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Original Article

Examining the Moderating Role of Network Density on the Relationship Between Social Norms and Behavioral Intention in the Context of Unfriending

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ABSTRACT

This study investigates the moderating effect of network density on the relationship between social norms and the intention to unfriend someone on social media. Specifically, it first explores whether this intention is influenced by the perceived prevalence of unfriending behavior. Then, the study examines whether the normative influence on this intention is more pronounced in a dense network (where members are highly interconnected), than in a sparse one (where members are seldom connected). To test these, a 2 (descriptive norms: high vs. low) × 2 (network density: high vs. low) between-subjects online experiment was conducted using a hypothetical unfriending scenario. The results reveal that perceived descriptive norms positively influence the intention to unfriend. Interestingly, contrary to expectations, the normative influence is stronger in sparse networks rather than dense ones. These findings highlight the significant role of social norms in shaping unfriending behaviors and underscore the importance of empirically testing theoretical relationships. They also call for further research to understand the complex interplay between norms and network density in various contexts. This study contributes to the growing body of literature on online social dynamics, offering insights into how digital interactions are influenced by the structure and perceived norms of social networks.

KEYWORDS
social norms, descriptive norms, network density, unfriending, social media

Humans are social beings. People who live in a society consistently develop relationships with others and follow certain societal or group norms that help them maintain their relationships. Notably, what makes this possible is communication: Communication plays a pivotal role in the formation and evolution of social norms and social networks (Geber et al., 2019; Monge et al., 2008), and social norms and networks often guide the way people communicate with others (Hogg & Reid, 2006; Rice & Love, 1987). Therefore, investigating how social norms and social networks function in relation to communication helps us better understand human interaction as social beings.

Studies of social norms and social networks exist in two largely separate spheres, driven in part by the use of different methodologies. Yet, there is great potential for communication scholars to blend these two areas of research (e.g., Lapinski et al., 2019). This study bridges these two literatures by testing the moderating role of network density on the norm-behavior relationship. In the social norms literature, evidence shows that social norms influence behavior, and this relationship is often strengthened or weakened by various moderators (e.g., Rimal & Yilma, 2021). In the social network literature, it has been theorized that the influence of norms is stronger in a network in which people are more densely interconnected rather than sparsely interconnected (Coleman, 1988, 1990; Valente, 2010). Nonetheless, the evidence for the interplay between norms and network density has rarely been reported. Thus, this study is designed to tackle this issue by empirically investigating the interaction between social norms and network density, thereby contributing to a more comprehensive understanding of how these two spheres intersect and influence human behavior.

This study delves into the dynamics of unfriending behavior on social media platforms. Unfriending is the intentional removal of someone from one's social media contacts (Sibona, 2014), thus ceasing all potential online interactions with the removed individual. Social media users typically resort to this behavior as a strategic form of avoidance when they encounter content they find inappropriate, offensive, or polarizing (Kim et al., 2022; Sibona, 2014; Skoric et al., 2018; Verswijvel et al., 2018). While unfriending can effectively prevent one from being exposed to potentially harmful content, research shows that it can also have negative consequences not only for those who unfriend (e.g., the formation of isolated and ideologically divided groups; Sasahara et al., 2021) but also those who are unfriended (e.g., psychological distress such as depression and frustration; Bevan et al., 2012).

This study particularly focuses on unfriending as its testing ground for several compelling reasons. Foremost among these is the role of social norms, which essentially entrench expectations of normalcy and appropriateness in social interactions (Lapinski & Rimal, 2005). Moreover, the very act of unfriending takes place in the digitally networked environment of social media, making it crucial to understand how an individual's network structure dovetails with social norms to shape such decisions. Notably, existing research indicates a significant positive correlation between perceived social pressures from one's close connections and the intention to unfriend (Verswijvel et al., 2019). Furthermore, certain aspects of network structures such as the size of one's network have been linked to unfriending actions (Barnidge et al., 2022), possibly because larger networks increase the chances of encountering disagreeable content. Despite these insights, there remains a paucity of research on how social norms and the structure of online social networks collectively drive unfriending behaviors. This study aims to bridge this gap in the literature.

In the subsequent sections, this paper provides an overview of the revised framework of normative influences (A. Chung & Rimal, 2016) and theories of social networks, serving as a basis for understanding how social norms and network density may interact with each other. Next, the paper moves on to the study hypotheses, followed by the method for testing the predictions, the results, and the discussion of the findings.

The Revised Framework of Normative Influences

Building on previous social norms literature, the revised framework of normative influences (A. Chung & Rimal, 2016) comprehensively describes when and how social norms can influence behavior. The framework suggests that three different types of social norms predict behavior. First, descriptive norms refer to perceptions of what most other people are doing, encouraging individuals to align with perceived widespread behavior by offering a guiding principle or cue that indicates what actions are effective and suitable for a given situation (Cialdini et al., 1990). Second, injunctive norms pertain to perceptions of what others approve of, motivating individuals to adhere to the norm to avoid social penalties for non-compliance (Cialdini et al., 1990). Third, subjective norms refer to perceived expectations from significant others to either engage in or refrain from a particular behavior, driving behavior through a combination of motivations to comply with those expectations (Fishbein & Ajzen, 1975).

The revised framework (A. Chung & Rimal, 2016) also suggests that the association between norms and behavior is moderated by variables classified into three categories: behavioral, individual, and contextual factors. Behavioral variables refer to characteristics of the actions in question, such as behavioral privacy (i.e., whether behavior is enacted in a public or private setting; M. Chung & Lapinski, 2019). Individual factors pertain to personal attributes like self-efficacy (i.e., perceived ability to perform a given behavior; Bandura, 1977). Contextual attributes relate to social and environmental backgrounds, such as time constraints (i.e., whether there is sufficient time for a behavioral decision; Cone & Rand, 2014).

This study proposes that a person's social network density can moderate the normative influence on behavior, categorizing it as a contextual factor. We argue that the effects of norms are likely stronger in a network where people are highly interconnected (i.e., a dense network) than in one with more sporadic connections (i.e., a sparse network). Such a relationship has been theorized and often assumed in social network literature (Coleman, 1988, 1990; Delgado-Marquez et al., 2013; Valente, 2010), but direct empirical evidence supporting this claim has been surprisingly scarce. The following sections review the theoretical foundation for the moderating role of network density on the norm-behavior relationship.

Network Density and Norms

Network density refers to the proportion of the number of actual links among people in a given network to the number of possible links (Monge & Contractor, 2003). Links generally indicate the relations between people, and communication network studies usually define them as connections between individuals, demonstrating how messages are sent, shared, or understood (Shumate & Contractor, 2013). In online social networks contexts, these links have often been operationalized as connections between friends (e.g., Centola, 2010; Meng et al., 2016).

There are at least three underlying mechanisms to explain how density can enhance normative influence or facilitate normative reinforcement. First, given that communication plays an essential role in the formation and diffusion of norms (Carcioppolo & Jensen, 2012; Kincaid, 2004; Yanovitzky & Rimal, 2006), dense networks, by definition, can provide more pathways than sparse networks along which communication about norms can flow and result in greater exposure to normative information (Cappella, 2017). Sparse networks may not provide sufficient channels for normative information to be circulated within a given network.

Second, a highly dense network means that network members are greatly interconnected. Thus, their deviant or norm-violating behaviors in such a network are more likely to be detected and punished by other members than in a sparse network. When pre-established norms exist in such a dense network, and people in the network are concerned about possible social sanctions from failing to conform to group norms, the norms arguably exert a strong influence (Coleman, 1988; Mohnen et al., 2012).

Third, an extremely dense network tends to be a closed network in which everybody has a direct relationship with everybody else. This structural characteristic reduces the likelihood of new information being introduced to the network members from outside and results in information circulating more within the network than between networks (Burt, 2000, 2005). In addition, closed networks enhance cohesion and group solidarity among members (Coleman, 1988; Shen et al., 2014), which in turn can strengthen normative influence (Rimal & Real, 2005). As a result, a network featuring thoroughly connected individuals can self-reinforce pre-existing conditions, including their normative beliefs.

Despite decades of theorization, there is little direct empirical evidence available on the moderating role of network density in the norm-behavior relationship. The scarcity of evidence may pose a problem because studies grounded in a theory that lacks empirical support can yield several issues, such as the existence of possible alternative explanations for the study findings (King, 1973). An exception to this is the Wikipedia research by Piskorski and Gorbatâi (2017). Guided by Coleman's (1988) argument, their study focused on undoing others' posts without proper justification or negotiation as a norm violation, and hypothesized that such norm violations would be less likely to occur in densely interconnected contributor networks than in sparsely interconnected ones. They analyzed Wikipedia contributors' behavioral data and showed that the norm violation was observed less frequently in dense networks than in sparse networks. Moreover, the punishment for the violation (operationalized as reverting the inappropriate undo) occurred more frequently in dense networks.

While the Wikipedia study (Piskorski & Gorbatâi, 2017) provides valuable evidence, there are some important shortcomings. For example, their study centered on proscriptive norms that could be perceived as both descriptive (e.g., “most contributors avoid undo”) and injunctive (e.g., “most contributors disapprove of undo”) norms (Bergquist & Nilsson, 2019). Thus, it is unclear what type of norms actually contributed to the findings. This uncertainty was also, in part, due to their methodological choice to collect behavioral data unobtrusively, without measuring the contributors' perceptions of such behavioral rules. Our study is designed to overcome these shortcomings.

Study Hypotheses

The literature on social norms suggests that the influence of norms on behavior can be both direct and contextual (A. Chung & Rimal, 2016). Additionally, the social network literature posits that the normative influence on behavior is likely to be more substantial in a dense network than in a sparse one (e.g., Coleman, 1988). Despite this, there has been limited reporting of empirical data concerning the interaction between norms and network density. This study aims to bridge this knowledge gap in the context of unfriending. We first plan to replicate the existing findings regarding the direct positive influence of social norms on unfriending intention (Verswijvel et al., 2019). The dependent variable was selected due to its robust association with actual behaviors as demonstrated in meta-analyses (i.e., a correlation coefficient of .82 after accounting for sampling and measurement errors, as per M.-S. Kim & Hunter, 1993), and to circumvent potential validity issues when observing the behavior experimentally. Following that, we will investigate whether the normative influence is indeed stronger in a dense network compared to a sparse one. In this study, the emphasis is specifically on descriptive norms, mainly because perceived descriptive norms are generally more susceptible to change in experiments with limited exposure to normative messages than injunctive norms are (Lapinski et al., 2013). Similarly, subjective norms were also deemed difficult to experimentally manipulate, as those perceptions involved participants' significant others' expectations. Considering these, the following hypotheses were proposed:

H1: Perceived descriptive norms will positively influence unfriending intention.

H2: The relationship between perceived descriptive norms and unfriending intention will be moderated by network density; specifically, the influence of perceived descriptive norms on unfriending intention will be stronger in a dense network than in a sparse one.

Table 1. *Demographic Information of the Study Sample Including Number* (N) *and Percentage* (%) *of Participants Representing Each Category*

		N	%
Gender			
	Male	35	19.0
	Female	148	81.0
Race			
	White	139	76.0
	Black/African American	15	8.2
	Asian	20	10.9
	Hispanic/Latino	4	2.2
	Other	5	2.7
Class standing			
	Freshman	31	16.9
	Sophomore	53	29.0
	Junior	45	24.6
	Senior	54	29.5

METHOD

Overview

This research employed a 2 (descriptive norms condition: high vs. low) × 2 (density condition: high vs. low) between-subjects online experiment. High-descriptive norms refer to the greater prevalence of unfriending a target person on social media, whereas low-descriptive norms mean the lesser prevalence of the same behavior. High-density networks (i.e., dense networks) refer to the greater interconnectedness among friends on social media, while low-density networks (i.e., sparse networks) indicate lower interconnectedness among them. A hypothetical scenario was used to induce experimental manipulations. The dependent variable of the study was participants' intention to unfriend the target person online.

Participants

In total, 220 college students signed up for the study from two different research participant pools at Michigan State University (MSU), and 200 of them participated in the study. Study participants received either $2 Amazon Gift Cards or class credits as compensation depending on the pools they used to sign up for the study. After removing 17 unusable cases (i.e., participants under the age of 18 and instances of duplicate participation), the data collected from 183 participants were used in the subsequent analyses. The sample was predominantly White (76%) and female (81%), with ages ranging from 18 to 29 (M = 20.42, SD = 1.69). The demographic characteristics of the study sample are presented in Table 1. There was no statistically significant difference in the dependent variable between the participants from the two pools or across the demographics.

Procedure

The experiment was listed and advertised on the university's research participation pools as a "Social Media Attitudes Study." Participants accessed an online experiment, and only participants who reviewed a consent form (which was presented on the first page of the experiment) and agreed to proceed were able to participate in the subsequent experiment and answer the survey questions.

Participants were randomly assigned into one of the four experimental conditions. They were first asked to provide their race and gender in the beginning of the experiment. This demographic information was used to match the hypothetical target person's race (i.e., White, Black/African American, Asian, Hispanic/Latino, or other) and gender (i.e., male, female, or other). For participants who identified their race or gender as 'other,' we presented a randomly selected avatar that corresponded to either their race or gender, depending on which was indicated. If participants selected 'other' for both categories, we randomly assigned one of the eight avatars. This matching mechanism aimed to enhance the experimental design's rigor by leveraging the tendency of individuals to prefer interacting with others online who share similar demographic characteristics (Al-Natour et al., 2005, 2011; Benbasat et al., 2020), and minimizing potential biases related to demographic features.

The hypothetical scenario was provided with visual stimuli using avatars (see Appendices A and B). Following the experimental treatments, participants were asked to complete the survey questions. The questionnaire first measured the outcome variable of the study (i.e., intention to unfriend) then the variables for induction checks (i.e., perceived descriptive norms and perceived network density). Next, the survey measured a potential covariate (i.e., attitude toward the target person's behavior), followed by other demographic variables (i.e., age, gender, and class standing). Upon completion of the survey, participants were thanked, debriefed regarding the purpose of the study. The experimental procedure and survey questionnaire were reviewed and exempted from the Institutional Review Board at MSU (#STUDY00000384).

The Hypothetical Scenario

The hypothetical unfriending scenario was developed for this study based on previous literature (Faucher et al., 2014; Gilbert & Karahalios, 2009; Holfeld, 2014; Schacter et al., 2016; Sibona, 2014). Participants were first asked to imagine a hypothetical social media friend (e.g., Sarah for White female participants) who was not particularly close to them. Then they learned that they and the friend originally had 32 mutual friends, and the relationships between the participants and these mutual friends were closer than with the friend. The extent to which these mutual friends were also friends with one another on social media was described but varied based on participants' network density conditions. Following that, a context behind the unfriending situation was given: The target friend recently has left some mean and rude comments on others' posts on social media quite often. Finally, based on participants' descriptive norms condition, either the greater or lesser prevalence of unfriending him/her among those mutual friends was presented.

Network Density Inductions

In the high-density condition, a highly interconnected network was described. For example: "29 of your 32 mutual friends with Sarah are also friends with each other on social media. In other words, about 91% of your mutual friends with Sarah are also friends with one another online." On the other hand, in the low-density condition, a sparsely interconnected network was illustrated: "6 of your 32 mutual friends with Sarah are also friends with each other on social media. In other words, about 18% of your mutual friends with Sarah are also friends with one another online." After this message, a brief question was presented to reinforce these experimental inductions and encourage participants to focus on the stimuli: "Approximately what percentage of your mutual friends with Sarah are also friends with each other on social media? 1. More than 90%; 2. Less than 20%."

Descriptive Norms Inductions

Consistent with the conceptual definition of descriptive norms (Park & Smith, 2007), high-descriptive norms messages showed a greater prevalence of unfriending in the participants' friends on social media: "You recently found out that a majority of your mutual friends with Sarah on social media have unfriended her. The number of your mutual friends with Sarah dropped from 32 to only 2 friends. In other words, about 94% of your mutual friends with Sarah have now unfriended Sarah." On the contrary, low-descriptive norms messages illustrated a lower prevalence of the behavior in the same network: "You recently found that a few of your mutual friends with Sarah on social media have unfriended her. The number of your mutual friends with Sarah dropped from 32 to 30. In other words, about 6% of your mutual friends with Sarah have now unfriended Sarah." Again, after each message, a brief question was presented: "Approximately what percentage of your mutual friends with Sarah have now unfriended Sarah? 1. More than 90%; 2. Less than 10%."

Measurement

Most of the items used in this study were drawn from prior research, with revisions made to the wording to fit the current study context. These items were selected for their demonstrated reliability and validity in previous studies, thus ensuring the robustness of the measures employed. The study variables, unless otherwise specified, were measured on a 5-point Likert-type scale (1 = *Strongly disagree*, 5 = *Strongly agree*) in which higher scores indicated greater agreement with the statement or higher levels of the variable.

Confirmatory factor analyses (CFA) using the *lessR* package in R (Gerbing, 2014) were performed for the scales that contained at least four items. The internal consistency and parallelism theorems were employed to generate predicted correlations between all items of the same latent variable (Hunter & Gerbing, 1982). These predicted correlations were then subtracted from their respective obtained correlations to produce the errors/residuals (Boster, 2023). The adequacy of the measurement models was assessed by the following two criteria: ample factor loadings and small residuals. In line with previous literature, factor loadings greater than .51 were considered large, and RMSE (i.e., root mean squared error) less than .05 were considered small (Boster et al., 2011; Gerbing, 2014; Grayson-Sneed et al., 2016). When the data did not meet the criteria, items that had the weakest factor loadings or produced the largest errors of fit were removed from each measure until the data were consistent with the measurement model. When the data were consistent with the unidimensional measurement model, the items were summed and averaged to form indices. The full correlation matrix of the study variables is reported in Table 2, and the retained items and their respective factor loadings are included in Appendix C.

Key Variables

Intention to unfriend (Cronbach's $\alpha = .92$, $M = 3.31$, $SD = 0.57$) was measured by four items (Park & Smith, 2007). For example, "I intend to unfriend Sarah" and "I will keep my online friendship with Sarah (reverse coded)."

Perceived descriptive norms (Cronbach's $\alpha = .94$, $M = 3.52$, $SD = 1.20$) were measured by four items (Lapinski et al., 2014; Park & Smith, 2007). Sample items include, "I think most of the mutual friends I originally had with Sarah on social media have now unfriended Sarah," and "I think the majority of the mutual friends I originally had with Sarah on social media have now unfriended Sarah."

Table 2. *Correlation Matrix of the Main Variables*

		1	2	3	4	5
1	Intention to unfriend					
2	Perceived descriptive norms	$.37^{***}$				
3	Perceived network density	$.19^{*}$	$.27^{***}$			
4	Attitude toward the target's behavior	$-.33^{***}$	$-.19^{*}$	$-.17^{*}$		
5	Age	.08	–.02	$-.15^{*}$	–.11	
6	Gender	–.11	–.06	$-.22^{**}$	$.18^{*}$	.04

Note. Gender: 0 = Female, 1 = Male. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Perceived network density (Cronbach's α = .87, *M* = 3.63, *SD* = 0.88) was measured by five items specifically designed for the current research, based on the conceptual definition of network density (Coleman, 1988, 1990). For instance, "I think the mutual friends I originally had with Sarah online are highly interconnected with each other," and "A majority of the mutual friends I originally had with Sarah online are connected to each other."

Covariate

Attitude toward the behavior of the target person online (Cronbach's α = .91, *M* = 1.45, *SD* = 0.58) was measured by four bi-polar items adapted from the source likability scale (Roskos-Ewoldsen et al., 2002), such as "*Negative – Positive*," and "*Unfavorable – Favorable*." Each item was measured on a 5-point scale, in which higher scores indicate more positive attitude.

RESULTS

Manipulation Checks

A one-tailed independent samples t-test was conducted to investigate the effectiveness of the descriptive norms induction on perceived descriptive norms. The data showed a significant difference between conditions, $t(181) = 12.94$, $p < .001$, Cohen's $d = 1.91$. Participants in the high descriptive norms condition, on average, reported greater prevalence perceptions of unfriending ($M = 4.31$, $SD = 0.71$) than those in the low descriptive norms condition ($M = 2.66$, $SD = 1.00$). Hence, the descriptive norms induction was considered successful.

Another one-tailed independent samples t-test was performed to examine the effects of the network density induction on perceived network density, revealing a significant difference between conditions, $t(181) = 4.33$, $p < .001$, Cohen's $d = 0.64$. On average, participants in the dense network condition perceived greater network density ($M = 3.91$, $SD = 0.92$) than did participants in the sparse network condition ($M = 3.37$, $SD = 0.86$). Thus, the network density induction was also considered effective.

Hypotheses Testing

To test the study hypotheses, a two-way analysis of covariance (ANCOVA) was performed with the intention to unfriend as the dependent variable. Descriptive norms conditions and network density conditions (and their interaction term) were the independent variables. The attitude toward the target person's online behavior, participants' age, and gender were included in the analysis as covariates. The ANCOVA results are summarized in Table 3.

Hypothesis 1 predicted that perceived descriptive norms would positively influence unfriending intention. The data showed a significant main effect for descriptive norms

Table 3. *Two-Way Analysis of Covariance Results Using Intention to Unfriend as the Dependent Variable: The Independent Variables are Descriptive Norms Conditions (High vs. Low Descriptive Norms) and Density Conditions (High vs. Low Density)*

	Partial SS	*df*	*MS*	*F*	*p*	Partial η^2
Model	10.74	6	1.79	6.50	< .001	.18
Descriptive norms conditions (a)	2.00	1	2.00	7.26	.008	.04
Density conditions (b)	0.55	1	0.55	2.00	.159	.01
(a) × (b)	1.37	1	1.37	4.96	.027	.03
Attituded toward the target's behavior	5.71	1	5.71	20.75	< .001	.11
Age	0.05	1	0.05	0.19	.661	< .01
Gender	0.16	1	0.16	0.59	.442	< .01
Residual	48.47	176	0.28			

Note. R^2 = .18, Adjusted R^2 = .15. Gender: 0 = Female, 1 = Male.

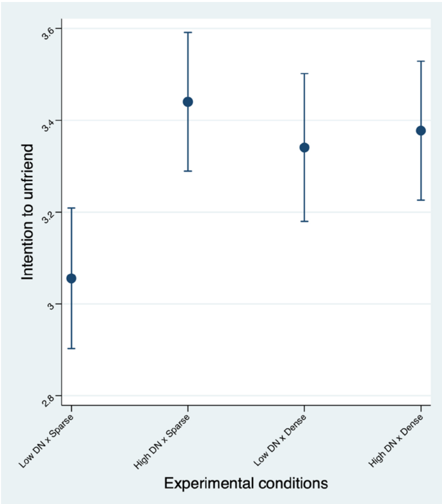
conditions, $F(1, 176) = 7.26$, $p = .008$, partial $\eta^2 = .04$. Participants who were exposed to high descriptive norms messages reported significantly greater intention to unfriend the target victim (adjusted $M = 3.41$, $SE = 0.05$) than did those who were exposed to low descriptive norms messages (Adjusted $M = 3.19$, $SE = 0.06$). Thus, the data were considered consistent with H1.

Hypotheses 2 predicted that the effect of perceived descriptive norms on the intention to unfriend would be moderated by network density, such that the normative influence would be stronger in a dense than sparse network. The data yielded a significant interaction effect between descriptive norms conditions and network density conditions, $F(1, 176) = 4.96$, $p = .027$, partial $\eta^2 = .03$. Simple effects analysis investigating the interaction pattern showed that the normative influence on behavior was stronger in a sparse than a dense network. In the sparse network condition, participants who were exposed to high descriptive norms messages reported significantly greater intent to unfriend ($M = 3.47$, $SD = 0.52$, adjusted $M = 3.44$, $SE = 0.08$) compared to those who were exposed to low descriptive norms messages ($M = 3.07$, $SD = 0.63$, adjusted $M = 3.06$, $SE = 0.08$), $F(1, 176) = 12.40$, $p < .001$, partial $\eta^2 = .07$. However, in the dense network condition, there was no significant effect of descriptive norms on behavior, although those who were exposed to high descriptive norms messages reported greater behavioral intention ($M = 3.37$, $SD = 0.49$, adjusted $M = 3.38$, $SE = 0.08$) than did those who were exposed to low descriptive norms messages ($M = 3.29$, $SD = 0.56$, adjusted $M = 3.34$, $SE = 0.08$), $F(1, 176) = 0.11$, $p = .743$. Despite the significant interaction effect, the data were considered inconsistent with H2 because of the unexpected interaction pattern (see Figure 1 for interaction plot).

DISCUSSION

Social norms are posited to exert a more substantial influence on a group's behavior when the individuals within are densely interconnected rather than sparsely connected. Although this interplay between social norms and network density is a recurrent theme in social network literature, direct empirical evidence to support it is scarce. This study addressed this gap by empirically examining the interaction effect in the context of unfriending behaviors. The findings revealed that the perceived prevalence of unfriending within a person's social network

Figure 1. *Adjusted Group Means by Experimental Conditions.*



Note. DN = Descriptive Norms. Error bars indicate the 95% confidence interval of each mean.

positively influenced their intention to unfriend. Additionally, a significant interaction between social norms and network density was observed, with normative influences on the intention to unfriend being stronger in sparse networks than in dense ones. These findings illuminate the critical role that an individual's perception of normative behaviors and the structure of their online network play in shaping their decision to unfriend, as well as the importance of empirical testing of theory. In subsequent sections, the results and their implications for both social norms and network literature will be discussed.

The perceived prevalence of unfriending a particular individual among one's social network members has been found to significantly shape one's own intention to unfriend the person. This supports theories asserting the direct impact of social norms on both behaviors and behavioral intentions (e.g., Rimal & Yilma, 2021) and aligns with findings from Verswijvel et al. (2019), which show a positive association between subjective norms favoring unfriending and the intention to unfriend. Such insights make a valuable addition to the body of research on unfriending, which has rarely examined the normative factors shaping this behavior. While the exposure to inappropriate content has been frequently identified as a primary motivator for unfriending (Sibona, 2014; Verswijvel et al., 2018), the influence of social norms on such decisions remains under-explored. As norms are fundamentally people's perceptions of what is normal and acceptable (Lapinski & Rimal, 2005), further research is imperative for a more nuanced understanding of the dynamics governing the dissolution of online connections.

The influence of prevalence perceptions on behavioral intention was also contextual (Chung & Rimal, 2016). Specifically, we found that the impact of perceived descriptive norms on unfriending intention varied depending on the interconnectivity among a person's group members. Social network literature has long argued that such normative influence is likely to be stronger in a network where people are densely connected rather than sparsely connected with each other (e.g., Coleman, 1988). However, we discovered that the effect of norms on behavioral intention was more potent in a sparse network rather than a dense one. This inconsistent interaction pattern with our prediction is both intriguing and served as the driving force behind this study. Frequently, studies rely on the empirical validity of theories without direct evidence or without identifying the boundary conditions that may apply to a given theory (Kraimer et al., 2023; Walther, 2009). While further evidence is required to draw a proper conclusion regarding the interaction between social norms and network density, the unexpected pattern can be attributed to at least the following three reasons.

First, even low-prevalent behavior in a dense network can strongly drive normative conformity if people within the network expect the behavior to become highly prevalent in the future. Recent literature on dynamic norms (e.g., M. Chung & Lapinski, 2023) elucidates this point: Behavior that is currently gaining traction but remains unpopular leads people to expect that it will become popular in the future, motivating them to engage in the behavior now. Although trending information was not presented in the current study, we cannot exclude the possibility that participants expected most of their highly interconnected mutual friends would soon unfriend the target. This expectation becomes particularly plausible when considering that a high-density network offers ample opportunities for communication, which can, in turn, foster behavioral contagion among network members (e.g., through social learning; Monge & Contractor, 2003). The intricate relationship between network density, normative perceptions, and behavioral trends requires further examination and could redefine our understanding of how social norms operate within highly interconnected networks.

Second, the density argument might apply more to injunctive norms than to descriptive norms. One of the key theoretical mechanisms of the density effect is that high-density networks enable members to monitor each other's behavior and collectively sanction non-normative, deviant actions (e.g., Coleman, 1988, 1990). The motivation to avoid social penalties is considered a driver for injunctive norms (Cialdini et al., 1990) rather than for descriptive norms. Although social network literature has not made clear distinctions between different types of social norms, it is reasonable to expect that the collective monitoring and sanctioning mechanism of the density effect would be more pertinent to injunctive norms. Given that our insights emphasize the need for a nuanced understanding of the relationship between norms and network density, we suggest that future research exploring this interaction should consider focusing on injunctive norms.

Third, normative influences on behavior may be more pronounced in sparsely connected networks than in densely connected ones, particularly when individuals perceive those in their sparse networks as distinct from themselves. Arguably, sparse networks are likely to be more heterogeneous than dense networks, driven by infrequent interactions and notable disconnections among network members (Valente, 2010). Observing a diverse array of people engaging in a specific behavior within such networks can provide compelling social proof, affirming the behavior's effectiveness in a given situation and its perceived universal benefits. This concept may be reflected in the findings of Rimal et al.'s (2005) study, where college students reported a greater belief in their ability to consistently practice yoga upon learning that the most common yoga practitioners were pregnant women, rather than their fellow college students. This argument may seem at odds with social norm theories, which posit that perceived similarity with a reference group enhances normative conformity (e.g., Rimal & Real, 2005). Nonetheless, the literature on the impact of perceived similarity with a reference group on normative influence is in fact inconsistent (Carcioppolo & Jensen, 2012; Carcioppolo et al., 2017; Rimal, 2008). This underscores the need for further research to delve into these complexities and to refine our understanding of the interplay between social norms and network density.

Limitations

The unique findings of the present study must be considered in the context of several limitations. First, the gender distribution within our sample was predominantly female, representing 81% of participants. This disproportion should be acknowledged when extending our findings to the general population. Nevertheless, gender has been reported as neither a significant predictor of unfriending decisions (Barnidge et al., 2022; Kim et al., 2022) nor a significant moderator in the relationship between social norms and behavior, including behavioral intentions (Rhodes et al., 2020), in extant literature. Furthermore, this research was fundamentally concerned with examining theoretical constructs, with a primary focus on internal rather than external validity. However, it is recommended that subsequent research expanding upon this study should ensure a more balanced gender distribution to strengthen the generalizability of the findings.

Second, while this study's online experiment with a hypothetical scenario ensured controlled manipulation of key variables for robust analysis, it may have limitations in external validity. For instance, the race-gender matching, although intended to bolster the design's rigor by reflecting individuals' tendencies online to engage with demographically similar others, might not fully represent the diversity encountered in real-world social media dynamics. Thus, questions remain about how social norms and network density interact with each other in pre-established real-world networks, where social dynamics among diverse group members have evolved over time (e.g., Lapinski et al., 2017). A fruitful approach for future research would be to base investigations on unobtrusive behavioral data collected from multiple pre-existing online networks with varying levels of network density (e.g., Jang et al., 2015), to further explore this area.

Conclusion

The social norms literature suggests that perceived norms lead to normative conformity, and the relationship between norms and behavior can often be contextual. In social network literature, it has been theorized that normative influence is stronger in networks where people are more densely interconnected than in those that are sparsely connected. This experimental study explored this relationship in the context of unfriending intention. The findings revealed that perceived descriptive norms did influence behavioral intention, and intriguingly, the normative influence was stronger in a sparse network rather than a dense one. These results underscore the influence of social norms on the decision to unfriend and highlight the necessity of empirical testing of theoretical propositions. They also emphasize the importance of further research to investigate the complex interplay between norms and network density in various contexts.

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Appendix A

The Hypothetical Scenario

Instruction

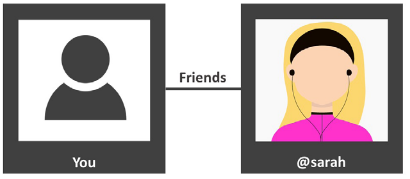
Please read the following story, then respond to the subsequent questions. The people you will read about are hypothetical. The subsequent questions are about your opinion of the situation described in the story (not the real world) unless otherwise specified.

Again, the data for this study are being collected anonymously. Therefore, neither the researchers nor anyone else will be able to link the data to you.

We appreciate your honest responses to the questions in the survey.

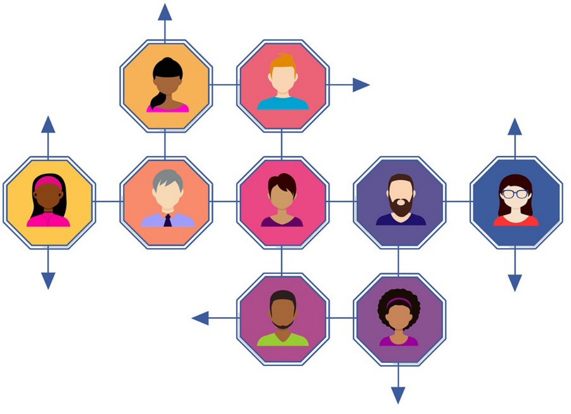
Background – Relationship strength with Sarah

Imagine that you and Sarah have been friends on social media since you first met her in person. You and Sarah have not frequently communicated with each other online, and you do not feel particularly close to her. On social media, you have previously sent her birthday wishes and she liked your posts and left a comment, "Thank you!" She also posted happy birthday posts on your last birthday, and you liked her posts.



Background – Relationship strength with mutual friends

You and Sarah have 32 mutual friends on social media. You and these mutual friends have frequently communicated with each other online and you feel close to them. You and these friends have been frequently exchanging intimate posts/direct messages (e.g., discussing private and personal matters), and usually like and leave comments on each other's posts.



Friends 32 Mutual

High Density Manipulation

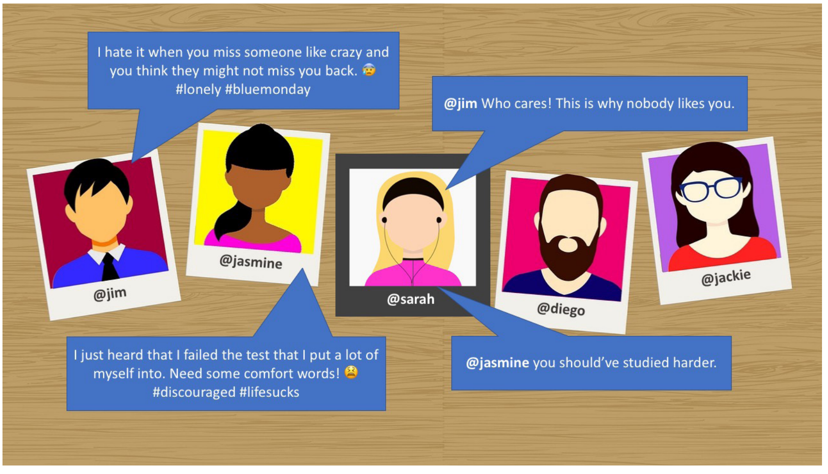
29 of your 32 mutual friends with Sarah are also friends with each other on social media. In other words, about 91% of your mutual friends with Sarah are also friends with one another online.
Approximately what percentage of your mutual friends with Sarah are also friends with each other on social media?
1. More than 90%
2. Less than 20%

Low Density Manipulation

6 of your 32 mutual friends with Sarah are also friends with each other on social media. In other words, about 18% of your mutual friends with Sarah are also friends with one another online.
Approximately what percentage of your mutual friends with Sarah are also friends with each other on social media?
1. More than 90%
2. Less than 20%

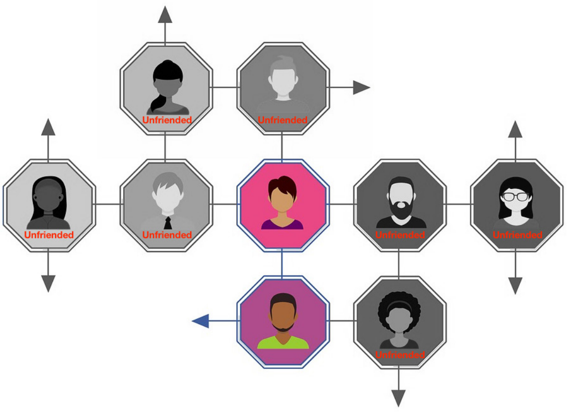
Context

You have just noticed that Sarah has left mean and hurtful comments on others' posts on social media. She has quite often behaved like this online. Below are examples of her comments.



High Descriptive Norms Manipulation

You recently found out that a majority of your mutual friends with Sarah on social media have unfriended her. The number of your mutual friends with Sarah dropped from 32 to only 2 friends. In other words, about 94% of your mutual friends with Sarah have now unfriended Sarah.

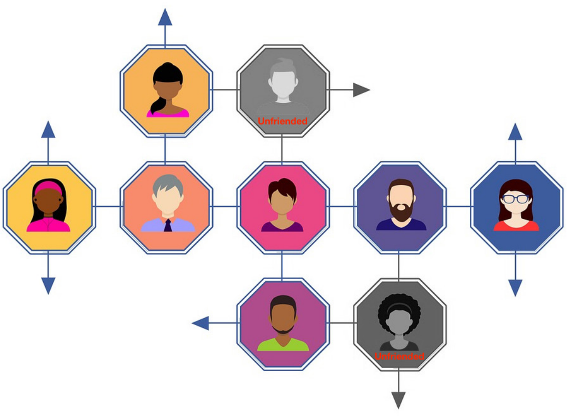


Friends 32 Mutual → **Friends** 2 Mutual

Approximately what percentage of your mutual friends with Sarah have now unfriended Sarah?
1. More than 90%
2. Less than 10%

Low Descriptive Norms Manipulation

You recently found that a few of your mutual friends with Sarah on social media have unfriended her. The number of your mutual friends with Sarah dropped from 32 to 30. In other words, about 6% of your mutual friends with Sarah have now unfriended Sarah.



Friends 32 Mutual → **Friends** 30 Mutual

Approximately what percentage of your mutual friends with Sarah have now unfriended Sarah?
1. More than 90%
2. Less than 10%

Appendix B

The Avatars Used for Matching Participants' Race and Gender

Note: The same avatar was utilized for both Asian and Latino/Hispanic male participants, due to the limited availability of racially diverse avatars and the neutral characteristics of the chosen avatar.

Appendix C

Retained Measurement Items and Factor Loadings

Item	Factor loading
Intention to Unfriend	
- I intend to unfriend Sarah.	.90
- I mean to disconnect my friendship on social media with Sarah.	.85
- I will keep my online friendship with Sarah.** (reverse code)	.80
- I will unfriend Sarah.	.90
Perceived Descriptive Norms	
- I think most of the mutual friends I originally had with Sarah on social media have now unfriended Sarah.	.95
- I think the majority of the mutual friends I originally had with Sarah on social media have now unfriended Sarah.	.94
- I think the majority of the mutual friends I originally had with Sarah on social media have now discontinued their friendship with Sarah.	.85
- I think it is quite prevalent among the mutual friends I originally had with Sarah online to have now unfriended Sarah.	.84
Perceived Network Density	
- I think the mutual friends I originally had with Sarah online are highly interconnected with each other.	.83
- I think it is possible for the mutual friends I originally had with Sarah to talk to each other directly on social media.	.54
- A majority of the mutual friends I originally had with Sarah online are connected to each other.	.86
- The mutual friends I originally had with Sarah on social media are mostly interconnected.	.86
- Most of the mutual friends I originally had with Sarah on social media can see each other's friends-only content.	.69
Attitude toward the Target Person's Behavior Online	
Based on the situation you just read, I think the way Sarah acts on social media is	
- Negative – Positive	.88
- Unfavorable – Favorable	.88
- Unlikable – Likable	.87
- Bad – Good	.78