificial network compared to non-brokers. Our findings confirm that subjects with experience as network brokers map networks and handle information diffusion more effectively than those without any broker experience.

Keywords: Information Diffusion, Network Brokers, Laboratory Experiment, Network Cognition, Network Experience

1 Introduction

Research on network brokers has gained traction in different disciplines, including sociology, economics, management, and epidemiology (Burt 2004; Burt, Reagans, & Volvovsky 2021; Goyal & Vega-Redondo 2007; Kwon, Rondi, Levin, De Massis, & Brass 2020; Li, Sun, Zhang, Zhang, & Kurths 2016; Watts 2004; Watts & Strogatz 1998). For instance, Burt (2004) and Burt et al. (2021) have shown that compared to non-brokers, network brokers are more likely to come up with creative ideas that receive widespread endorsement and be perceived as leaders by peers – two integral aspects of social capital and individual success within organizations. This is because they are strategically positioned to span and bridge structural holes within social networks, thus playing a crucial role in connecting two or more otherwise disconnected alters or groups (Burt 1992; Labun & Wittek 2014).

By their unique structural position, network brokers can reap material or symbolic benefits in various contexts (Burt 1992, 2000, 2004; Cook & Emerson 1978; Gould & Fernandez 1989; Kwon et al. 2020). Acting as intermediaries between groups, they are exposed to different sources of information, opinions, norms and cultural frameworks, thus gaining a strategic edge for recognizing and capitalizing on rewarding opportunities like no other. As expressed by Burt (2004), brokers: *[...] "Are able to see early, see more broadly, and translate information across groups. [...] Brokerage across the structural holes between groups provides a vision of options otherwise unseen*".

It is also commonly accepted that network brokers play a crucial role in diffusion processes, especially in accelerating information spread (e.g., Burt 1999; Centola and Macy 2007; Goldenberg, Libai, and Muller 2001; Granovetter 1973, 1983; Li et al. 2016; Neal 2022; Rogers 1995; van Liere 2010; Watts and Strogatz 1998). For instance, Granovetter (1973) proposed the relevance of brokers in swiftly disseminating valuable information about job posting to potential applicants, Rogers (1995) and Goldenberg et al. (2001) emphasized their contribution to word-of-mouth marketing, particularly for promoting innovations, and Burt (1999) argued that the frequently discussed "opinion leaders" in diffusion research are, in fact, network brokers.

Suppose that upon receiving information, individuals disseminate it by mere social contact (Centola 2018). Figure 1 illustrates who would eventually receive this information after 3 iterations when the *seed* of diffusion would either be the broker (node 17) or the most well-connected individuals within the two groups. This example clearly demonstrates that, although diffusion from any seed would eventually reach everyone in a fully connected network, those initiated by brokers would achieve this outcome in the shortest time.

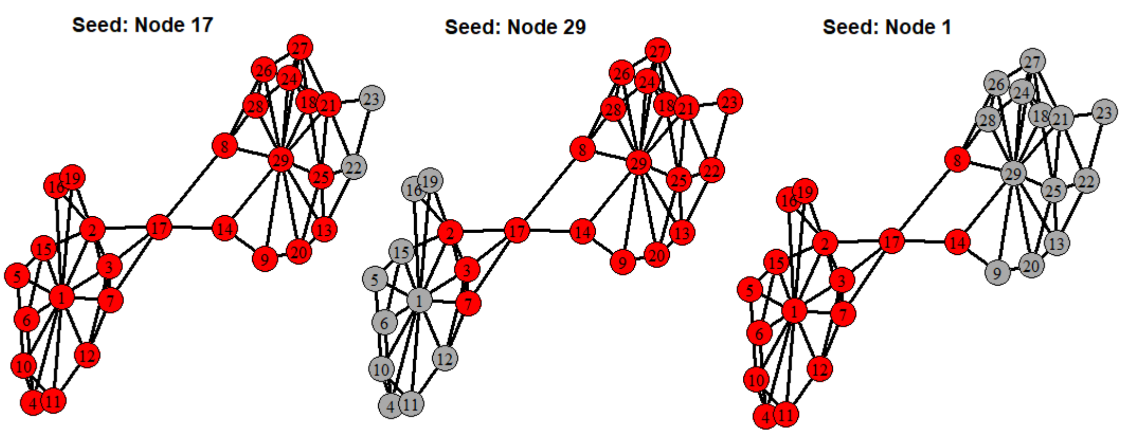

Figure 1: Nodes in red represent those receiving the information after 3 iterations. "Seed: Node 17" means that the diffusion process originates from the broker (node 17), while the other two originate from nodes 29 and 1.

Nevertheless, the relevance of brokers for information diffusion greatly depends on the nature and type of information (Centola 2018; Centola & Macy 2007). For instance, consider a scenario where information is about the identity of a murder suspect. Whenever sharing inaccurate information, a broker could face charges of defamation or retaliation. Consequently, nobody would share such a sensitive information before actively seeking confirmation from multiple reliable sources. Research indicates that in situations where information is risky or controversial, and gathering costly social reinforcement is essential, brokers could not be the most effective spreaders (Centola & Macy 2007, 2015; Guilbeault, Becker, & Centola 2018).

Even when information is not risky or controversial, there is no guarantee that brokers would be the most effective spreaders either. Indeed, even in these cases, information dissemination requires effort to overcome potential obstacles and does not happen automatically, as with infectious diseases (Iribarren & Moro 2007; Kim & Fernandez 2023; Larson 2017). Various contingencies might lead individuals to intentionally delay or entirely avoid spreading information in their social groups, and these frictions might be more systematically influenced by personal preferences or characteristics, such as personality traits (Iribarren & Moro 2007; Larson 2017). If this is true, brokers would be the most effective spreaders only if they inherently possess the highest willingness to overcome obstacles and actively disseminate information (Kim & Fernandez 2023; Neal 2022). This casts serious doubts on the analogy between information diffusion and the spread of infectious diseases, often made by many mathematical and computational modelers (e.g., Centola 2018; Centola and Macy 2007; Goffman and Newill 1964; Gomez-Rodriguez, Leskovec, and Krause 2012; Larson 2017; Milli, Rossetti, Pedreschi, and Giannotti 2018; Ugander, Backstrom, Marlow, and Kleinberg 2012; Watts and Peretti 2007).

Here, we propose to study whether previous individual experience associated with specific network positions may leave cognitive traces or footprints that could shape intentional action regarding information dissemination (Hackel, Kalkstein, & Mende-Siedlecki 2024). Strategically positioned to direct non-redundant information flows to their contacts in different groups and exert more control over their surroundings than others (Burt 1999), network brokers may develop a more comprehensive understanding of the importance of information diffusion (Burt 2004; Kim & Fernandez 2023), thus being able to overcome frictions and becoming active spreaders (Burt 1999). Conversely, individuals deeply embedded within a social group are exposed to redundant information flows. Therefore, they might take for granted that if they encounter a piece of information, their contacts already know it. This situation might foster a more passive attitude towards information dissemination.

Yet theoretically intriguing, there is scant evidence of these network footprints. On the one hand, research on network cognition indirectly suggests that brokers may be more inclined to diffuse information than others. For instance, cognitive social structures research indicates that individuals' perceptions of network connections depend on their structural positioning (Brands 2013; Krackhardt 1987). Casciaro (1998) has shown that individuals develop different mental representations of social connection patterns depending on their network centrality. Similarly, network brokers may have developed a more accurate understanding of the network (Janicik & Larrick 2005), and learnt from experience (Hackel et al. 2024) that information circulating in dense and redundant parts of the network would take longer to reach other parts – a phenomenon that they would exactly accelerate whenever acting as spreaders (Burt 1999).

On the other hand, individuals may find themselves in a brokerage position purely due to contingencies, such as the spatial arrangement of offices or a given administrative position in an formal organization. Then, they could be even unaware of their own centrality despite enjoying substantial material or symbolic benefits from their position (Greenwald & Banaji 2017; Kilduff & Lee 2020; Son, Bhandari, & FeldmanHall 2023). In these cases, the variability of information-sharing propensities could be attributed to certain individual factors, such as personality traits, beyond any network experience.

Here, we present a laboratory experiment that explores potential differences in how network brokers engage with an information diffusion task on an artificial network compared to non-network brokers. The focus is on understanding the impact of network experience on individuals' mapping of networks for diffusion processes. Our subjects were university students, and their past experience as network brokers was evaluated through personal network data (Janicik & Larrick 2005), and a 16-item behavioral questionnaire, incorporating 12 items adapted from previous research (Grosser, Obstfeld, Labianca, & Borgatti 2019; Obstfeld 2005).

In the treatment group, participants examined a visually rearranged version of the network shown in Figure 1. They were asked to select the node they believed would facilitate the fastest dissemination of information to all other nodes. In the control group, participants viewed the identical network but were required to select the node they believed would transmit an infection to the entire network most rapidly if infected first.

We expected that participants with prior experience as network brokers would indicate node 17 (i.e., the artificial broker) as the best seed for information diffusion. This experience, however, would not extend to the diffusion of an infectious disease, which is not an intentional process (Jackson & Yariv 2011, p.568). In short, we expected an effect of the out-of-the-lab brokerage experience of individuals on their network mapping and strategization in the lab, when exposed to a task eliciting intentional action of diffusion. More specifically, we expected to find no difference in the choices of the seed for diffusion between brokers and non-brokers in the control group. Second, we expected that, in the treatment group, individuals with prior brokerage experience would be more inclined to identify node 17 as the optimal seed for information diffusion compared to non-brokers. These hypotheses were pre-registered before conducting the experiment (see Renzini and Squazzoni 2023).

The remainder of the article is structured as follows. Section 2 describes the experimental design and the key measures. Section 3 presents the modeling strategy. Section 4 presents our results. Finally, Section 5 discusses our findings, outlines study limitations, and discuss future research directions.

2 Experimental Design

2.1 Recruitment and overall organization

Our sample included 252 students from the Faculty of Political, Economic and Social Sciences at the University of Milan, who were recruited via emails from our ORSEE platform (`http://orsee.org/web/`). The platform included a large pool of students who voluntarily registered to participate to experimental studies upon information campaigns regularly run in the faculty. The participant pool included only bachelor's and master's students who did not have any prior formal exposure to network-related courses. The experiment was conducted in Italian only with participants required to be native speakers (an English translation is provided in the Supplementary Materials (SM)).

Participants were assigned to various sessions scheduled every hour and a half, spanning from 9 am to 6 pm, with each group comprising a maximum of 24 individuals. The experiment lasted 45 minutes, and participants, on average, completed it in approximately 25 minutes, excluding registration and payment. Due to session scheduling and variable participants attendance, the experiment required three days for completion: June 14, September 27, and October 18, 2023. These dates were selected to avoid summer holidays and maximize the number of students present on campus. Importantly, these dates fall within the time-frame defined by the trial's start and end dates as reported in the pre-registration (Renzini & Squazzoni 2023).

Subjects were all equally compensated with 10 euros upon successful completion (i.e., 5 show-up fee + 5 for the task). The only participant unable to complete the experiment received a show-up fee of 5 euros. During each session, participants were seated in their assigned workstation without the possibility to see each other's screen. The experimental task was organised as a series of dynamic web pages (refer to the Code Section), with the first including the experimental instructions read by the experimenter (the same experimenter for each session).

2.2 Personal network sampling

After carefully reviewing the instructions and giving their consent, participants were presented with a series of name generator questions on consecutive web pages. These questions were designed to elicit participants' contacts or alters within different social settings relevant to their own personal life (Bianchi, Piolatto, Marengoni, & Squazzoni 2023; Janicik & Larrick 2005; Kalish & Robins 2006; McCarty, Lubbers, Vacca, & Molina 2019).

More specifically, participants were prompted to nominate up to five individuals they deemed important among family members, pre-university & university friendships, coworkers, roommates, associates, individuals sharing similar hobbies but not part of a formal association, and an open-ended category where participants could identify other significant individuals. We selected these settings as representative of the social life of university students (e.g., see Kalish and Robins 2006).

Participants were then asked to consider the relationships between their own alters. For each unordered pair of cited alters (i, j), we asked the following question: 'Does i interact with j in your absence?' (Bianchi et al. 2023; McCarty et al. 2019). We clarified that by 'interact', we meant that i and j communicated or met even without participants' personal involvement or regardless of their presence. To help participants in this task, we built a scrollable table reporting each potential pair of alters, and participants were simply required to flag a checkbox if the answer to the previous question was affirmative (see Figure 2 for a simplified example).

Contacts		Do they interact in your absence?	Settings of Contacts	
Mark	Lucy	☑	Family	Family
Mark	John	☐	Family	University-Era Friends
Lucy	John	☑	Family	University-Era Friends

Figure 2: Interface for sampling connections among alters.

2.3 Personality traits and brokerage behavior

Before the main seed selection task, participants were required to complete a simple attention check and a questionnaire assessing various personality traits and familiarity with behaviors typically associated with network brokers. They were presented with a set of items and asked to rate, on a scale from 1 to 7, the extent to which they agreed that each of the proposed statement was accurately describing themselves – where 1 denoted "completely disagree" and 7 denoted "completely agree".

The sampling of participants' personality traits was motivated by previous research showing that individuals occupying brokerage positions would tend to exhibit certain specific traits (Janicik & Larrick 2005). Indeed, Burt, Jannotta, and Mahoney (1998), Mehra, Kilduff, and Brass (2001), Kalish and Robins (2006), and Sasovova, Mehra, Borgatti, and Schippers (2010) found that brokers, defined according to different network metrics, often share certain characteristics such as individualism, high self-monitoring tendencies, and a perception of dissimilarity from other group members. Moreover, as mentioned in the Introduction, personality traits can in theory play a role in influencing the decision related to information dissemination of individuals occupying certain network positions. Therefore, we decided to measure personality traits, especially those associated with a sense of independence from others and self-monitoring tendencies.

The battery of items used to evaluate personality traits was adapted from Gosling, Rentfrow, and Swann Jr. (2003), who developed a concise measure of the Big-Five personality dimensions with high test–retest reliability. The battery consisted of 10-items featuring opposing traits, such as the pair "Extroverted, Enthusiastic" followed by "Reserved, Quiet". In addition to these 10 items, we included six questions related to self-monitoring, chameleon-like behavior, individualism, the need for social approval, and the tendency to distinguish oneself from the reference group (Burt et al. 1998; Kalish & Robins 2006; Mehra et al. 2001; Sasovova et al. 2010).

For brokerage behavior, we developed four items to assess participants' self-reported familiarity with prototypical behaviors exhibited by brokers when leveraging informational advantages (Burt 1992, 2004). An example is: *I can spot that people have different opinions, and this ability is beneficial in certain situations when deciding how to interact with these people.*

Beyond controlling information flows, brokers also play a pivotal role in mediating opportunities for personal encounters between disconnected alters or groups (Kwon et al. 2020; Quintane & Carnabuci 2016). For instance, a broker can organize a dinner for members of different organizational units to meet, thus acting as a *tertius iungens*. Conversely, brokers can strategically prevent their contacts from meeting for personal gain or convenience, acting as *tertius separans*, or mediate various conflicts between contacts, thus acting as *mediators*.

For the self-reported familiarity with *tertius iungens* behaviors, we utilized a battery of items developed by Obstfeld (2005), while for *tertius gaudens* and *mediator* roles, we employed a battery of items developed by Grosser et al. (2019). The combined number of items from these two batteries was 12. This led to a total of 16 sampled items (for detail, please refer to the SM).

2.4 Seed selection task

Participants were randomized into treatment and control groups during the personal network sampling phase. Before engaging in the actual seed selection task, participants were initially introduced to the network depicted in Figure 3 to familiarize themselves with the concepts of networks and diffusion. Therefore, the network in Figure 3 served a "pedagogical" purpose.

Figure 3: "Pedagogical" network presented to participants to familiarize with the concepts of networks and diffusion.

Participants were informed that the network in Figure 3 was a graphical representation of relationships within a fictitious social group. A connection between two fictitious characters implied direct interaction, whereas individuals without a direct link could still interact through common contacts shared between them.

In the treatment group, participants were instructed that networks could disseminate information. We made clear that fictitious characters could share information with their contacts, who, in turn, could pass it on to their own connections, and so on. In the control group, instead of information, participants were told that an infectious disease could spread in the same way among these fictitious characters. We assessed each participant's comprehension of these concepts with a simple test.

Subsequently, in both cases, participants were given 45 seconds to examine the network in Figure 4, with a warning issued at the 20-second mark, and asked to select a node from a drop-down menu in response to a specific question. In the treatment group, participants were prompted with:

> *"In your opinion, who among these individuals would allow information to circulate more quickly among subjects if informed first?"*

while in the control group:

> *"In your opinion, who among these individuals would allow a virus to circulate more quickly among subjects if infected first?"*

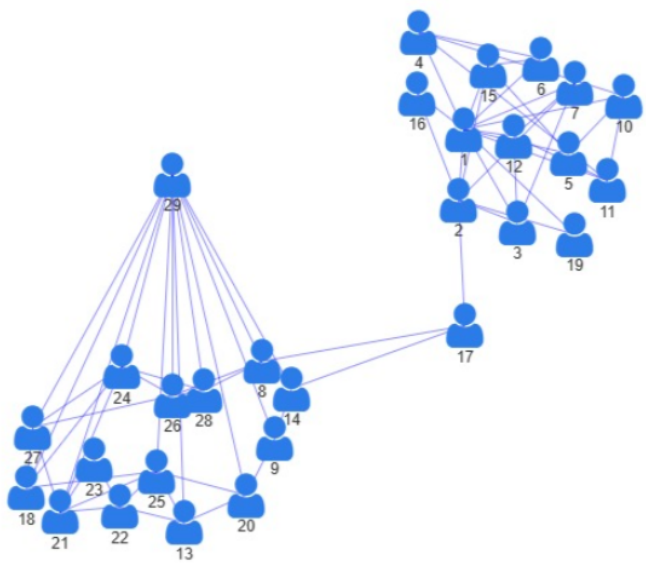

Figure 4: Network designed for the seed selection task. We deliberately positioned nodes 29 and 17 to stand out from the surrounding others.

If participants failed to select a node within the 45-second time frame, the experiment was terminated, and they only received the 5 euro show-up fee (as said, this only happened to one participant).

The layout was designed to highlight nodes 29 (i.e., the hub of one of the two groups) and 17 (i.e., the broker). We conducted a pilot two weeks before the first experimental day with 15 randomly selected (non-sampled) individuals, who were asked to look at the network in Figure 4 and identify which nodes immediately captured their attention. Each individual reported that nodes 29 and 17 were those standing out visually. While node 29 was considered "the most popular" or "the leader of one group", node 17 was seen as "connecting the two groups" or "being in between the two groups."

By combining the visual arrangement of the network with the time pressure to complete the task, we wanted to confront participants with a dilemma: "*Should I select the most popular node or the one connecting the two groups*?" In the control scenario, we did not expect any effect of previous broker experience on individual responses to this question. We assumed that participants could not have developed experience in disseminating a virus due to the non-intentional nature of this action and its implications (see Janicik and Larrick 2005 for a similar example).

Following the seed-selection task, we collected socio-demographic information, encompassing participants' gender, residence in Milan, enrollment year, and two additional questions pertaining to their social lives. Specifically, we asked whether participants engaged in extracurricular activities (e.g., sports, music, or theater lessons, study of a second or third language) solely due to parental or family influence, and whether most of their contacts were established by their own efforts or introduced by others. This information was collected to provide a more comprehensive characterization of participants in our sample.

Figure 11 in the Appendix provides a graphical summary of the sequences of tasks encountered by participants during the experiment.

3 Modeling Strategy

3.1 Causal effect of interest

We wanted to assess how the causal impact of brokerage experience, denoted as B, on seed selection in the diffusion task, denoted as S, varied across treatment assignment, denoted as T, thus estimating the effect of the interaction between B and T on S.

By following Interaction DAGs (I-DAGs) (Nilsson, Bonander, Strömberg, & Björk 2021), we defined the causal effect of B on S as ΔS_B, thus concentrating on $T \rightarrow \Delta S_B$. As previously discussed, personality traits P of participants, such as self-monitoring tendencies, could have an influence on ΔS_B as well. Following Nilsson et al. (2021), controlling for the main effect of P without interacting P with B was sufficient as P and T were conditionally independent or d-separated by design. Figure 5 shows our I-DAG of interest.

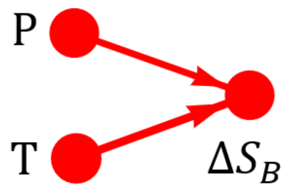

Figure 5: Our I-DAG (Nilsson et al. 2021).

The I-DAG in Figure 5 also helped us to formalize our hypotheses. Let us denote a broker as B_{High} and a non-broker as B_{Low}. Here, we considered non-brokers those scoring low on an arbitrary measure of network brokerage (Janicik & Larrick 2005). Let T be an indicator variable returning 1 for the treatment group, with $T = 0$ indicating the control group. Moreover, let $O(B_{High})$ be the odds that a brokers selects node 17 (i.e., the artificial broker), while $O(B_{Low})$ the odds that a non-broker selects node 17. We expected to find the following effect for the treated participants:

$$E\{\frac{O(B_{High})}{O(B_{Low})}; T = 1, P\} > 1 \tag{1}$$

whereas for the control group, we expected:

$$E\{\frac{O(B_{High})}{O(B_{Low})}; T = 0, P\} = 1 \tag{2}$$

Equation 1 captures our expectation that the odds ratio of selecting node 17 between brokers and non-brokers, when treated and given personality, should be greater than one. This implies that we would be more likely to find brokers selecting node 17 than non-brokers under these conditions. Conversely, Equation 2 reflects our expectation that no significant differences should manifest within the control group. Thus, referring to these quantities as $OR_{T=1}$ and $OR_{T=0}$ respectively, our interaction effect can be succinctly represented as:

$$\frac{OR_{T=1}}{OR_{T=0}} > 1 \tag{3}$$

3.2 Analytical sample and S

As anticipated, only one participant failed to complete the seed selection task within the 45-seconds time-frame, and consequently was excluded from the sample. Among the remaining 251 participants, we initially had 128 observations for $T = 1$ and 123 for $T = 0$.

However, note that we had to remove certain entries from participants who inaccurately responded to the name generator questions. For instance, in the hobby setting, some participants entered their actual activities (e.g., watching TV) instead of the names of individuals with whom they engaged in such activities. Moreover, despite clear instructions to insert one name at a time for each setting in a designated box in the web interface, some participants entered all the names in the box at once (an example can be found in the SM). These errors posed challenges to the reconstruction of the participants' alter-alter ties (see the SM). Therefore, we chose to exclude these observations and consider only 121 observations for $T = 1$ and 118 for $T = 0$.

Finally, 2 participants for $T = 1$ and 3 participants for $T = 0$ forgot to save their socio-demographics. However, as these data were collected in the post-treatment phase, these cases did not have any impact on our analysis, but led us to consider socio-demographic data only for 119 observations for $T = 1$ and 115 for $T = 0$. However, note that other sample descriptions and our hypotheses were tested on 121 observations for $T = 1$ and 118 for $T = 0$.

For S, we assigned $S_i = 1$ if participant i selected node 17, $S_i = 0$ otherwise. Approximately 30% (36/121) of participants selected node 17 in $T = 1$. While among the 85 who did not choose node 17 in $T = 1$, 69 selected node 29, others chose either node 1 or nodes in its close proximity (e.g., 12, 15, 7; see Figure 4). Note that node 1 was the hub of the other group (Figure 1), intentionally "hidden" in close proximity to nodes 12, 15, 7, as we wanted to highlight, for simplicity, only the other hub (node 29). Consequently, we are confident that those who chose neither 17 nor 29 picked 1 for the same reason others selected 29, i.e., 1 was the most popular within a group. Concerning

$T = 0$, the pattern mirrored $T = 1$. Indeed, 31% (37/118) chose node 17 and, among the 81 for which $S_i = 0$, 68 of them chose node 29, while the others opted for node 1 or nearby nodes.

In summary, the overall probability of selecting node 17 was very similar for both $T = 1$ and $T = 0$ groups, and $S_i = 0$ accurately identified participants choosing a hub, predominantly 29, or alternatively, 1.

3.3 Brokerage measure B

To evaluate participants' brokerage experience in their personal networks, we applied Burt's (1992) *efficiency* measure, following Borgatti's (1997) implementation. The concept is straightforward: consider an individual personal network structured as a star (left panel of Figure 6). In this configuration, *ego*, the central individual, has complete control over non-redundant information flows among alters, as they are not directly connected to each other (Cook & Emerson 1978). Accordingly, we hypothesized that individuals in such configurations may have had more opportunities to act as brokers, accumulating higher overall experience. As the number of ties among alters increases (right panel of Figure 6), the individual's brokerage potential diminishes, as alters can directly communicate among themselves. In Burt's terminology, the network on the right exhibits higher *redundancy*, resulting in a decrease in ego's brokerage potential and experience (Burt 1999).

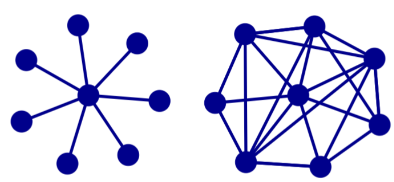

Figure 6: In a star configuration (left), there is no redundancy, and ego exerts maximum control and power over information flows. Conversely, as the number of ties among alters increases (right), ego experiences a diminishing control and power over information flows. Consequently, individuals with personal networks resembling those on the right should have lower brokerage experience.

For each participant i, denoting as t_i the number of ties between alters (excluding ego-alters ties) and as n_i the number of alters, redundancy for an undirected personal network, denoted as

ρ_i, can be expressed as:

$$\rho_i = \frac{2t_i}{n_i} \tag{4}$$

Using ρ_i, we defined brokerage power, B_i, as follows (Borgatti 1997):

$$B_i = \frac{n_i - \rho_i}{n_i} \tag{5}$$

where the numerator represented the difference between the actual personal network size and its redundancy, normalized by the actual size. B_i attains a maximum value of 1 when the personal network is a star ($t_i = 0$, hence $\rho_i = 0$), and a minimum value of 0 when alters are fully interconnected.

Following our pre-registered design, we intended to perform a robustness check by defining brokerage experience based on participants' self-reported familiarity with behaviors typically associated with network brokers (Renzini & Squazzoni 2023). However, regardless of the structural features of their personal networks, participants consistently reported high familiarity with most of these behavioral measures, especially those related to *tertius iungens* and *mediator* roles, possibly due to social desirability bias. Consequently, also considering their minimal variability (see the SM), we excluded them from our analysis, except for sample description purposes. Only measures related to *tertius separans* behaviors were weakly correlated with structural brokerage potential (Spearmank rank correlation approximately 0.10-0.13).

3.4 Measuring personality P

We measured personality by considering the self-reported scores on specific items from the personality questionnaire (see Section 2.3). Here, we focused on items assessing participants' sense of independence from others, self-monitoring or chameleon-like tendencies, and their ability to adapt behavior to create a favorable impression on others (as detailed in Section 2.3).

3.5 Statistical model

We employed logistic regression to estimate the interaction effect outlined in Equation 3, with P_i as the sole confounding variable. This approach enabled us to assess how the odds of selecting the artificial broker varied for participants with brokerage experience compared to those without brokerage experience when transitioning from the control to the treatment group – our target estimate. Additionally, it facilitated the comparison of odds among participants within the control group (Equation 2).

4 Results

4.1 Descriptive results

Tables 1 and 2 provide summary statistics on the personal networks for both the treatment ($T = 1$) and control ($T = 0$) groups. Table 1 shows the number of nominated alters across the 8 elicited social settings (n_i in Equations 4 and 5), while Table 2 presents the number of alter-alter ties (t_i in Equation 4).

The distribution of n_i was similar in both groups. We found some differences for t_i, albeit not particularly prominent. We found certain outliers in both groups for both metrics. For instance, in $T = 1$, 75% of t_i values were below 49, yet one participant reported an unusually high count of 241 alter-alter ties (the same participant unusually reported $n_i = 35$ alters). In the same group, another participant indicated only 2 alters out of 40 possible nominations (5 names $\times$ 8 settings), reporting just one family member. Considering the overall distribution of responses, these participants probably misunderstood the instructions for name generators. For example, the participant reporting 241 alter-alter ties likely misinterpreted "does i interact with j?" as "does i know j?"

The distribution of brokerage power B_i in Table 3 is naturally influenced by the values reported in Tables 1 and 2 (i.e., Equations 4 and 5). For instance, the participant who reported only two names out of 40 in $T = 1$ had a B_i value of 0.5. The majority of observations in both groups fell

	Min	1Q	Median	Mean	3Q	Max
$T = 1$	2	15	19	18.76	24	35
$T = 0$	5	13	17	17.9	22	35

Table 1: Distribution of number of nominated alters (n_i) in the treatment ($T = 1$) and control ($T = 0$) groups. 1Q and 3Q denote the first and third quartiles.

	Min	1Q	Median	Mean	3Q	Max
$T = 1$	1	17	31	40.04	49	241
$T = 0$	2	16	25.50	37.47	54.25	176

Table 2: Distribution of alter-alter ties (t_i) in the treatment ($T = 1$) and control ($T = 0$) groups. 1Q and 3Q denote the first and third quartiles.

approximately between 0.75 and 0.85.

	Min	1Q	Median	Mean	3Q	Max
$T = 1$	0.5000	0.7422	0.8077	0.7906	0.8550	0.9320
$T = 0$	0.5571	0.7512	0.8046	0.7913	0.8456	0.9290

Table 3: Distribution of brokerage power (B_i) in the treatment ($T = 1$) and control ($T = 0$) groups. 1Q and 3Q denote the first and third quartiles.

Figure 7 illustrates the inter-item Spearman rank correlation matrix for the personality questionnaire in the treatment (left) and control group (right). The Figure suggests that the correlation patterns were consistent between both groups. This means that when a set of items exhibited positive or negative correlation in $T = 1$, the same was true in $T = 0$, with a very similar magnitude.

Furthermore, we found distinct clusters of correlation or anti-correlation, which made theoretical sense: individuals who reported high values for ”Reserved” in both groups tended to report low values on ”Extrovert”. This testifies to the interval validity of these measures.

Items designated as proxies for P in our statistical modeling included ”Independence,” ”Chameleon-Like”, and ”GoodImpression.” Notably, the latter two exhibited a high degree of correlation with each other, while showing a moderate to non-existent correlation with ”Independence” (for additional detail on the sample characteristics, please see the SM).

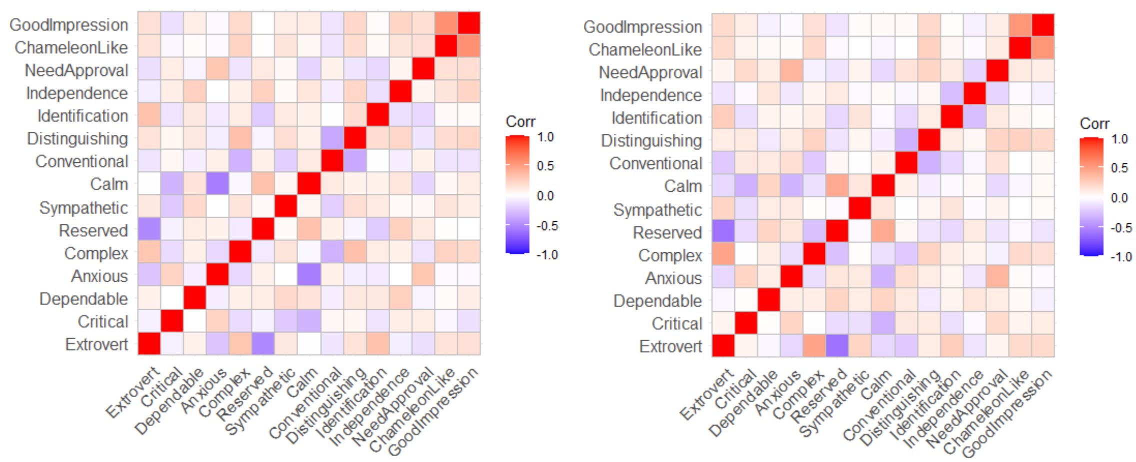

Figure 7: Inter-items Spearman rank correlation matrices for the personality battery in the treatment ($T = 1$, left) and control ($T = 0$, right) groups. More intense shades of red indicate stronger positive correlations, deeper shades of blue indicate more negative correlations, and white signifies no correlation.

4.2 Hypothesis testing

Figure 8 presents combined box- and violin-plots overlaid on raw data, depicting the relationship between seed selection (S_i) and B_i for participants in the treatment (left) and control (right) groups.

Results showed a clear pattern. Consider participants who chose $S_i = 1$ in both groups. In $T = 1$, they tended to cluster around higher B_i values (approximately $B_i \geq 0.80$, the median of the whole group; see Table 3), thinning out with the decrease of B_i. Conversely, in $T = 0$, those who selected $S_i = 1$ were more evenly distributed across a broader range of B_i values. In both cases, participants not choosing node 17 (i.e., $S_i = 0$) showed B_i more homogeneously distributed. At the same time, we found certain clearly visible outliers.

To avoid incorporating responses from outliers who probably have misinterpreted name generators, we limited our investigation to observations with $B_i \in [0.65; 0.90]$. This resulted in the exclusion of 11% of the sample. We conducted detailed sensitivity analysis with alternative restrictions on B_i, retaining observations with $B_i \in [0.60; 0.90]$ (8.7% sample reduction), and with $B_i \in [0.60; 0.91]$ (6.7% reduction). Additionally, we presented results for the full sample, including

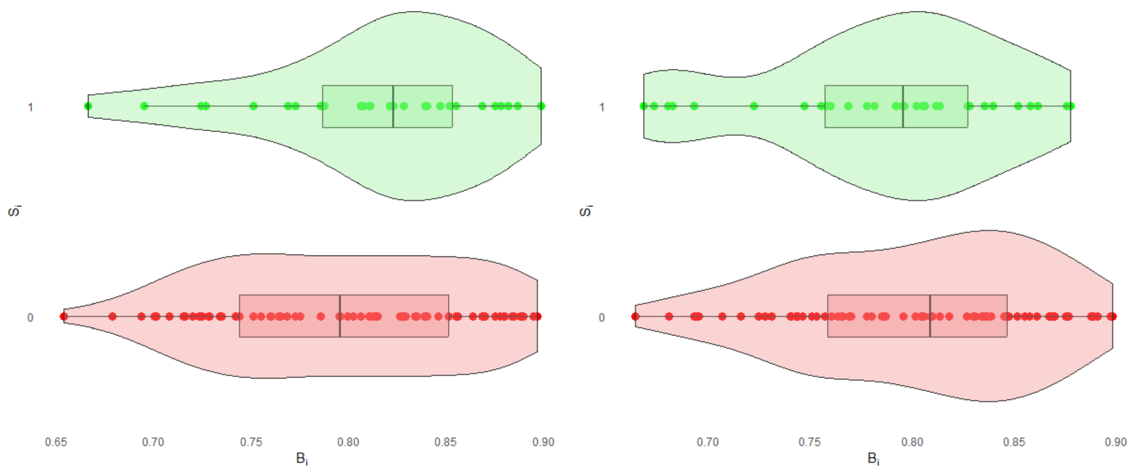

Figure 8: Seed selection (S_i) by brokerage power (B_i) in the treatment ($T = 1$, left) and control ($T = 0$, right) groups. Participants who chose node 17 ($S_i = 1$) as the initial seed are highlighted in green, while those selecting another node ($S_i = 0$) are marked in red.

outliers (detail can be found in the SM).

Furthermore, we decided to treat B_i not as a continuous variable. In a continuous measure of brokerage power and experience, even slight differences (e.g., 0.05 points) could have important substantive implications. However, in our case, these differences were more likely due to individual response styles and random reporting errors in the interface for eliciting t_i illustrated in Figure 2 (for a detailed explanation, refer to the SM). Despite recognized limitations in converting continuous variables into dichotomous ones (Austin & Brunner 2004; Harrell 2022; MacCallum, Zhang, Preacher, & Rucker 2002), we chose to categorize B_i into two groups. Specifically, as the interaction effect materialized around $B_i = 0.80$ (i.e., the median; see the SM), we classified individuals with B_i below the median as non-brokers, assigning them a value of $B_i^{dich} = 0$, and those with B_i greater than or equal to the median as brokers, assigned a value of $B_i^{dich} = 1$.

We then explored various methods of defining B_i^{dich} for each sample restriction (see the SM). We classified individuals as brokers if their B_i exceeded the 45th, 47.5th, 52.5th, and 55th percentiles, respectively. We then applied the model outlined in Section 3.5 treating B_i as continuous in the full sample and its three restricted versions.

Figure 9 illustrates the interaction effect on an odds ratios scale, while controlling for various personality traits (for the log-odds ratios scale, refer to the SM). In Model 1, we examined "ChameleonLike" behavior; in Model 2, we explored "Independence", and in Model 3, we considered the sum of these traits. Note that we excluded "GoodImpression" due to its high correlation with "ChameleonLike", which also shared a similar correlation pattern with "Independence" as did "GoodImpression". Both "ChameleonLike" and "Independence," as well as their sum, were centered on their medians.

Regardless of the selected personality trait for control, the interaction parameter between treatment assignment and B_i^{dich} was consistently positive and significant. This shows that the odds ratios of selecting node 17, as a function of B_i^{dich}, varied between the treatment ($T = 1$) and control ($T = 0$) groups. Indeed, the odds of choosing node 17 for a broker ($B_i^{dich} = 1$) compared to a non-broker ($B_i^{dich} = 0$) in the treatment group ($T = 1$) were more than five times greater than the corresponding odds in the control group ($T = 0$).

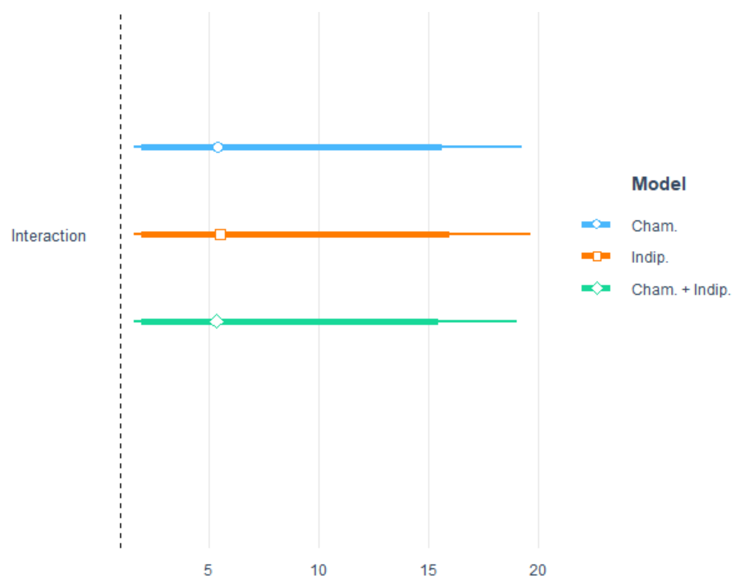

Figure 9: Coefficients plot illustrating the interaction between treatment assignment T and brokerage power, measured as B_i^{dich} instead of B_i, while controlling for "ChameleonLike", "Independence" and the sum of the two traits. The vertical dashed line indicates that the odds ratios of selecting node 17 as a function of B_i^{dich} do not change between the treatment ($T = 1$) and control ($T = 0$) groups. 95 % CI are shown, along with 90 % CI (thicker lines).

Table 4 shows the coefficients obtained from logistic regressions for each model. Specifically, the coefficients associated with B^{dich} indicate the odds of selecting node 17 for a broker compared to a non-broker when $T = 0$ (i.e., in the control group), given a median score on the personality scale. We observe no statistically strong signal suggesting that the expected number of participants choosing node 17 for every participant choosing another node (i.e., 29 or 1) depended on brokerage experience in the control group, and this did not vary for different personality scores. In contrast, when $T = 1$, the odds ratio differs substantially. For example, in the case of "ChameleonLike", the odds ratio is $0.548 \times 5.406 = 2.96$, meaning that subjects who selected node 17 were nearly three times more likely to be brokers than those who selected another node.

Table 4: Coefficients Table for the same models as in Figure 9. In parenthesis: 95% CI.

	Cham.	**Indip.**	**Cham. + Indip.**
T	0.399**	0.399**	0.406*
	(0.154, 0.971)	(0.155, 0.968)	(0.158, 0.982)
B^{dich}	0.548	0.537	0.552
	(0.229, 1.269)	(0.223, 1.249)	(0.231, 1.275)
Cham.	0.967		
	(0.778, 1.208)		
Indip.		1.060	
		(0.860, 1.322)	
Cham. + Indip.			1.013
			(0.874, 1.181)
$T \times B^{dich}$	5.406***	5.505***	5.365***
	(1.600, 19.241)	(1.621, 19.660)	(1.590, 19.054)
Constant	0.549**	0.569**	0.561**
	(0.311, 0.943)	(0.322, 0.981)	(0.316, 0.971)
Observations	211	211	211
Log Likelihood	-124.663	-124.565	-124.693
Akaike Inf. Crit.	259.327	259.130	259.386

Note $^{*}p < 0.1$ $^{**}p < 0.05$ $^{***}p < 0.01$

To simplify the involved interpretation in the odds ratios scale, Figure 10 presents predicted probabilities for choosing node 17 across treatment and control groups, by B_i^{dich} (i.e., red for non-brokers, blue for brokers). This analysis is conducted with "ChameleonLike" trait as the control, as Figure 9 indicated no discernible difference across various models. More specifically, we derived predicted probabilities holding "ChameleonLike" scores to their median (left) and maximum values (right) (for comparison, in the SM we report the predicted probabilities from a linear probability model adjusted for heteroskedasticity).

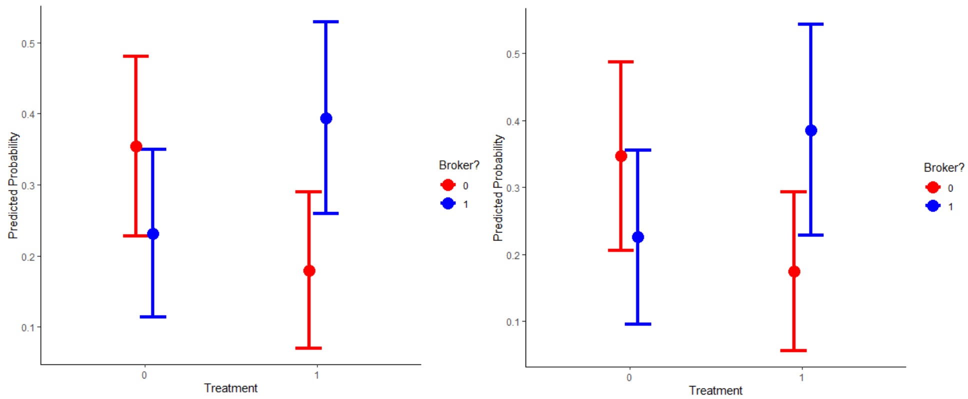

Figure 10: Predicted probabilities for choosing node 17 in the control group ($T = 0$) and treatment group ($T = 1$). Non-brokers are represented in red, brokers in blue. 95% confidence intervals are displayed. Left: predicted probabilities holding "ChameleonLike" to its median value. Right: predicted probabilities holding "ChameleonLike" to its maximum value.

In both cases, in the control group ($T = 0$), brokers showed a lower probability of selecting node 17 compared to non-brokers, although the differences were not statistically significant. Conversely, in the treatment group ($T = 1$), brokers were significantly more likely to choose node 17 than non-brokers, thus confirming our hypothesis (Renzini & Squazzoni 2023). This suggests that prior network brokerage experience has led participants to differently interpret the artificial networks they were exposed to, and frame their decisions accordingly.

5 Discussion and Conclusions

Previous research has recognized network brokers as key-individuals for accelerating information dissemination within social groups (Centola & Macy 2007; Goldenberg et al. 2001; Granovetter 1973; Kim & Fernandez 2023; Li et al. 2016; Neal 2022; Watts & Strogatz 1998). Analogous to how parallel computation accelerates programs execution by distributing tasks across multiple cores, brokers would facilitate information diffusion by concurrently spreading information within different communities (e.g., see Figures 1 and 4; Burt 1999). In contrast, starting diffusion from the most well-connected node in a community would only sequentially and redundantly propagate information to the other community, passing through the broker. This means that diffusion processes originating from brokers would efficiently reach most other nodes in the shortest time.

However, these propositions rely on the assumption that individuals would exhibit similarity in their decisions regarding information spreading (Larson 2017). Analogous to infectious diseases, individuals are presumed to effortlessly and indiscriminately forward information to their contacts (Kim & Fernandez 2023). Yet, if we consider that individuals might delay or avoid spreading information for various reasons, such as contingencies, shyness, or other circumstances (Kim & Fernandez 2023; Larson 2017), the effectiveness of brokers in accelerating diffusion would persist only if they prioritize disseminating information above all other considerations. This implies that when brokers encounter previously unheard information (Burt 1999, 2004), their network experience would function as an activated alarm bell, enabling them to grasp the importance and potentialities of disseminating it to their contacts. This bell would not ring for anybody deeply embedded in a particular group, thus without experience in managing and directing non-redundant information flows. This suggests that brokers would be efficacious spreaders because their unique network experience provides them with superior awareness of their importance in information diffusion.

To investigate the effects of this experience, we conducted a laboratory experiment involving 252 university students with no formal training in networks and diffusion theories and applications. We collected data on their personal networks, personality traits, and asked them to choose the seed node to start a diffusion process, either for information (treatment group) or a virus (control group), within an artificial network.

Our findings revealed that, in the treatment group, participants with higher brokerage power in their personal networks were more likely of selecting node 17 (the artificial broker) for starting information diffusion. In the control group, participants with similar brokerage power and comparable characteristics across all other sampled dimensions to those in the treatment group were not significantly more likely to select node 17 as the seed for viral diffusion. If anything, they were less likely than non-brokers to do so, although the statistical signal for this difference was relatively weak.

The treatment condition was designed to activate participants' brokerage experience (Burt 1999), while the control condition served as a comparable baseline where participants had no practical firsthand experience of deliberate viral spread (similar to the roads network case in Janicik and Larrick 2005). The observed difference between brokers and non-brokers exclusively in the treatment group, where such a distinction should have emerged, would imply that brokers were more aware of their structural importance for information diffusion than for viral spread. Our findings would support the idea that when information is not risky or controversial to share, brokers would be the most effective spreaders, thanks to their enhanced understanding of diffusion processes afforded by their unique network position.

However, these results should be interpreted with caution, as the study has certain limitations and the data analysis leveraged on certain assumptions, albeit empirically and theoretically grounded. First, the sample size was relatively small, and university students represent an atypical and selectively chosen reference population for empirical investigations on network brokers (e.g., see Grosser et al. 2019). In our defence, it is also worth noting that ex-ante power calculations were challenging due to the absence of prior baselines. Furthermore, while studies on brokers have typically focused on professionals in organizational settings, one could argue that if these results hold for university students, they may also apply to organizational environments where brokers might be even more cognizant of their structural importance in information diffusion. Nonetheless, this is only an interesting hypothesis to be tested in a cross-sample study, not a sound justifications against our study limitations.

Secondly, our pre-registered design intended to incorporate behavioral measures of brokerage as robustness checks for results obtained using structural definitions (Renzini & Squazzoni 2023). However, our participants consistently indicated high familiarity with many brokerage behaviors, especially those associated with *tertius iungens* and *mediator* roles. This resulted in variables with questionable validity and power, as detailed in the SM. This could be attributed to the social desirability bias that these items may have generated. For example, one item for the *tertius iungens* battery was stated as follows: "*I encourage the meeting between two people when I believe both can benefit from knowing each other*". Participants might have perceived such behaviors as "good behaviors", possibly influenced by their expectations of the experimenter's endorsement.

The fact that we could not consider behavioral aspects related to network brokerage undermined our capacity of contributing to recent research suggesting to move beyond purely structural definitions (e.g., see Burt et al. 2021; Kwon et al. 2020). Moreover, our problems with behavioral brokerage items allow us to outline the importance of cautions whenever applying questionnaires targeted to a sample of professionals working in organizational contexts (i.e., Grosser et al. 2019; Obstfeld 2005) to other social settings, such as – in our case – university students.

Finally, in our data analysis, we excluded certain observations and classified participants into two groups based on B_i. This was to eliminate potentially inaccurate responses to network name generators and reduce the impact of measurement noise in estimates. Indeed, we followed the assumption that differences between neighboring B_i values were not sociologically interesting since influenced by idiosyncrasies in response styles or reporting errors. To assess the robustness of these decisions, we conducted a comprehensive sensitivity analysis (see the SM). Generally, our results found a relative consistency in effect sizes and the precision of our estimates across various types of operationalization. However, as expected, scenarios involving continuous B_i did not generate univocal results (see the SM).

To sum up, with all due caveats, we believe that our study represents a pioneering effort to explore the potential impact of network experience derived from distinctive positions and network learning on diffusion processes. Unlike typical experiments in network cognition, often characterized by relatively abstract tasks (Brashears 2013; Son et al. 2023), our experimental manipulations were inspired by real-life scenarios. While this doesn't imply exceptionally high external validity standards for our study, it does point towards new avenues for sociological research.

First, future research could explore incremental developments of our design by testing various examples of information risk (e.g., see Guilbeault et al. 2018). By varying costs, risk, and strategic implications of information sharing, we could explore whether prior experience as brokers could lead subjects to either refrain from sharing – if disadvantageous – or strategically opt for a different seed to start diffusion – if it is advantageous to target particular groups. Secondly, a lab-in-the-field replication could target a non-student population (Baldassarri & Abascal 2017), such as professionals in different organizational contexts characterized by various degrees of built-in competition (e.g., see Lazega 2001), where information sharing and brokerage could be highly strategic. Furthermore, it could also be relevant to verify whether network brokers would persist with the same seed selection choices across various contexts by applying analogical reasoning. Finally, our design could be replicated in different cultural contexts where there is prevalence of bureaucratic organizations with administratively built-in brokerage positions or more flexible and informal organizations where network brokers are emerging and there is more room for network strategization (e.g., Burt 2004; Lazega 2001). This would also help us considering the effect of alignment vs. misalignment between personality traits and structural roles on information diffusion within organizations.

Appendix

Figure 11 summarizes the set of tasks encountered by participants during the experiment.

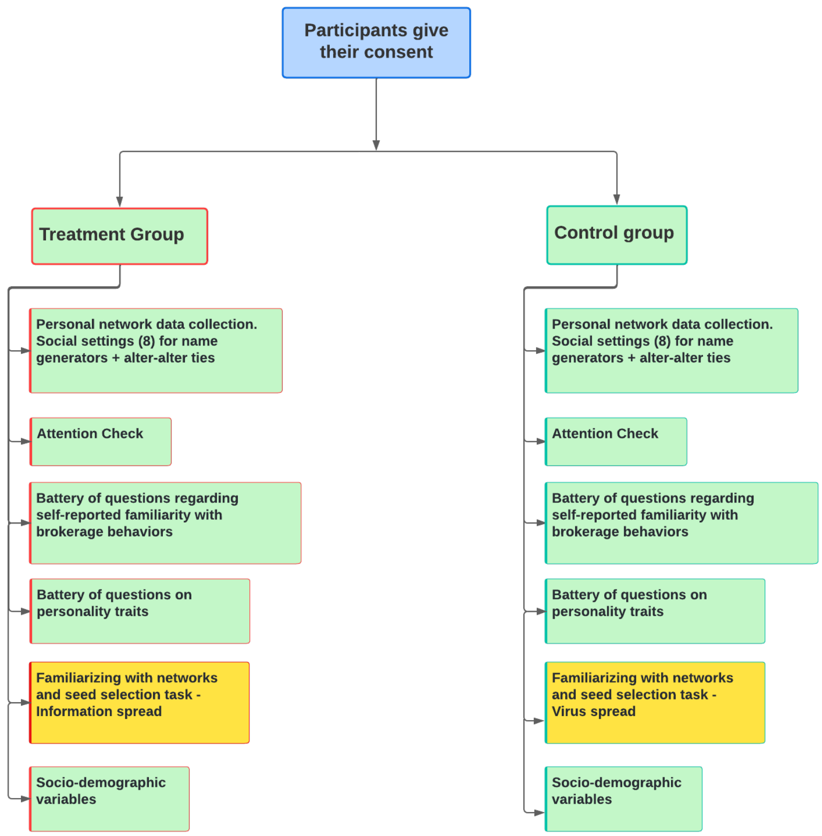

Figure 11: Tasks encountered by participants in the treatment and control groups, with the unique difference between the two groups highlighted in the yellow box.

Supplementary Materials

The Supplementary Materials can be found here: `https://gitfront.io/r/france10cescfr7/GmeqqGRu8w7j/SM-Exper/blob/SM_network_footprints.pdf`

Declaration of Competing Interest

The authors declare no competing interests.

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IRB Approval

The Ethics Committee of the University of Milan granted approval to the experimental design on July 17th, 2023.

Code

The HTML and JavaScript code used to design the dynamic web interfaces is available at the following link: `https://gitfront.io/r/user-2172385/32nQoisWqD1y/Experiment-Brokerage/`.

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