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# Social Network Influence on Online Behavioral Choices: Exploring Group Formation on Social Network Sites

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**Abstract**

Social media communication is characterized by reduced anonymity and off-to-online social interactions. These characteristics require scholars to revisit social influence mechanisms online. The current study builds on social influence literature to explore social network and gender effects on online behavior. Findings from a quasi-experiment suggest that both network-related variables and gender are significantly associated with online behavior. Perceived social environment, measured by personal network exposure rate, is more significant than objective reality, measured by frequency of received social messages, in determining behavior. We discuss the implications of social contagion effects on web-based strategic communication—including advertising, political campaigns, and social mobilization. Data limitations and the difficulty of measuring social network influence via social media are also discussed.

**Keywords**

social influence, personal network exposure, social networking sites, online social networks, interpersonal influence, social contagion

Social exchange via social networking site (SNS) challenge what nearly two decades of computer-mediated communication (CMC) research has revealed about the impacts of anonymity and reduced social cues, on the mechanisms of social influence. In the

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age of SNS, anonymity is no longer a precondition of CMC. Not only do community policies require users to disclose real names (Youmans & York, 2012), users overwhelmingly engage in social interaction with formerly offline friends and acquaintances (Ellison, Steinfield, & Lampe, 2007). Subsequently, personal networks mediated via SNS tend to compile expansive and multiplexed reference groups including friends, families, coworkers, classmates, and others, broadly defined as peers (Rainie & Wellman, 2012). The personalized sharing among this network of online friends breeds networked social information, which exerts influence to a varying degree on individuals' attitudes, opinions, and online activities.

The success of Facebook's social context advertising, which utilizes social plug-in technologies, makes the power of compiled personal networks evident. Public communication campaigners and activists also adapt ad strategies using Facebook to leverage the networked influence for collective good. This is seen in success stories ranging from the American Public Health Association's Facebook page (Thackeray, Neiger, Hanson, & McKenzie, 2008) to the successful mobilization of Egyptian protesters in 2011 (Lim, 2012). As echoed by these examples, the enhanced interpersonal visibility and immediate dissemination of social information via expansive, nonanonymous personal networks, influences individual's attitudes and behaviors.

Normative influence, arising from online personal networks, is a distinctive phenomenon from early CMC experiences. Text-based social cues and greater anonymity either weakens reference group's influence (e.g., Ho & McLeod, 2008) or engenders deindividuated social influence based on enhanced group identity (Postmes, Spears, & Lea, 1998). Considering that the use of SNS is integrated into many Internet users' everyday social communication practices, especially among young adults and adolescents (Rainie & Wellman, 2012), it is worth scholarly attention to investigate how online personal networks influence online behavior. We conducted a quasi-experiment to explore the ways visible social information, available through SNS influences users' behavior.

## Social Networks and Social Influence

Social networks are the conduit for both social information and social influence. Therefore, the social network analytic approach provides researchers with insights into the mechanisms and processes behind social influence. In the diffusion literature, for example, Valente (1995) used this approach to investigate the influence of "personal network exposure" (p. 43). This refers to the observed rate of adoption, within an individual's immediate social environment, on the individual's adoption decision toward new information or products. According to Salganik, Dodds, and Watts (2006), the cultural market is also driven by social influence, where a best-seller item is determined by adoption patterns rather than the item's inherent quality. The social network's influence on psychological and physical wellbeing has also been widely investigated, ranging from college drinking behavior (e.g., Reifman, Watson, & McCourt, 2006) to contagion of happiness or obesity (e.g., Christakis & Fowler, 2009), drug use (e.g., Bauman & Ennett, 1996), and sexual behavior and diseases (e.g., Latkin, Forman, Knowlton, & Sherman, 2003).

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In organizational settings, network influence was theorized via the social information processing model (Salancik & Pfeffer, 1978). According to the model, attitudes and perceptions toward organizational tasks are not just influenced by personal traits or the nature of the task. The attitudes and perceptions are also constructed by "socially relevant others," who are identified based on their network positions relative to the focal actor. Researchers found that employee turnover is associated with direct communication networks (i.e., who talks with whom) as well as structurally equivalent positions (i.e., having equivalent communication links or nonlinks) occupied among the employees (Feeley & Barnett, 1997). Other studies examined the adoption of information technologies within an organization, concluding that individuals' perceptions and adoption behaviors are determined by contact frequency, physical and social proximity, and structural equivalence with their coworkers (Fulk, 1993; Rice & Aydin, 1991).

While much research about social influence has been conducted offline, network-based perspectives should also be applied in the context of SNSs. The increased prevalence and frequency of nonanonymous social interactions via SNSs enhances interpersonal visibility and salience—the two preconditions of interpersonal influence (Friedkin, 1993, p. 861). Interpersonal visibility refers to a focal actor's knowledge about others' opinions, attitudes, and behaviors. It is a fundamental precondition because Actor A cannot exert influence on Actor B unless B is aware of A's opinion (Friedkin, 1993). On SNSs, interpersonal visibility is often more profuse than in offline contexts because the public availability of a wide range of conversations and other forms of self-disclosure is not just conventional but also inevitable if users want to actively participate in the online community.

Interpersonal salience refers to perceived relevance or the value that a focal actor places on the new knowledge the person learned from social information (Friedkin, 1993). In other words, Actor A will be influenced by Actor B's opinion only when A finds the opinion interesting, relevant, or important. Although SNSs make large volumes of social information available to users, obviously not all of that information will be salient to individual users. Due to the limited human cognitive capacity (Roberts, Dunbar, Pollet, & Kuppens, 2009), individuals tend to bypass much of the available social information. This is especially true when the information originates from very casual acquaintances and friends (i.e., weak ties). It is important to note that research has shown that the majority of SNS is composed of very weak ties (Bond et al., 2012). However, if similar attitudes or behaviors are *repeatedly* observed from multiple weak ties, this information will increase in salience over time. Such repeated exposures to similar attitudes via weak ties are common on SNSs.

The enhanced interpersonal visibility and salience inherent on SNSs requires the reconceptualization of online social interactions and subsequent social influence dynamics. As Lange (2007) and Papacharissi (2009) suggest, traditional and anonymous online communities are known as "privately public" spaces. In these communities users publicly express themselves while keeping their real identity private. In contrast, recent SNS platforms are "publicly private" in that private activities are

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presented publicly and users' employ their real identities (Papacharissi, 2009). Studies have only recently delved into the impact of such publicly private practices on social influence dynamics. Based on an experiment with six million Facebook users, Bond et al. (2012) found that the automated information about strong ties online behaviors induce social influence on political self-expressions, information searching, and actual voting turnout. However, the same information about weak ties was not found significant. Bakshy, Eckles, Yan, and Rosenn (2012) confirm these strong ties effects on Facebook browsing behavior. The current study complements these findings by investigating the effects of other network variables and the effects of repeated message exposure (opposed to direct solicitation).

## Research Hypotheses

The current study is based on a quasi-experiment in which confederates solicited SNS friends (i.e., Facebook) to accept and react to a call for action. SNSs are multilevel, complex social spaces in which sociocognitive relationships can be uncovered between regular SNS interactions and opinion/attitude influence. We acknowledge that this study, as a preliminary step, takes a simplistic approach to the influence mechanism, rather than fully capturing the sociocognitive dynamics. Details about the study design are provided in next section.

### *Direct Interpersonal Contact*

Traditionally, social influence is most easily enacted through direct solicitation. Direct solicitation makes specific attitudes and behaviors visible and induces compliance, depending on the quality of the relationship between the solicitor and the responder (Cody & McLaughlin, 1980). According to Bond et al. (2012), more than 90% of online social network relationships are weak ties, so it may be difficult to induce compliance via SNSs. Nonetheless, if the request is received via personalized modes of communication, a compliance effect may be generated even among these casual relationships. Specifically, the one-to-one message system implemented in Facebook is operationalized as a more personal, direct communication channel than public wall posting. Personal, one-to-one disclosure correlates with interpersonal attraction because the recipient feels that he or she has been singled out as trustworthy (Stefanone, Kwon, & Lackaff, 2011, 2012; Taylor, Gould, & Brounstein, 1981). Accordingly, we define direct interpersonal contact as one-to-one private solicitation via Facebook. Furthermore, if participants receive direct messages with the same request from multiple friends, the request is perceived as more important. In other words, direct contact from multiple social relationships increases the perceived salience of messages. Thus,

> *Hypothesis 1 (H1):* Direct contacts from multiple sources are positively associated with enacted online behavior.

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## Social Contagion

Another type of social information via SNSs is an automated *social message*, by which information about attitudes or behavior of a focal actor's networked friends is automatically produced and distributed (Bond et al., 2012, p. 295). For example, Facebook news feeds commonly push social messages like "John likes The Simpsons," which increases the visibility of John's preference for that television program to a focal actor whose personal network includes John as an alter. While direct interpersonal contact should induce compliance, exposure to social messages produces a *social contagion* effect. Social contagion is the process of adopting attitudes or behaviors through observational learning (Polansky, Lippit, & Redl, 1950), while compliance is operationalized as a response to outspoken requests (Wheeler, 1966, p. 182). In other words, the availability of observed information about others' attitudes and behaviors is essential to inducing contagious influences (Burt, 1987). If an individual learns that many of his or her Facebook friends indicate that they "like" a specific issue, that individual will be more likely to also "like" that issue, even in the absence of direct solicitation.

One primary mechanism of social contagion is defined as *personal network exposure* (PNE). PNE refers to the proportion of adopters to the total members in the focal actor's personal network (Valente, 1995, p. 43). According to Valente (1995), social cognitive processes are more important than the simple numbers of adopters because individual thresholds for accepting certain ideas or innovations are determined by one's perceived social environment. For instance, the existence of three adopters in a five-person personal network (60% PNE) will spawn a more convincing perception in favor of adoption, opposed to three adopters in a personal network of 300 others (1% PNE). Therefore, we treat the frequency of social message exposure and PNE as distinct independent variables, and propose two hypotheses:

> *Hypothesis 2a (H2a):* The frequency of social message exposure has a positive relationship with enacted online behavior.
> *Hypothesis 2b (H2b):* PNE has a positive relationship with enacted online behavior.

## Gender

Gender is an important individual attribute that influences susceptibility to social influence. According to Eagly (1983), females are more likely to be socially influenced than men even when social status is controlled. Research shows that females not only use SNSs more frequently than males (McAndrew & Jeong, 2012) but also use SNSs for the purpose of friendship maintenance more than males (Thelwall, 2008). Stefanone et al. (2012) found that female users were more likely to comply to requests for instrumental support (i.e., asking help for a school project) when the request was directed and personal. Based on these findings, we examine gender differences by proposing the following:

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*Hypothesis 3 (H3):* Women are more likely than men to enact online behavior.

We also examine whether gender differences moderate the relationship between social influence and behavior. Scholars have previously attempted to examine gender as a moderator in determining the level of social participation on SNS, although there was no significant moderating effect discovered (e.g., Ellison et al., 2007). We wonder if gender difference is found significant if the participatory actions are directly requested or contagious via social networks. Based on previous findings on females' susceptibility to social influence, we hypothesize that females should be likely to partake in online behavior more so than males when they are exposed to greater levels of network effects. Thus,

*Hypothesis 4 (H4):* Gender moderates the social network effects on enacted online behaviors such that females will be more likely to enact online behavior when exposed to (a) more frequent direct contacts, (b) more frequent social messages, and (c) higher PNE.

## Method

### *Participants*

A quasi-experiment was conducted. Confederates tried to mobilize their peers by asking their Facebook friends to join a campus action group. In collaboration with the undergraduate student government at the State University of New York at Buffalo (UB), we created a publicly open Facebook group called Students Who Want Better Campus Libraries (or, the "library group"). The library group's mission was to raise awareness about the condition of the UB's libraries and to generate ideas for improvement. All participants' behavior was observed after they were contacted by confederates. Note that the study is a quasi-experiment without a control group. Comparisons were made between two response groups: one that accepted the call for action and joined the group, and the other group that did not respond.

The procedure was as follows: First, researchers recruited 72 volunteer confederates from three introductory undergraduate classes in communication. Each class had about 200 students enrolled. Recruitment was based on the following qualifications: Confederates had to express support for the goals presented by the library group and demonstrate a willingness to recommend their own Facebook friends join the group. Confederates also were required to have a minimum of 50 Facebook friends, at least 20 of whom were affiliated with UB. The minimum network size was determined arbitrarily based on researchers' experiences with Facebook as the website users.

Next, confederates made recommendations to their university-affiliated Facebook friends. They asked that their friends join the library group through direct, one-to-one messages to specific friends in their network. Confederates were required to use a scripted message provided by the researchers. The message stated, "Hey, this group is

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trying to raise awareness about the poor conditions in the campus libraries. Please join the group and show your support for our effort to make the libraries better." They were also instructed not to select friends who were enrolled in the classes in which the general recruitment announcements were made. Regardless of how many of their friends responded to their messages, all confederates were rewarded research credit for the participation. Finally, they were instructed not to disclose the true nature of the study to their invitees until 2 weeks after data collection was complete.

## Social Network Data

After the messages were sent, a researcher recorded each confederate's personal network on Facebook. Personal networks are also called ego networks (Marsden, 2005), in which a network owner is defined as *ego* (the confederates themselves) and the subjects as *alters* (confederates' Facebook friends who received the direct messages). We used the terms *ego* and *confederate* interchangeably, as well as *subject* and *alter*. Each ego network was composed of two types of information. The first is simply a list of alter names. The list of alters was used to track who joined the library group. This procedure was done manually by matching the library group membership with the names identified in the list. The second type of information was sociometric data about alter–alter relationships. The first row and column of the square matrix displays every alter name, and each cell identified whether a pair of alters were Facebook friends with each other (1 = *friends*, 0 = *not*). The resulting matrix was binary and symmetric.

Although ego network data were collected independently of each other, the majority of confederates were actually Facebook friends with at least one of the other confederates ($n$ = 56 out of 72) and a nontrivial number of alters ($n$ = 911) were affiliated with more than one ego network, indicating that these alters were contacted more than once. Figure 1 depicts the real structure of overlapping ego networks of the current project in comparison with the separate personal network structures that are conventionally assumed in ego network analysis.

A non-negligible portion of network overlap could distort the positional properties associated with each alter. As exemplified in Figure 1, if personal networks were treated as independent of one another in contrast to the real structure, the number of friends that Actor A has would be calculated incorrectly. This is because the result would vary depending on which ego network Actor A is designated as nested in. More important, multiple occurrences across different ego networks implies that alters received the invitation message multiple times from different confederates. Obviously this will affect how the *direct interpersonal contact* variable is calculated.

To address these issues, all 72 ego networks were aggregated into one system-level network. An automated process then extracted alter–alter relations that were not revealed in separate ego networks (denoted with the dashed and dotted line in Figure 1). They were uncovered by scanning alters' friend lists in their profiles. If any name in the data set was found from the alter profiles and the relationship was not included in the system-level network, a link was assigned between the pair of alters.

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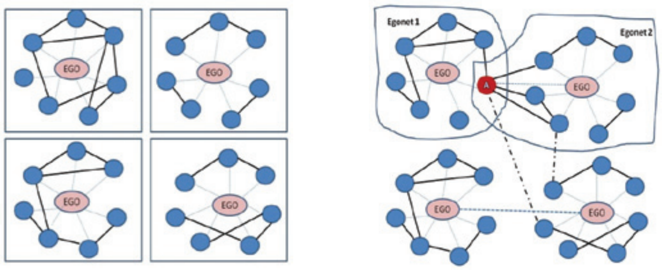


(a) Conventional setting:
Each ego-networks independent to each other

(b) Current study: The vertex A's degrees vary depending on which ego network A is considered to be nested

Note. — — — : edges connecting egos
▬▬▬ : edges between alters
▬ ▪ ▬ ▪ ▬ : edges hidden until networks were aggregated

**Figure 1.** Ego network structure comparison between conventional and current study setting.
The dashed line indicates edges connecting egos. The solid line indicates edges between alters. The dashed and dotted line indicates edges hidden until networks were aggregated.

## *Social Influence Variables*

*Frequency of direct interpersonal contact.* This variable was computed by simply counting the number of confederates who directly invited each subject via one-to-one message. Among the total of 911 (22.9%) alters who received the message from multiple confederates, there was a decrease in numbers from three confederates: 648 alters (16.3%) received messages from two confederates, 194 (4.9%) from three, 51 (1.35%) from four, 12 (0.3%) from five, and 6 (0.1%) from more than six confederates. Given the small sample size for the cases of three or more times, all the multiple contact cases were combined into one group. This variable was dummy coded (0 = *contacted by a single confederate*, 1 = *contacted by two or more confederates*).

*Frequency of Social Messages (FSM).* If Actor A joins the group, the message "A joined the group" is automatically generated and disseminated to A's Facebook friends. Therefore, FSM was computed by simply counting the number of individuals who joined the group among the subject's friends as identified from the sociomatrix.

*Personal Network Exposure (PNE).* PNE refers to the proportion to which an individual witnesses others' adoption behaviors within their personal network. PNE was computed by dividing FSM by the total number of a subject's Facebook friends identified from the sociomatrix. Thus, PNE is a continuous variable ranging from 0 to 1, consistent with the measure proposed by Valente (1995).

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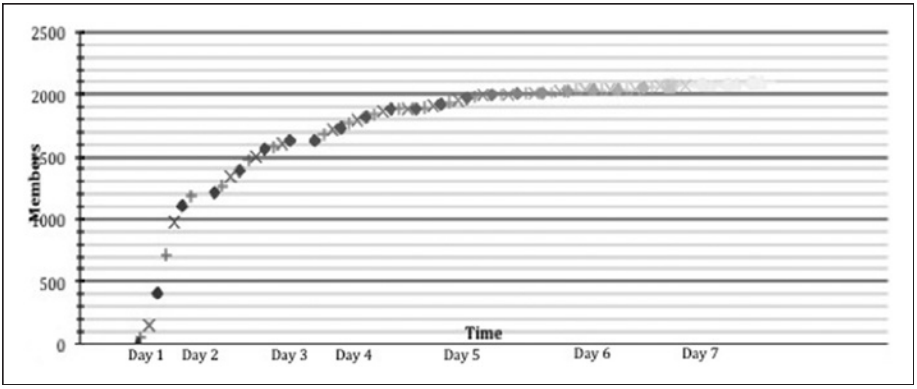


**Figure 2.** The cumulative graph of group membership change during one week.

*Other variables.* Given that we could not directly survey the gender of each alter, we recorded subjects' gender based on their Facebook user names (1 = *female*, 0 = *male*). Note, however, that the name-based gender coding is not a perfect method to represent the gender information. The dependent variable consists of binary data indicating if subjects joined the Facebook library group.

## Results

### *The Facebook Library Group Growth: A Brief Report*

The initial library group included 34 members from the student government. During the 7 days this project spanned, group membership increased to 2,038 members. We also observed that discussions developed, including a total of 137 discussion threads, 47 wall posts with 63 subcomments, and 93 "likes." Three days after the project launched, the library group received front-page coverage on the campus newspaper. The news article also included interviews from several administrators including the director of the library's technology department. Figure 2 shows how the group size increased over the course of one week.

Although it was not part of our hypothesis testing, it is worth noting that it took only 3 days for the group to achieve their aim to have student voices heard by administrators. Rapid information cascade is common for information and communication technology-driven propagation, which results in the r-curve-shaped diffusion process (Barnett, 2011). The estimated curve shape underlying the process of our Facebook group development shows that more variance was explained by the cubic/r-curve model ($R^2$ = .97) than by the sigmoid model or the traditional s-curve diffusion process ($R^2$ = .89).

The rapid network growth observed in the library group suggests that word-of-mouth communication occurred through multiple steps beyond the initial pool of alters

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**Table 1.** Variables Descriptions (*N* = 3,971).

| | *M* | *SD* | *N* | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|---|
| 1 DV | 0.222 | 0.499 | 3,890 | | | | | | |
| 2 Gender | 0.468 | 0.499 | 3,971 | .055** | | | | | |
| 3 DIC | 0.229 | 0.421 | 3,971 | .088*** | .048** | | | | |
| 4 FSM | 3.369 | 4.808 | 3,958 | .036* | .041* | .416*** | | | |
| 5 PNE | 0.117 | 0.127 | 3,960 | .064*** | –.026 | .049** | .412*** | | |
| 6 Gender × DIC | 0.116 | 0.320 | 3,889 | .071*** | .391*** | .668*** | .318*** | .025 | |
| 7 Gender × PNE^ | –0.002 | 0.082 | 3,971 | .043** | –.021 | .040* | .311*** | .642*** | .046** |

DIC = direct interpersonal contacts (1 = *more than twice*, 0 = *once*); DV = joining the group (1 = *yes*, 0 = *no*); FSM = frequency of social messages; gender (1 = *female*, 0 = *male*); PNE = personal network exposure rate; PNE^ = mean-centered value of PNE.
*$p$ < .05. **$p$ < .01. ***$p$ < .001.

directly contacted by the confederates. While 43.33% of the total group members ($n$ = 883) were mobilized by the confederates, the rest were mobilized through other channels. These participants may have heard about the group from campus media or from social messages via chains of Facebook friend networks. While interesting, our data are limited to address these word-of-mouth processes.

## Descriptive Statistics

The size of each ego network ranged from 20 to 222 alters ($M$ = 73.21, $SD$ = 53.99). The aggregate network included a total of 3,971 alters. Among them, there were 1,820 (45.8%) females and 2,070 (52.1%) males. We were unable to account for the gender of 81 (2.1%) participants. On average, alters received direct interpersonal contact 1.32 times ($SD$ = 0.68). Among the 3,971 alters, a total of 883 joined the group (22.2%).

The average size of alters' personal networks was 23.37, ranging from 0 to 281 ($SD$ = 30.4). Some alters were also friends with one another. About 63% had at least one friend who became a member of the advocacy group. Specifically, 554 (14%) were connected to one of the group members, 356 (9%) to two, 316 (8%) to three, 251 (6.3%) to four, 181 (4.6%) to five, and 843 (21.1%) to more than five library group supporters ($M$ = 3.37, $SD$ = 4.81). The mean proportion score for PNE was 0.12 ($SD$ = 0.13), indicating that on average 12% of friends identified from each alters' personal network became group members. Table 1 summarizes descriptive and correlation statistics for the variables used in this study, as well as the interaction terms between gender and social influence variables.

## Hypotheses Testing

A model that can address network autocorrelations (i.e., stochastic actor-oriented models) would be ideal metrics to investigate network influence. To our knowledge, there is no such analytic program available for a network as large as several thousand nodes. Though this view is a limitation, we alternatively view our data condition as if

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**Table 2.** Logistic Regression Results ($N$ = 3,971).

| | $B$ | $SE$ | Wald | Significance | E($B$) | 95% CI for E($B$) Lower | Upper |
|---|---|---|---|---|---|---|---|
| Model 1 | | | | | | | |
| Gender (female)** | 0.267 | 0.078 | 11.673 | .001 | 1.306 | 1.121 | 1.522 |
| DIC*** | 0.557 | 0.097 | 32.872 | .000 | 1.745 | 1.443 | 2.111 |
| FSM | –0.018 | 0.010 | 3.474 | .062 | 0.982 | 0.963 | 1.001 |
| PNE*** | 1.139 | 0.322 | 18.835 | .000 | 4.039 | 2.150 | 7.588 |
| Constant*** | –1.473 | | 544.858 | .000 | 0.229 | | |
| Model 2 | | | | | | | |
| Gender (female)** | 0.313 | 0.092 | 11.527 | .001 | 1.367 | 1.141 | 1.638 |
| DIC*** | 0.631 | 0.131 | 24.001 | .000 | 1.898 | 1.469 | 2.452 |
| FSM | –0.018 | 0.010 | 3.271 | .071 | 0.982 | 0.964 | 1.001 |
| PNE^** | 1.382 | 0.406 | 11.561 | .001 | 3.983 | 1.796 | 8.835 |
| Gender × DIC | –0.165 | 0.174 | 0.899 | .343 | 0.848 | 0.603 | 1.192 |
| Gender × PNE | 0.023 | 0.593 | 0.001 | .969 | 1.023 | 0.320 | 3.271 |
| Constant*** | –1.497 | 0.069 | 476.297 | .000 | 0.224 | | |

DIC = direct interpersonal contacts (1 = *more than twice*, 0 = *once*); FSM = frequency of social messages; gender (1 = *female*, 0 = *male*); PNE = personal network exposure rate; PNE^ = mean-centered value of PNE.
**$p$ < .01. ***$p$ < .001.

the binary categorical DV is based on an independent, cross-sectional observation predicted by network variables and chose logistic regression to test the hypotheses (Table 2). The first model includes gender, direct contact, FSM, and PNE in one block. The omnibus chi-square tests, $\chi^2(4) = 60.650$, $p < .001$, and the Hosmer and Lemeshow goodness-of-fit tests, $\chi^2(8) = 7.504$, $p = .483$, indicated that the model as a whole performed well.

The results showed that gender (female), direct contacts, and PNE were significant predictors of joining the library group. Specifically, subjects who received multiple direct requests were more likely to join the group, with log odds $B = 0.557$, Wald $\chi^2(1) = 32.872$, $p < .001$. The predicted odds of joining the group changed by 1.745 times if participants received direct requests two or more times, holding other variables constant. PNE was also significant, log odds $B = 1.396$, Wald $\chi^2(1) = 18.835$, $p < .001$. A one-unit change in PNE increased the likelihood of joining the group member 4.039 times. In addition, females were more likely to act on requests, with the log odds $B = 0.267$, Wald $\chi^2(1) = 11.673$, $p < .001$. Female subjects were about 1.3 times more likely to join the group than males. FSM was not significant. Therefore, H1, H2b, and H3 were supported, while H2a was not.

To test the interaction effects, interaction terms were included in the second block. Given that FSM was not significant in the first model, the interaction between gender and FSM was not considered. Thus only two interaction terms, gender × direct interpersonal communication and gender × PNE, were entered. The continuous variable PNE was mean-centered. Neither interaction term was significant, indicating that gender did not moderate the relationship between social influence and subjects' behavioral choice. Therefore, H4a, 4b, and 4c were not supported.

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## Conclusion and Discussions

Today's "publicly private" social media environment (Papacharissi, 2009) calls on researchers to revisit online social influence as a phenomenon which can be distinguished from traditional anonymity-based CMC theories. The current study applied the social network perspective to Facebook to explore the effects of interpersonal visibility and salience on behavior. This study leveraged sociometric data acquired from an online quasi-experiment and the findings highlight the significance of multiple direct contacts and PNE. This confirms that repeated exposure is associated with user's behavioral choices online.

Our findings suggest that online social networks offer alternative venues for strategic communication, distinct from direct solicitation (e.g., email). While e-solicitation like email can be effective for compliance gaining, frequent solicitation may be perceived as spam, resulting in feelings of intrusiveness (Cao, Knott, Xu, & Chau, 2009). Our study did not reveal a negative relationship between the frequency of direct interpersonal contact and subjects' choice, possibly due to the shared interest and low stakes associated with the solicited action. However, the level of intrusiveness can negatively affect message recipients' perceptions in other contexts like product purchases (Nam, Kwon, & Lee, 2010).

Meanwhile, social contagion induced from networked exposure can increase favorability assessments of ideas or products. Although social contagion might occur more incidentally than direct solicitation, our findings suggest that Facebook messages manifest the effectiveness of network exposures. They may reduce emotional byproducts such as intrusiveness, boredom, or message avoidance. Furthermore, the nonsignificant result of FSM, in contrary to the significant effect of PNE, implies that the *perceived* social environment may be more critical in increasing interpersonal salience and prompting individuals to adopt attitudes or behavior. The recent research on social message effectiveness among strong ties (Bakshy et al., 2012; Bond et al., 2013) could be supplemented by considering PNE as an additional metric. Weak ties were not found significant in the previous researches, but they might be influential as well if they function to increase the overall level of PNE. Meanwhile, consistent with other extant literature, we found that females were affected more strongly by social influence. However, the interaction test revealed no moderating effect of gender between the social network variables and behavior. Other factors such as age, ethnicity, and personality-related factors should be studied in future research to see whether individual traits moderate social network effects.

Understanding the spread of social influence via SNS, and Facebook in particular, has implications on strategic communication. As mentioned above, campaigners can benefit from delving into how expansive online personal networks play in the process of word-of-mouth advertising. Interface designs that maximize the visibility of networked others and their shared content, can facilitate the spread of political and civic engagement, especially among youths and young adults. Second, the impact of online social networks may present moral questions especially in the context of public deliberation. It is important when considering long-lasting discussions

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about social conformity as a hindrance from rational group decision-making processes (Noelle-Neumann, 1993). While anonymous CMC has been suggested as a solution to reduce social conformity (Ho & Mcleod, 2008), the enlarged visibility of reference groups articulated via SNSs can posit even stronger normative constraints on opinion expression.

Several limitations of our data set reflect the difficulty of measuring influence through social media. First, undirected binary relational data does not address the directionality of social contagion and the qualitative variation of relationships such as tie strength, relationship type, and the overlap between on- and offline interaction (Garton, Haythornthwaite, & Wellman, 1997; Wellman, 1992). As Easley and Kleinberg (2010) suggest, social computing techniques avail to quantify the quality of social interactions by mining behavioral traces recorded on SNS. While future research could pursue access to the enriched relational data, the tension between user privacy and data access is a possible ethical issue that must be addressed. Second, the total size of each participant's Facebook network was not considered. In large networks, the volume of social information may be quite high. As a result, social messages pushed to individual users from all of their contacts likely become hard to follow. Instead of the total personal network size, we computed the personal network size only within the boundary of college friendship. Not considering the total size remains a limitation of this study because it is possible that some subjects maintain large networks outside of the university boundary. As another technical limitation, the additional alter–alter relationships were collected only from publicly accessible user accounts when ego networks were aggregated into one network. Therefore, we cannot assert whether the network was a complete configuration composed of every possible alter–alter relationship.

Understanding network structural aspects is important for understanding the dynamics of social media influence. While the current study found that Facebook-mediated social networks are effective venues for social context advertising and campaigns, their real-life impact should be discussed cautiously when higher levels of commitment—more than clicking a liking button or leaving a few comments—are expected. For example, Hurst (2008) is doubtful about the efficacy of Facebook mobilization when soliciting financial donations. He even contends that Facebook "lets millions of people get on the 'wall' with no donation," giving away "one of the few 'benefits' nonprofits can offer donors." In a similar tone, Gladwell (2011) argues that high-stakes collective behaviors, such as street protest participations that sometimes put participants' security and safety at risk, are mostly mobilized through strong-tied, offline social interactions rather than online networks. The broader conversation about social media influence is in its early stage. Future research will deepen our understanding of what is required to produce meaningful changes in attitudes and behaviors from online network-driven campaigns. While the current study is based on relatively small-scale experiments, the theoretical mechanisms of interpersonal visibility, salience, and social contagion help lay the groundwork to explore nonexperimental, naturally occurring, and often highly complex real-life word-of-mouth phenomena in Facebook and other SNSs.

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