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## BLATANT BENEVOLENCE AND SOCIAL CAPITAL ATTAINMENT ON SOCIAL NETWORK SITES – A MULTI-METHOD APPROACH

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BLATANT BENEVOLENCE AND SOCIAL CAPITAL ATTAINMENT ON SOCIAL  
NETWORK SITES – A MULTI-METHOD APPROACH

BY

JIAYUAN ZHANG

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DOCTOR OF PHILOSOPHY DISSERTATION  
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2021

## ABSTRACT

While information systems literature includes multiple studies on knowledge contribution or sharing, blatant benevolence in general has received less attention. To extend the knowledge of the blatant benevolence concept, this dissertation analyzes the blatant benevolence – social capital link on social network sites based on three different studies.

The first study implements an interview method to explore antecedents, forms, and consequences of blatant benevolence. More importantly, it also explores the moderators that change the relationship between blatant benevolence and social capital attainment on social network sites. After conducting 126 interviews with social media users, we find that five most common online blatant benevolence forms are: donation behavior, volunteering behavior, participating at a soup kitchen, paying forward for a customer behind, and attending a mission trip. We identify several moderators, such as frequency of the posts, others vs. self-posting the prosocial behavior etc., which could impact the relationship between blatant benevolence and social capital attainment.

The second study implements a 2x2x2 online experiment to empirically test the (i) relationship between blatant benevolence and social capital attainment on social network sites, (ii) moderating effect of frequency of the prosocial post, and (iii) others vs. self-posting the prosocial behavior. We find that blatant benevolence increases relational social capital and structural social capital. We also find that the frequency of the prosocial post increases the effect of blatant benevolence on relational social capital and cognitive social capital. Others posting the prosocial behavior, rather than self-post, increases the effect of blatant benevolence on relational and structural social capital.

The third study relies on observational Twitter data to empirically test the main effect - relationship between blatant benevolence and social capital attainment - to validate

the findings of the second study. We randomly identify 100,000 Twitter users from Twitter and download their personal profile within a certain period. From the 100,000 Twitter users, we identify users who posted prosocial contents within that period and labelled them as prosocial group. We then apply a propensity score matching to identify similar Twitter users as our control group. Applying the dynamic panel analysis, we compare the growth rate of the followers between the prosocial group and the control group by controlling the individual differences. Our results show that the prosocial group has gained more followers than the non-prosocial group - hence providing additional support to the significance of the main effect: blatant benevolence – social capital link.

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## PREFACE

Please note that this dissertation is organized in manuscript format with chapters. The first chapter discusses the introduction. The second chapter discusses the theoretical background. The third chapter discusses the interview study. The fourth chapter discusses the online experiment. The fifth chapter discusses the observational study on Twitter. The sixth chapter provides the general discussion of the results, while the seventh chapter concludes the dissertation and provides future research directions. The whole dissertation will be submitted to a business or management journal as one individual manuscript.

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**MANUSCRIPT PUBLICATION STATUS**

**BLATANT BENEVOLENCE AND SOCIAL CAPITAL ATTAINMENT ON  
SOCIAL NETWORK SITES (SNSS): A MULTI-METHOD APPROACH**

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The manuscript is under preparation to be submitted to Management Science

## CHAPTER 1 - INTRODUCTION

While charity organizations (COs) find it necessary to raise awareness of prosocial behaviors including donating or volunteering, they need to spend money on advertising campaigns to raise awareness for the causes. A rough estimate of annual nonprofit sector marketing spending puts it at \$7.6 billion (Pallotta, 2009), occupying a large cost proportion. Are there any ways to help COs raise awareness of the causes in a cost-saving way? Social network sites (SNSs), which spread information fast and reach a large audience, are an alternative option for COs. As of 2019 and 2020, the average daily social media usage of internet users worldwide amounted to 145 minutes per day, up from 142 minutes in the previous year<sup>1</sup>. Indeed, COs are turning to SNSs to promote prosocial behaviors. However, it still costs to advertise prosocial behaviors on SNSs. Overall, a nonprofit that generated online revenue of 1\$ million spent an average of \$40,00 on branding<sup>2</sup>. With the need for COs to use SNSs to promote prosocial behaviors, COs can turn to SNSs users for help to distribute and promote prosocial behavior.

People stay on SNSs to socialize and connect with others (Levina and Arriaga, 2014). The relationship people build with others on SNSs may increase their influence, reputation, or power online. They also can receive tangible or intangible resources from the relationship they have with others. Some studies discuss the potential benefits of social capital. When viewed from a macro-perspective, social capital is beneficial to higher level units, such as societies or communities (Adler & Kwon, 2002). Viewed from a micro-perspective, social capital is beneficial to an individual person. For example, empirical research has linked social capital to many positives, such as improved mental and physical

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<sup>1</sup> <https://www.statista.com/statistics/433871/daily-social-media-usage-worldwide>

<sup>2</sup> [https://www.thenonproffitimes.com/npt\\_articles/1-digital-donors-cost-charities-4%C2%A2](https://www.thenonproffitimes.com/npt_articles/1-digital-donors-cost-charities-4%C2%A2)

health, economic well-being, etc. (Bargh & McKenna, 2004; Helliwell & Putnam, 2004). As major platforms for people to connect with others, SNSs are also suitable for people to create and maintain social capital (Ellison, Steinfield, and Lampe, 2007). People value social capital online because of the potential benefits. Helping SNSs users to increase social capital in the nonprofit advertising campaign has not been studied before in the literature. Research on convincing SNSs users to promote prosocial behaviors for COs by social capital attainment is also scarce. If a link between promoting prosocial behavior and social capital attainment is established, there is a win-win situation for COs and social media users, with the COs utilizing the social media users to raise the awareness of the cause and the social media users increasing their social capital.

Therefore, if finding empirical evidence on such a relationship, we can claim that SNSs users benefit from sharing their prosocial behavior with the public. They can expand their networks while promoting prosocial behaviors on SNSs. Non-profit organizations can benefit from such evidence since they can encourage donors to share more of their prosocial activities. It is costly for nonprofits to acquire new donors, and they spend an average of \$67 on advertisements to acquire a donor on SNSs (Mansfield, 2019). With the increasing frequency and magnitude of disasters in the 21st century (Özpolat et al., 2015), motivating donors to spread the word online and reach out to new donors is becoming more important for humanitarian organizations to raise resources. By having more donors post prosocial events online, humanitarian organizations can save a large amount of money on SNSs ads.

In the literature, posting prosocial behavior to let others know can be referred to as blatant benevolence. Blatant benevolence is defined as a type of prosocial behavior that is (i) costly in terms of time and effort, (ii) useful for publicizing one's prosocial nature, but

(iii) not necessarily efficient at providing aid to those in need (Griskevicius et al., 2007, p87). Previous studies have investigated blatant benevolence in an offline setting and find that blatant benevolence leads to status attainment (Hardy and Van Vugt, 2006; Van Vugt and Hardy, 2010; McAndrew and Perilloux, 2012). However, these findings may not be generalizable to SNSs, where users sometimes connect with random users on virtual platforms and may not know each other offline.

This paper intends to establish the linkage between blatant benevolence and social capital attainment on SNSs. We interviewed people on their perception of blatant benevolence and then developed an online experiment to test the relationship. We then validated the main effect through a real SNSs platform – Twitter. We found the main positive effect of blatant benevolence and that both moderators positively impact the relationship.

This paper contributes to the literature in the following. First, we investigated a new antecedent of social capital attainment online. Studies in the past focus more on the consequences of social capital. However, there are limited studies that investigate the antecedents of social capital on SNSs. In this paper, we provided empirical evidence on one of the antecedents of social capital on SNSs – blatant benevolence. Second, we identified and test two moderating variables – post frequency and other post – between blatant benevolence and social capital attainment. Our interview and experimental results confirmed the importance of these two moderators and the online experiment study results provide empirical evidence on their effectiveness.

The rest of the paper is structured as follows: First, we discuss the theoretical background of the study and introduce our hypotheses. We then introduce our exploratory

study in study one and use findings from this study to design the studies in the following two studies. We triangulate the results by the second study – online experiment and the third study – an observational study. A general discussion is provided after the three studies. At the end, theoretical implications, managerial implications, and limitations are discussed.



## **CHAPTER 2 - THEORETICAL BACKGROUND**

### **Blatant Benevolence**

Prosocial behavior covers a broad scope (Batson and Powell, 2003). However, according to Bierhoff (2002), any paid helping, comforting, sharing, and cooperating behaviors cannot be considered prosocial behavior. For example, when we go to the convenience store and ask for help, the helping behavior from the salesperson is not considered as prosocial behavior because the staff is paid to help us. Only when the helping, sharing, and cooperating behavior are not in the paid form, they are classified as prosocial behavior (Bierhoff, 2002). Prosocial behavior that is solely motivated by empathy is defined as altruistic behavior (Batson and Powell, 2003; Bierhoff, 2002). In addition to empathy, prosocial behavior can be stimulated by social norms, egoism, reciprocity principles, and warm-glow. These prosocial behaviors initiated by motivations other than empathy are considered egoistically motivated prosocial behavior (Batson et al., 1981).

While empathy is a motivation, benevolence is a goodwill or trait to do good. According to Mayer, Davie, and Schoorman (1995), benevolence is the extent to which a trustee is believed to want to do good to the trustor, aside from an egocentric profit motive. Hwang (1999) provides a description of the benevolence, which is the characteristic attribute of personhood. Benevolence also refers to the pattern in which both the donor and the recipient gain from the behavior (Ferguson, Farrell, and Lawrence 2008). Although benevolence is a goodwill people perform to others, blatant benevolence here refers to a type of prosocial behavior that can be observed by others. More specifically, blatant benevolence is used to refer to those prosocial behaviors as long as they are conspicuously shown to others. There are studies that have been done on blatant benevolence and its

beneficial impact on the individual (Griskevicius et al., 2007; Van Vugt and Hardy, 2010; McAndrew and Perilloux, 2012; Van Vugt and Iredale, 2013; Savary and Goldsmith, 2020). In this study, we follow Griskevicius et al. (2007), and Van Vugt and Hardy (2010) to refer blatant benevolence to any observable prosocial behaviors on SNSs. Blatant benevolence signals one's prosocial nature to others.

### **Prosocial behavior and social capital online**

Cox et al. (2019) find that online volunteering associates significantly and negatively with offline self-rated social capital levels, whereas offline volunteering associates significantly and positively with levels of online self-rated social capital levels. Different from Cox et al. (2019), we specifically focus on the effect of sharing prosocial behavior on the social capital attainment, which is measured from others' perspective instead of self-rated social capital levels. In addition, we study the moderators that modify the effect of posting prosocial behavior on social capital attainment. Alsharo et al. (2017) find that knowledge sharing positively influences trust and collaboration among virtual team members. O'Mahony and Ferraro (2007) discuss that knowledge contribution behavior is associated with leadership in open-source projects. Faraj et al. (2015) find that structural social capital is related to online leadership and Chen et al. (2012) provide evidence on the positive effect of structural capital on knowledge contribution. Chiu et al. (2006) show that social interaction ties, reciprocity, and identification increased individual's quantity of knowledge sharing. Dholakia et al. (2009) link the social benefit perceptions to self-reports of helping oneself and helping others. Kosonen et al. (2013) show that trust in the hosting company has a significant effect on knowledge sharing intentions, while collaborative norms do not. Nambisan and Baron (2007; 2009) posit that customers' interactions

influence their participation in value co-creation within a community. Porter and Donthu (2008) show that trust results in customers' willingness to share information. Wiertz and De Ruyter (2007) validate the impact of relational social capital on knowledge contribution within commercial online communities. Yan et al. (2019) show that bi-directional relationships between social capital and knowledge contribution. Even though previous studies have focused on relationship between social capital and prosocial behaviors, the current study is totally different from the perspectives of the past studies. First, the prosocial behaviors considered in the previous studies are mainly knowledge contribution within a community. For example, one of the purposes of developing such community is to let users help solve problems for others. Users on such community platforms will have more intimate feelings towards each other than on SNSs. Second, instead of focusing on the antecedents of social capital, most of these studies examine the effect of social capital on knowledge contribution. Third, knowledge contribution or a prosocial behavior within a community provide benefits to the members within the community, while we focus on people's behavior of posting the prosocial behavior, which is not directly beneficial to the members within the online community. We mainly focus on the effect of the blatancy of prosocial behavior on social capital attainment. Table 1 below summarizes the studies

Table 1 Summary of literature

Study	Relationship between social capital and prosocial behavior	Prosocial behavior	Focus on blatancy	Moderating factors on social capital attainment	Platform(s)	Social capital
Our work	Effect of showing prosocial behaviors on social capital attainment	General prosocial behaviors	Yes	Yes	Social network sites (SNSs)	Structural, relational, cognitive social capital
Cox et al., 2019	Relationship between social capital and online/offline philanthropy	Donating and volunteering	No	No	Online communities	Bring and bonding
Alsharo et al., 2017	Effect of knowledge sharing on trust	Knowledge sharing	No	No	Virtual teams	Trust
Faraj et al., 2015	Effect of knowledge sharing and of structural social capital on leadership	Knowledge sharing	No	No	Online communities	Structural social capital
O'Mahony and Ferraro, 2007	Effect of technical contribution on leadership	Technical Contribution	No	No	Online communities	Status
Chen et al., 2012	Effect of structural social capital on knowledge contribution	Knowledge contribution	No	No	Online users communities (OUC)	Structural social capital
Chiu et al., 2006	Effect of structural, relational, cognitive social capital on knowledge contribution	Knowledge contribution	No	No	Online users communities (OUC)	Structural, relational, cognitive social capital
Dholakia et al., 2009	Effect of relational social capital on knowledge contribution	Knowledge contribution	No	No	Online users communities (OUC)	Relational social capital
Kosonen et al., 2013	Effect of relational social capital on knowledge contribution	Knowledge contribution	No	No	Online users communities (OUC)	Relational social capital
Nambisan and Baron, 2007	Effect of cognitive social capital on knowledge contribution	Knowledge contribution	No	No	Online users communities (OUC)	Cognitive social capital
Nambisan and Baron, 2009	Effect of cognitive social capital on knowledge contribution	Knowledge contribution	No	No	Online users communities (OUC)	Cognitive social capital
Porter and Donthu, 2008	Effect of relational social capital on knowledge contribution	Knowledge contribution	No	No	Online users communities (OUC)	Relational social capital

Wiertz and De Ruyter, 2007	Effect of relational social capital on knowledge contribution	Knowledge contribution	No	No	Online users communities (OUC)	Relational social capital
Yan et al., 2019	Bi-directional effect of knowledge contribution and social capital	Knowledge contribution	No	No	Online users communities (OUC)	Structural, relational, cognitive social capital

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investigating social capital and prosocial behavior and differentiations our studies from them.

Nahapiet and Ghoshal (1998) define social capital as the sum of actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit. They introduce three dimensions of social capital. The structural dimension of social capital refers to the overall pattern of connections between actors — that is whom people reach and how people reach them. The relational dimension refers to the kind of personal relationships people have developed with each other through past interactions. The cognitive dimension refers to those resources providing shared representations, interpretations, and systems of meaning among parties. Glaeser, Laibson, and Sacerdote (2002) develop a standard optimal investment model to analyze an individual's decision to accumulate social capital. They propose that there are two types of evidence on which social capital focuses: trust and organizational membership. We operationalize structural social capital on SNSs as the general pattern of connections, such as followers on Twitter (Hofer and Aubert, 2013) and network expansion (Lee and Kim, 2014). We operationalize relational social capital as the perceived trust on SNSs (Nahapiet and Ghoshal, 1998; McKnight, Choudhury, and Kacmar, 2002). We operationalize cognitive social capital as the shared perspectives on SNSs (Cummings and Dennis, 2018).

### **Signaling theory in user generated content (UCG)**

We view the impact of blatant benevolence on social capital attainment through the lens of costly-signaling theory (CST) (Grafen, 1990; Zahavi, 1975). Previous research on people's display of prosocial nature applies CST (Griskevicius et al., 2007; Hardy and Van Vugt,

2006; Van Vugt and Hardy, 2010). CST posits that certain traits and behaviors of a person, such as altruism, have a signaling function as they convey important information about the person to relevant others. Such behavior benefit the actor by increasing the likelihood that he or she will be chosen as an ally (McAndrew, 2018). The blatant benevolence on SNSs fits the criteria to be considered as a costly signal (Smith and Bird, 2000; Griskevicius et al., 2007). First, the sharing of the prosocial behavior on social media is costly in terms of energy or resources of the subject, (eg., birthday donation and ice-bracket challenge). Second, once the subject posts the prosocial behaviors on SNSs, the behaviors are highly observable to other users. Third, the behavior indicates that the subjects are willing to help others. According to CST, people publicize the prosocial behavior to signal their advantages and increase their cooperative values (Grafen, 1990; Zahavi, 1975).

CST predicts that a member will have a higher chance to be selected as an ally after he or she displays prosocial behavior to others (McAndrew, 2018). Structural social capital, defined by Nahapiet and Ghoshal (1998) as the impersonal configuration of linkages between people or units, increases with the increased chance to be selected as allies. The structural social capital reflects the overall pattern of the relationship people develop with others, and a person who displays such behavior is predicted to increase the overall pattern - structural social capital - by CST.

CST also predicts that people who contribute to the collective with considerable costs indirectly recoup the cost of the high-cost display in the form of increased social prestige or recognition within the community (Barclay, 2010; Smith and Bird, 2000; McAndrew, 2018). Publishing prosocial behavior reinforces the all-around quality of the actor, such as status and trustworthiness (McAndrew, 2018). Trustworthiness may develop

based on certain characteristics of the subjects (Cumming and Dennis, 2018; Dong, Li, and Sivakumar, 2019). The prosocial post of the subject signals the information of prosocial orientation, and when other users receive the signals, they tend to have a higher perception of trustworthiness toward the subject since benevolence is one of the factors of perceived trustworthiness (Mayer, Davie, and Schoorman, 1995). Therefore, relational social capital, which also is reflected by the quality of the actor, is predicted to be increased by the display of prosocial behavior.

Lastly, cognitive social capital refers to the resources providing shared representations, interpretations, and systems of meaning among parties (Nahapiet and Ghoshal, 1998). There are studies discussing that prosocial content leads to the subsequent prosocial thoughts (Greitemeyer, 2009; Greitemeyer, 2011; Greitemeyer and Mügge, 2014). These studies show that exposure to prosocial contents activated the accessibility of prosocial thoughts. Building on this insight, we assume that the prosocial post of the user signals the user's perspectives and thoughts, and foster observers' prosocial thoughts. The raised similarities on the mindsets decrease the communication cost, contributing to the attainment of cognitive social capital. Based on the discussions above, we propose our first hypothesis:

*H1: SNSs users increase their a) relational social capital, b) structural social capital, and c) cognitive social capital, after they post the prosocial behavior on SNSs.*



### **CHAPTER 3 INTERVIEW (STUDY 1)**

The purpose of the interview is to (i) identify the common forms of blatant benevolence and (ii) identify the moderators of the main effect. The qualitative method is more capable of identifying constructs and interactions between complex mechanisms (Zachariadis, Scott, and Barrett, 2013). In the first part of the interview, we asked participants how they view other people who share the prosocial behavior on social media from third-person perception (TPP; Davison, 1983). In the second part, we asked participants questions on posting prosocial behavior from their own perspectives (FPP; Duck & Mullin, 1995). Before the formal interview was conducted, the questionnaire was pretested with 15 participants. During the pre-testing process, the questionnaire was revised in iterative rounds until it was finalized. The questionnaire is provided in Appendix A. All the formal interviews took an average 30 minutes and were audio-recorded. To make our samples general, we interviewed a total of 126 social media users from different sources. We continued the interviews until theoretical saturation occurs (Glaser and Strauss, 1967).

#### **Analysis**

The authors first discussed the coding procedure and developed a one-page writing-up containing the operational definition of each component to code the transcripts. 30% of the transcript were randomly selected. Two graduate assistants (coder 1 and coder 2) who were blind to the purpose of the research study followed the procedure and used the one-page write-up to code the 30% randomly selected transcriptions. The first author also coded the same 30 transcripts in the meantime. The Kappa values – a measure of the inter-rater reliability- between coder 1 and coder 2 on the 30 transcripts were greater than 0.7 (Landis and Koch, 1977). Almost all the Kappa values among the three coders were greater than

0.7. The Kappa results indicated substantial interrater reliability (Landis and Koch, 1977). The first author then coded the rest of the transcripts. The analysis was conducted based on the coded illustrative quotations.

A within case study analysis was first conducted to extract keywords from the illustrative quotations. We analyzed the illustrative quotations with a recommended two-stage process of analysis (Gioia, Corley, & Hamilton, 2013; Pratt, Rockmann, & Kaufmann, 2006). Stage 1 aimed to give voice to the informants through inductive coding using participant's evocative. After the within-case analysis, 149 first-order codes were generated in the moderator variables in the FPP. 617 first-order codes were generated in the moderators in the TPP. In stage 2, a cross-case study analysis was conducted to find the themes among the first-order codes. Several iterative discussions among the authors were conducted to classify the first order coders into second order themes. Eventually, 3 second-order themes were identified in the moderator in the FPP. 8 second-order themes were identified in the moderators in the TPP. The blatant benevolence categories were calculated based on the frequency.

## **Results**

**Blatant benevolence on social media:** Two open-ended questions were asked to explore the blatant benevolence on SNSs. Because participants specifically mentioned the type of prosocial behavior, we counted the frequency of each prosocial behaviors that participants mentioned. Monetary donation, volunteering, blood donation, mission trips (etc., help rebuild houses in disaster places), volunteering at soup kitchen, animal saving, and charity events were the prosocial behaviors that were most mentioned in the interview. These prosocial behaviors also occur in previous research (Gneezy et al., 2012; Lacetera, Macis,

and Slonim, 2014; Sun, Gao, and Jin, 2019). In the TPP perspective, monetary donation, volunteering, and blood donation were the three most frequent prosocial behavior people usually see on SNSs. In the FPP, monetary donation, volunteering, and charity events were the three most frequent prosocial behavior people usually post on SNSs. The categories in both perspectives are identical while the frequency of each category is different in both perspectives. Table 2 and Table 3 below summarize the results.

Table 2. Blatant benevolence (TPP)

Main categories of blatant benevolence	Subcategories from open coding	Share of respondents, n=126(%)
Monetary donation	Monetary donation, fundraising, birthday donation, GoFundMe page, etc.	52.38
Volunteering	Volunteering, charity helping, pay for a customer behind, sharing knowledge school cleanup, etc.	31.75
Blood donation	Blood, bone marrow donation	13.49
Mission trips	Mission trip, service trip, volunteering trip	11.90
Food bank	Soup kitchen, food donation, food bank	11.11
Saving animals	Saving animals	8.73
Charity events	Charity event, charity post, Senior citizen ball, Charity race, A tally for women, Rotary club of good deed	6.35
Other	Saving environment, promote extraordinary work, internship in dangerous work, etc.	7.94

Table 3. Blatant benevolence (FPP)

Main categories of blatant benevolence	Subcategories from open coding	Share of respondents, n=89 (%)
Monetary donation	Fundraising, charitable donation, birthday donation, GoFundMe page	49.44
Volunteering	Church work, helping students to college, pay for a customer behind, sheltering homeless, volunteering, community work, etc.	35.96

Charity events	Special children program, literacy program, Women's March, Girl Scout program, Charity race, etc.	14.61
Animal saving	Saving animals, person	8.99
Mission trips	Mission trip, service trip	7.87
Material donation	Blood, book, shoes, house material, hair donation	6.74
Food bank	Soup kitchen, food drive	6.74
Other	Environmental protection, social project	13.48

We observed that monetary donation is the prosocial behavior that people usually see others post on SNSs (52.38% of respondents). 49.44% of respondents also mentioned they have posted monetary donation on SNSs. The popularity of the monetary donation is because SNSs platforms facilitate the monetary donation platforms (etc., birthday donation, GoFundMe page), which make people relatively easy to perform such prosocial behavior. Normally, monetary donation platforms also provide donors a link to post their donation on SNSs. The next category of prosocial behavior is volunteering activity. 31.75% of respondents mentioned they saw volunteering activities on SNSs, and 35.96% of respondents said they post their volunteering activities on SNSs. The rest of the prosocial behaviors share similar percentage values in both perspectives, while the order of their rank may change. We next examined the moderators that impact the relationship between blatant benevolence and the attainment of social capital.

**Moderator variables:** Investigating the moderator variables can help us better understand the conditions that change the relationship between blatant benevolence and social capital attainment. In the TPP moderator questions, we asked participants: “Under what conditions do you think a user’s social capital will increase (decrease) after he/she shared the prosocial behavior on SNSs?” Table 4 below summarizes the second-order themes and quotations of the moderator variables in the other-perspective. The IRR measured by Cohen’s Kappa

on the categories is 0.83, indicating substantial interrater reliability (Landis and Koch, 1977).

Table 4. Moderator variable (TPP)

Second-order themes	First-order code	Illustrative quotations
<b>Frequency of prosocial post</b> (122 excerpts)	<ul style="list-style-type: none"> <li>• Repetition</li> <li>• Keep on posting</li> <li>• High frequency</li> </ul>	<ul style="list-style-type: none"> <li>• Yeah, I think I would just be like, "Okay, this is the eighth time you've donated. You don't need to say it every single time you donated." It's just-- it almost gets like just repetition and repeating it over and over.</li> <li>• I think it just depends what they keep on posting, you know what I mean? If they post the same thing, for example, every time, like the same good deed every time, like people won't care, you know what I mean?</li> </ul>
<b>Other posts the prosocial behavior</b> (119 excerpts)	<ul style="list-style-type: none"> <li>• Posted by others</li> <li>• Posted by organization</li> </ul>	<ul style="list-style-type: none"> <li>• I would feel positive about that person especially if they didn't post it themselves so that they weren't giving themselves the glory but other people were saying, "Look at this person. We're very grateful and thankful." So I would feel good about that person. Yeah.</li> <li>• Honestly, it probably makes them look even better in my opinion. Because they're the type of person who does it without asking for praise or without asking for reward, right?</li> </ul>
<b>Personal relationship</b> (46 excerpts)	<ul style="list-style-type: none"> <li>• Know the person depends on the relationship with the person</li> </ul>	<ul style="list-style-type: none"> <li>• Well, if you like the person, to begin with, you're a close friend, and they post this, and it's a great deed that they're doing, like mission work or whatever. Your perception of them will only go higher. And you'll go, "Wow. They're even better than I thought they were. They're doing all these great things. They're a nice person, so I think in that aspect, you will definitely go up. Yes.</li> <li>• If you know that person or you have the same opinions. The opposite of how it would decrease.</li> </ul>
<b>Self-presentation</b> (26 excerpts)	<ul style="list-style-type: none"> <li>• Don't show off</li> <li>• They speak highly of themselves</li> </ul>	<ul style="list-style-type: none"> <li>• So it varies depending on the person. So like I said before, if this person is posting for showing off, I</li> </ul>

		<p>think that I will be able to tolerate a very low percentage.</p> <ul style="list-style-type: none"> <li>• It could just be people's perspective. They could think he's doing that because he just wants the attention.</li> </ul>
<p><b>Agree or disagree</b> (20 excerpts)</p>	<ul style="list-style-type: none"> <li>• If agree or not</li> <li>• If it's prosocial behavior for something don't believe in</li> <li>• Disagreement with the post</li> </ul>	<ul style="list-style-type: none"> <li>• If it's prosocial behavior that I agree with, then yes.</li> <li>• If it's something that I either am already interested in or something that I don't really know a lot about that their post, whatever I saw intrigued me and it's something maybe I would want to help with, I would follow them just to get more information.</li> </ul>
<p><b>Personal experience with the good deed</b> (14 excerpts)</p>	<ul style="list-style-type: none"> <li>• Something could relate to</li> <li>• Share things that have a connection</li> </ul>	<ul style="list-style-type: none"> <li>• Definitely sharing things that have a connection to that person. If they share it with something close to their heart, for example, you're supporting Alzheimer's because your grandmother died of Alzheimer's and you include that saying, "I want to raise money. I want to do this for that purpose." And then someone reads it and they feel that empathy and that, "Wow, my grandfather did too." And that connection is formed, and so people are more likely to have a positive reaction to it.</li> </ul>
<p><b>Genuine manifestation</b> (10 excerpts)</p>	<ul style="list-style-type: none"> <li>• Continue to do the same thing over and over again</li> </ul>	<p>I would say the relationship would stay the same but depending on what they do going forward, that might change. Depending if they do any more good deeds or what have you.</p> <ul style="list-style-type: none"> <li>• I know it's not always the best thing, but if I could validate, find some trust in what they did, that it was honest and whatnot, yeah, I would definitely.</li> </ul>

Participants mentioned that when they see others post their prosocial behavior frequently, they are less likely to make friends with the person posting it. This is consistent with the over-posting effect on SNSs (Pham, Shancer, and Nelson, 2019). Pham, Shancer, and Nelson (2019)'s interview results showed that over-posting can irritate followers. In our study, we also found that high frequency of prosocial behavior will irritate people

easily. The subject posting prosocial behavior also influences people's perception of blatant benevolence. Our interview results show that people generally favor prosocial post by third parties, but not the post posted by the subject performing it. In such a situation, they think it's more genuine of the subject not to post it but to be posted by others. The third moderator is the personal relationship. Some participants mentioned that if they know the person posting the prosocial behavior, they are more likely to be friends with the person. The fourth moderator is self-presentation. Approximately 21% of respondents indicated that if the prosocial post reflects boastfulness, he/she is less likely to friend that individual.

The fifth moderator is whether the participants agree or not agree (with the posted statement). Normally, if participants agree with the posts, they tend to have more positive thoughts. The sixth moderator is personal connection with the good deed. This result is consistent with Small and Simonsohn (2008)'s result that friends of patients suffering from a certain disease are more likely to donate to COs to fight such disease. Our participants mentioned they are more likely to feel close to the prosocial behavior that they have personal experience with. The last moderator is the genuine manifestation which shows that participants are more positive toward a more genuine prosocial post.

In the FPP moderator questions, we asked participants: "Under what conditions do you think your social capital will increase(decrease) after sharing your prosocial behavior on social media?" Table 5 below summarizes the second-order themes and quotations of the moderator variables in the self-perspective. The IRR measured by Cohen's Kappa on the categories is 0.90, indicating substantial interrater reliability (Landis and Koch, 1977). The results in FPP are the same as that in TPP, even we have only three moderators. Again, frequency and other post are the lead moderators in both TPP and FPP.

Table 5. Moderator variable (FPP)

Second-order themes	First-order code	Illustrative quotations
<b>Other posts the prosocial behavior</b> (82 excerpts)	<ul style="list-style-type: none"> <li>• Posted by other people</li> <li>• Posted by organization</li> </ul>	<ul style="list-style-type: none"> <li>• So, I definitely have had my mom's friends from work or people like that go to my page and friend request me. They are like, "Hi. I saw your face on your mom's page." But I think it definitely brings more people to your page.</li> <li>• You'd probably get more likes and views and shares if it was by an organization just because they're more apt to have more people subscribing or following to them than an individual would.</li> </ul>
<b>Frequency of prosocial post</b> (23 excerpts)	<ul style="list-style-type: none"> <li>• Share over and over again</li> <li>• Too repetitive or too often</li> <li>• Post every single day or something</li> </ul>	<ul style="list-style-type: none"> <li>• I would say if I posted every single day or something, it can get annoying to some people.</li> <li>• I mean if I get too repetitive or posting too often.</li> </ul>
<b>Agree or disagree</b> (12 excerpts)	<ul style="list-style-type: none"> <li>• Don't agree with</li> <li>• Does not align with other's core values</li> </ul>	<ul style="list-style-type: none"> <li>• Just if they don't agree with what I'm donating or doing.</li> <li>• I know a lot of the people I grew up with they're very different religious and political background. There's things that if I shared it, I know they wouldn't like it because they just don't agree.</li> </ul>

## Study 1 discussion

Findings from the in-depth interview provide important implications. Overall, we found that monetary donation, volunteering (charity and pay for a customer behind), blood donation, mission trips, and food banks are prosocial behaviors people normally see and post on SNSs. These findings provide a general understanding of the various forms of blatant benevolence on SNSs and evidence that blatant benevolence is common on SNSs and worth investigating. In study 2, we also utilized these forms of blatant benevolence in the design of the online experiment.

Study 1's preliminary findings are subjected to a more rigorous test in study 3 which uses actual Twitter data and a larger sample size. The moderators of the main relationship identified from the literature were also confirmed through interviews in study



1 – to be empirically tested later in study 2. The frequency of the prosocial post and other posting the prosocial behavior are the two moderators most frequently mentioned by the participants to influence the relationship between blatant benevolence and social capital attainment.

### **Frequency of blatant benevolence**

According to our interview results, high frequency of the prosocial posts is associated with negative impact. Sibona and Walczak (2011) find that respondents were more likely to dissolve an online friendship if they receive too many posts from the person. Weiser (2015) discusses that selfie-posting frequency is correlated with grandiose exhibitionism. Supporting the discussion, Moon et al. (2016) also find the same result. Their finding is also consistent with Pham, Shancer, and Nelson (2019)'s interview result that people usually get annoyed by the over-posting behavior. Further supporting the result, Schoendienst and Dang-Xuan (2011) find that increased frequency of a post plays a significant role in reducing the interaction individuals experience on Facebook. Based on our interview results, we found that when seeing too many prosocial posts from a user, people may think that the user is bragging the prosocial behavior and kindness, losing their interests to connect with the subject. Under such a condition, the impact of blatant benevolence on social capital is weakened by the high frequency of the prosocial posts. Based on the conflicting perspectives on the role of frequency, we develop the following competing hypotheses:

*H2: The impact of blatant benevolence on a) relational social capital, b) structural social capital, and c) cognitive social capital, is weaker when the frequency of the posts increases.*

### **Others posting the blatant benevolence**

Our interview results indicate that when the prosocial posts are shared by others instead of self, observers tend to have more positive feelings toward to the posts. This interview finding is also theoretically supported in the literature. Toulmin's (2003) model discusses that the strength of an argument is dependent on the inclusion of specific elements, such as claims, grounds, and warrants. Based on Toulmin's model, the claim is the central assertion of the argument; the grounds are the evidence or data; and the warrants are the principles supporting the backing of the groups to the claims (Toulmin, 2003). Individuals are able to establish the validity of their arguments through a wide variety of means (Berente et al., 2011). For example, when the prosocial post is shared by the subject, the post is only a claim made by him/her. The behavior in the post is less validated because of the lack of evidence. However, when the prosocial post is posted by others. The behavior is supported by the evidence from others. In this case, the impact of the post is strengthened by the evidence. A similar study also discusses that trust-assuring arguments with claim plus ground generate higher consumers' trusting belief than trust-assuring arguments with claim only (Kim and Benbasat, 2006). The impact of an impression on perceived social capital attainment is also stronger with data and backing support (Cummings and Dennis, 2018). We argue that the self-post content is only the claim itself, while the other-post content is the claim plus ground because it is the third party posting the content and thus supporting the claim. The impact of the contents changes when people perceive different degrees of validation of the contents. With a higher degree of validation, people will perceive more

positively toward the claim supported by the ground. Therefore, we have the following hypotheses:

*H3: The impact of blatant benevolence on a) relational social capital, b) structural social capital, and c) cognitive social capital, is stronger when it is posted by other people (tagging the owner of the prosocial behavior) than when it is shared by subjective oneself.*

## CHAPTER 4 ONLINE EXPERIMENT (STUDY 2)

In study 1, we reported preliminary evidence on the main effect and identified two factors (frequency of the prosocial post and others posting the prosocial behavior) that moderate the impact of blatant benevolence on social capital attainment. In study 2, we designed an online experiment to test the main effect and the moderating variables as well. Employing a randomized online experiment allows more direct control of the conditions of the prosocial behavior, thus helping establish causality. An online experiment with a 2 (blatant benevolence versus blatant non-benevolence)  $\times$  2 (low frequency versus high frequency)  $\times$  2 (other post versus self-post) factorial design was conducted to test the proposed hypotheses. Specially, we developed a mock-up Facebook profile of a fake person (Alex Smith). Facebook was chosen because it is the platform that 73% of the interviewees in study 1 mentioned they saw others post prosocial behavior on and over 70% of the interviewees mentioned they has posted prosocial behavior on Facebook before. Previous studies (Choi, 2006; Ellison et al., 2007; Lampe et al., 2006) argue that SNSs like Facebook are used to maintain or extend connections to existing offline relationships. We studied the function of extended connections of the Facebook users in our study. Mock-up Facebook experiment (Choi et al., 2015) and social networking profile (Cummings and Dennis, 2018) have been used in the IS literature. Studies (Frison and Eggermont, 2016; Su and Chan, 2017) find that gender impacts the perception of the Facebook profile. We choose the name Alex Smith to neutralize the gender effect. Blatant benevolence was manipulated by the post content on the profile. In the blatant benevolence condition, Alex Smith posted a

prosocial behavior (paying for a customer behind in a coffee drive-through). While in the non-blattant benevolence condition, Alex Smith posted a non-prosocial behavior (having dinner in a new restaurant). In the low frequency condition, Alex Smith posted only one prosocial behavior within a week. While in the high frequency condition, Alex Smith posted 4 different prosocial behaviors within a week. According to the fair frequency of posts on Facebook, 3 times per week is ideal<sup>3</sup>. Therefore, 5 posts (4 prosocial post and 1 baseline post) a week is considered high frequency. In the self-post condition, Alex Smith shared the post(s) himself/herself. While in the other-post condition, Alex Smith was tagged by friends, whose names were also chosen to neutralize the gender effect. Across the eight conditions, we included the same base post (non-prosocial: park visiting) to make the profile more real. When participants started the experiment, they first were required to give the consent to participate in the study. They then were randomly assigned one out of eight profiles on the computer screen, and they could only see the posts of the profile with a one-week window, meaning that participants don't have access to the historical content of the manipulated account. The Table 6 below shows the manipulation in the conditions. The profiles of the eight conditions are presented in Appendix B.

Table 6. Conditions in the 2x2x2 experimental design

	Experimental variable			
	Blatant Prosocial Behavior		Blatant Non-Prosocial Behavior	
	High Frequency	Low Frequency	High Frequency	Low Frequency
Self-post	Four different prosocial behaviors posted by Alex Smith	One prosocial behavior posted by Alex Smith	Four non-prosocial behaviors posted by Alex Smith	One non-prosocial behavior posted by Alex Smith
Other post	Four different prosocial behaviors posted by 4 friends of Alex Smith	One prosocial behavior posted by a friend of Alex Smith	Four non-prosocial behaviors posted by 4 friends of Alex Smith	One non-prosocial behavior posted

<sup>3</sup> <https://louisem.com/144557/often-post-social-media>

				by a friend of Alex Smith
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### **Pilot studies**

A pilot study with 150 online participants from an online crowdsourcing website was conducted prior to the main experiment to determine the experimental stimulus. Subjects were randomly assigned to 1 of the 15 behaviors posted on social media (seven prosocial behaviors and eight non-prosocial behaviors). We used the common prosocial behaviors from the interview results: Mission trip, Pay for a customer behind (Pay forward), Soup kitchen, Volunteering to the cancer society, Beach clean-up, Money donation, and Blood donation. The eight non-prosocial behaviors under consideration are the behaviors people usually see on social media: Movie, Car show, Restaurant, Travel, Concert, Music festival, County firework events, and Park visiting (Fu, Wu, and Cho, 2017; Morry, Sucharyna, and Petty, 2018; Pham, Shancer, and Nelson, 2019; Kelly, Keaten, and Millette, 2020). Subjects were asked to rate how prosocial the behavior they saw based on a 7-point likely scale (1=no prosocial and 7=prosocial). Results show that money donation (mean, 4.22) is significantly different(lower) from the other six prosocial behaviors ( $F(6,71)=2.62, p=0.024$ ). No significant difference was found among the remaining six prosocial behaviors ( $F(5,62)=0.62, p=0.68$ ). No significant difference was found among the eight non-prosocial behaviors ( $F(7,71)=0.48, p=0.846$ ). Except Money donation, there was a significant statistical difference in prosocial ranking between the six prosocial behaviors and the eight non-prosocial behaviors ( $F(13, 134)=20.134, p=0.00$ ). Participants gave the restaurant post the lowest prosocial score (mean, 2.07). Therefore, we selected going to the restaurant in the non-prosocial behavior low frequency groups. We selected park visiting as a base pose in all of the conditions, including non-prosocial and prosocial manipulation.

In the high frequency non-prosocial groups, we selected the five behaviors with the lowest prosocial scores - restaurant, movie, concert, travel, and go to park - as the non-prosocial behaviors (see Table 7 below). Since the participants gave Pay forward (mean,5.80) and Soup kitchen (mean, 5.83) similar prosocial scores, we enrolled additional 44 online participants to rate how often they see other people post Pay forward and Soup kitchen activities on social media on a 5-point scale (1=never and 5=always). Results showed that people see Pay forward (mean, 2.61) more often than Soup kitchen (mean, 2.11) on social media, and the results are significantly different ( $F(1,87)=4.35,p=0.04$ ). Therefore, we selected Pay forward activity as the stimulus in prosocial behavior low frequency groups. For the high frequency prosocial group, we used the four behaviors with the highest prosocial ranking- pay forward, soup kitchen, blood donation, and volunteer to the cancer society.

Table 7 Means of the Prosocial and Non-prosocial behavior

Prosocial behavior	N	Mean	SD	Non-prosocial behavior	N	Mean	SD
Soup Kitchen	12	5.83	0.83	Restaurant	14	2.07	1.07
Pay Forward	10	5.80	1.32	Go to Park	11	2.27	1.19
Blood Donation	9	5.56	0.88	Concert	10	2.30	1.64
Volunteer to Cancer Society	11	5.55	0.82	Movie	8	2.38	0.92
Beach Clean-up	10	5.50	0.85	Travel	8	2.38	1.3
Mission Trip	11	5.18	1.17	County Fireworks Event	4	2.75	1.26
Money Donation	9	4.22	1.39	Music Festival	9	2.78	1.2
				Car Show	8	2.88	1.46

Another 186 non-repeat Facebook users from an online crowdsourcing website were enrolled to check the manipulations of the experiment in the second pilot study. Using the results from this pilot-study, we refined our experimental design, and the manipulation check questions. The final experimental design is provided in Appendix B.

## **Participants**

386 participants were enrolled on Qualtrics in the study. Data was collected using participants drawn from several undergraduate and graduate courses, at a university in the northeastern United States. Participation was voluntary and the participants received course credit. The requirements to be enrolled in the study are 1) to be equal or greater than 18 years old, and 2) have a Facebook account. Each participant was randomly assigned to one of the eight treatments, and the screenshot of each treatment is attached in the appendix. The experiment was conducted on Qualtrics. The average age of the participant was 21 with 50.5 % being male. The average number of Facebook friends was 489.

## **Questionnaire and measurement**

There are three dependent variables (relational, structural, and cognitive social capital). To measure the relational social capital, we focused on trust. Identification can also be considered as a component of relational social capital (Nahapiet and Ghoshal, 1998; Cummings and Dennis, 2018). However, identification is not feasible in our research context, because it's hard to develop identification between two strangers when they know each other based on only one post. Therefore, we focused on the trust component of relational social capital. We adapted two constructs – perceived goodwill and perceived integrity from McKnight, Choudhury, and Kacmar (2002) to measure the trustworthiness on Web based settings. For structural social capital, we adapted the construct from Lee and Kim (2014) to measure the willingness of others to make connection with the subject. For cognitive social capital, we adapted construct from Cummings and Dennis (2018) and Nahapiet and Ghoshal (1998) to measure the shared meanings.



There are seven control variables we considered. Jarvenpaa and Leidner (1999) show that trust disposition impacts the perceptions of others, and Cummings and Dennis (2018) show that trust disposition impacts the perceived relational social capital. Therefore, we included trust disposition (Cummings and Dennis, 2018) as one of our control variables. SNSs usage intensity influences the formation of social capital (Cummings and Dennis, 2018). We included Facebook usage adapted from Choi et al. (2015) to control for the Facebook experience and intensity. The formation of social capital may be influenced by the self-reported sociability, so we included sociability adapted from Choi et al. (2015). Griskevicius et al. (2007) mention that blatant benevolence is impacted by gender, so we included gender as a control variable. Altruism may influence the perception of blatant benevolence and we included self-reported altruism adapted from Galizzi and Navarro-Martínez (2019) as a control variable. We also collected age, and number of Facebook friends. Details of control variables are provided in Appendix C.

## **Results**

**Manipulation Checks:** We assessed the manipulation of benevolence and non-benevolence by asking participants whether they recognized Alex posted at least a type of prosocial behavior or not. Out of 521, 68 participants recognized wrong, yielding a manipulation effectiveness rate 86.95%. We asked participants “how many posts they saw in Alex’s profile” to assess the manipulation of low frequency versus high frequency. Thirty participants recognized wrong, yielding a manipulation effectiveness rate 94.24%. The questionnaire also inquired “who created the posts on Alex” to assess the manipulation of other post versus self-post. Out of 521 participants, 56 recognize wrong, yielding a manipulation effective rate of 89.25%. The aggregate effectiveness rate on the three

manipulation questions is 74.08%, which is consistent with other studies (Abbey and Meloy, 2017). Eventually, we obtained a final sample size of 386 in our study.

**Randomization:** We utilized the Qualtrics randomization technique to randomly assign the participants into 8 conditions. The MANOVA results reported no significant differences (Wilk’s  $\lambda = 0.845$ ,  $F=0.952$ ,  $p=0.577$ ) among the conditions with respect to the control variables of age, gender, number of Facebook friends, sociability ( $\alpha = 0.77$ ) (Choi et al., 2015); trust disposition ( $\alpha = 0.79$ ) (Cummings and Dennis, 2018), self-reported altruism ( $\alpha = 0.83$ ) (Galizzi and Navarro-Martínez, 2019), and Facebook Usage (Facebook familiarity & Facebook intensity) ( $\alpha = 0.83$ ) (Choi et al., 2015), indicating the success of randomization. Table 8 below shows the number of participants in each condition.

Table 8. Number of participants in each condition

	Blatant Benevolence		Blatant Non-Benevolence	
	Low	High	Low	High
Other-post	52	45	45	45
Self-post	57	51	45	46

The correlation matrix shows that the correlations between control variables and dependent variables are below 0.3 (Bagozzi, Yi, and Phillips, 1991), suggesting common method bias is not an issue here (see Table 9 below). Table 10 shows the descriptive statistics of the measures.

Table 9. Correlation matrix

	RSC	SSC	CSC	FU	AL	TD	S	G	Age	#FBF
RSC										
SSC	.600**									
CSC	.466**	.508**								
FU	.161**	.154**	.030							
AL	.080	.050	-.050	.050						
TD	.146**	.121*	.140**	.160**	-.020					
S	.040	.090	.020	.125*	.070	.188**				
Gender	.132**	.188**	-.050	.219**	.070	.145**	.000			

Age	-.050	-.060	.000	.050	.243**	.070	-.070	.080	
#FBF	-.060	-.030	-.070	.242**	.060	.040	.163**	-.090	.080

\*\* . Correlation is significant at the 0.01 level

\* . Correlation is significant at the 0.05 level

RSC= Relational Social Capital; SSC= Structural Social Capital; CSC= Cognitive Social Capital; FU= Facebook Usage; AL= Altruism; TP= Trust Propensity; S=Sociability; G=Gender; FBF=Number of Facebook friends.

Table 10. Descriptive Statistics of the Measures

Variable	N	Min	Max	Mean	SD
Relational <i>Social Capital (RSC)</i>	386	1.00	7.00	4.45	1.10
Structural Social Capital (SSC)	386	1.00	7.00	3.65	1.31
Cognitive Social Capital (CSC)	386	1.00	7.00	3.63	1.21
Sociability (S)	386	1.00	7.00	5.37	1.10
Trust Disposition (TD)	386	1.00	7.00	4.03	1.00
Altruism (AL)	386	1.00	5.00	2.61	0.48
Facebook Usage (FU)	386	1.00	7.00	5.05	1.48
Gender	384	0	1	0.51	0.50
Age	375	18	56	21.28	4.06
Number of Facebook friends (#FBF)	332	0	5000	489.75	507.97

**Confirmatory Factor Analysis:** A confirmatory factor analysis (CFA) using AMOS 26 was conducted to further validate the measures used in the model. The model was tested for both reliability of measures and model validity using the recommendation outlined by Hair et al. (1998). Because relational social capital consists of two constructs, we ran a secondary order CFA and loaded the two trust constructs on relational social capital. The measurement model suggested good fit ( $X^2(85)=312.65$ ,  $p=0.000$ , comparative fit index (CFI)=0.95, incremental fit index (IFI)=0.95, RMSEA=0.08, SRMR=0.05). All the loadings to the corresponding items are greater than 0.7 (see Table 11 below). We then tested the measurement model for its reliability, convergent validity, and discriminant validity.

Table 11. Scale and measurement properties

Scale and Factor Loadings		Standardize d Estimates
Construct (1=strongly disagree, 7=strongly agree)		
<b>Relational Social Capital</b>		
Perceived Goodwill		0.88
Perceived Integrity		0.89

<b>F1: Perceived Goodwill</b> (McKnight, Choudhury, and Kacmar, 2002).	
Alex would act in my best interest.	0.80
If I need help, I believe Alex would want to help me.	0.87
Alex would be interested in my well-being, not just his/her own.	0.90
Alex prioritizes others' needs before his/her own work.	0.80
I believe Alex would help an individual in need without expecting any rewards.	0.84
<b>F2: Perceived Integrity</b> (McKnight, Choudhury, and Kacmar, 2002).	
Alex would be truthful when dealing with me.	0.85
I would characterize Alex as honest.	0.92
Alex would keep his/her commitments.	0.81
Alex seems to be sincere and genuine.	0.84
<b>Cognitive Social Capital</b> (Cummings and Dennis, 2018)	
Alex and I would speak the same 'social media' language.	0.76
If I talk to Alex about issues on social media, we would have a common understanding of how things should be handled on social media.	0.80
<b>Structural Social Capital</b> (Lee and Kim, 2014)	
I would be willing to share my interests with Alex on social media.	0.84
I would be willing to express my feelings to Alex on social media.	0.85
I would be willing to express my thoughts to Alex on social media.	0.81
If given a chance, I would like to be friends with Alex on social media.	0.76
<b>Chi-squared &amp; Model Fit Indices</b>	
$X^2$ (df=85)	312.65
CFI	0.95
IFI	0.95
RMSEA	0.08
SRMR	0.05

Results from the analysis indicate both validity and reliability for the constructs evaluated (see table 12 below). Cronbach's  $\alpha$  values and composite reliability (CR) for all three constructs are greater than 0.7, demonstrating the reliability of the measures (Hair et al., 1998). Factor loadings for all constructs were strong and significant with composite reliability (CR) greater than the average variance extracted (AVE), which are above the recommended minimum of 0.50 suggesting convergent validity in the current model (Hair et al., 1998). To evaluate discriminant validity, the square roots of the shared variance between constructs were found to be greater than the correlation across constructs, providing evidence of the discriminant validity (Hair et al., 1998). Additionally, maximum

shared squared variance (MSV) and average shared variance (ASV) were all less than the AVE further suggesting the discriminant validity.

Table 12. Construct Validity, Correlation, and Descriptive Statistics

	M	SD	CR <sup>1</sup>	$\alpha$	AVE	MSV	ASV	Correlation Matrix <sup>2</sup>		
								RSC	SSC	CSC
RSC <sup>3</sup>	4.45	1.1	0.87	0.94	0.78	0.47	0.41	0.88		
SSC	3.65	1.31	0.89	0.89	0.67	0.47	0.42	0.68	0.82	
CSC	3.63	1.21	0.76	0.75	0.61	0.37	0.36	0.59	0.61	0.78

Note: 1. CR=composite reliability. 2. Square root of the average variance shared are across diagonal with off diagonal elements being correlations between constructs. Diagonal elements should be larger than off-diagonal elements for discriminate validity. 3.

RSC= Relational Social Capital; SSC= Structural Social Capital; CSC= Cognitive Social Capital

**ANCOVAs of individual and joint effects:** We first conducted MANCOVA on the three dimensions of social capital using the SPSS26. Results showed that the blatant benevolence was significant (Wilk's  $\lambda = 0.75$ ,  $F=41.15$ ,  $p<0.000$ ), the interaction effect between blatant benevolence and frequency was significant (Wilk's  $\lambda = 0.98$ ,  $F=2.93$ ,  $p=0.03$ ), the interaction effect between blatant benevolence and other post was significant (Wilk's  $\lambda = 0.98$ ,  $F=3.18$   $p=0.24$ ). We then conducted univariate ANCOVAs to test the main effect and interaction effects of blatant benevolence, frequency and other post on each of the three dimensions of social capital. Table 13 summarizes the results of the ANCOVAs.

Table 13. Summary of ANCOVA results ( $F$  statistics)

	Dependent Variables		
	Relational Social Capital	Structural Social Capital	Cognitive Social Capital
<b>Independent variables</b>			
Blatant Benevolence	109.76***	12.98***	3.78 <sup>M</sup>
Blatant Benevolence x Frequency	5.46*	3.99*	7.17**
Blatant Benevolence x Other post	8.55**	4.93*	4.65*
Frequency	0.71	1.18	1.30
Other post	11.08**	6.43*	18.39***
Frequency x Other post	0.11	0.03	1.35
Blatant Benevolence x Frequency x Other post	0.31	4.87	7.19**
<i>F-value</i>	18.86***	4.42***	6.04***

Note: \*\*\* $p < .001$ ; \*\* $p < .01$ ; \* $p < .05$ ; <sup>M</sup> $p < .1$

We report the full factorial ANCOVAs model and report relationships not formally hypothesized.

Regarding the individual effect of blatant benevolence on social capital, we found that blatant benevolence significantly influences relational social capital ( $F_{blatantb_R} = 109.76, p < .001$ ) and structural social capital ( $F_{blatantb_S} = 12.98, p < .001$ ), in support of H1a and H1b. However, we found that blatant benevolence did not significantly influence cognitive social capital ( $F_{blatantb_C} = 3.78, p < .1$ ), but its effect is on the marginal significance level. H1c is not supported. Mean comparisons, as shown in Table 14, Panel A, are consistent with what we expected. Compared with blatant non-benevolence, blatant benevolence showed higher relational social capital ( $Relational_{bb} = 4.94, Relational_{bnb} = 3.92, p < .001$ , by approximate 14.43% out of 7 scale points) and structural social capital ( $Structural_{bb} = 3.89, Structural_{bnb} = 3.42, p < .01$ , by approximate 6.57% out of 7 scale points). Blatant benevolence showed higher cognitive social capital, even the difference is only marginally significant ( $Cognitive_{bb} = 3.75, Cognitive_{bnb} = 3.52, p < .01$ ).

Table 14. Main Comparisons of the ANCOVAs

A. Mean comparisons of the Main Effects of Blatant Benevolence on Social Capital						
		Blatant Benevolence				
		Blatant Benevolence		Blatant Non-Benevolence		
Relational Social Capital		4.94***		3.92***		
Structural Social Capital		3.89***		3.42***		
Cognitive Social Capital		3.75		3.52		

B. Mean Comparisons of the Moderating Effect of Frequency						
		Relational Social Capital		Structural Social Capital		Cognitive Social Capital
		Blatant Benevolence	Blatant Non-Benevolence	Blatant Benevolence	Blatant Non-Benevolence	Blatant Non-Benevolence
Low Frequency		4.79	4.00	3.68	3.48	3.66
						3.75

High Frequency	5.10	3.85	4.09	3.36	3.85	3.30
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C. Mean Comparisons of the Moderating Effect of Other pose						
	Relational Social Capital		Structural Social Capital		Cognitive Social Capital	
	Blatant Benevolence	Blatant Non-Benevolence	Blatant Benevolence	Blatant Non-Benevolence	Blatant Benevolence	Blatant Non-Benevolence
Self-post	3.94	3.90	3.58	3.40	3.37	3.40
Other-post	5.25	4.63	4.19	3.44	4.14	3.65

Note: Main comparisons are significantly different across the two conditions with the same subscript: <sup>a</sup> $p < .001$ ; <sup>b</sup> $p < .01$ ; <sup>c</sup> $p < .05$ ; <sup>M</sup> $p < .1$

We further examined the two-way interactions between blatant benevolence and frequency. The interaction effects are significant on relational social capital ( $F_{blatantb \times frequency_R} = 5.46, p < .05$ ), structural social capital ( $F_{blatantb \times frequency_S} = 3.99, p < .05$ ), and cognitive social capital ( $F_{blatantb \times frequency_C} = 7.2, p < .01$ ). All the dimensions of social capital increased under the high frequency condition: relational social capital ( $Relational_{bb-low} = 4.79, Relational_{bb-high} = 5.10$ ), structural social capital ( $Structural_{bb-low} = 3.68, Structural_{bb-high} = 4.09$ ), and cognitive social capital ( $Cognitive_{bb-low} = 3.66, Cognitive_{bb-high} = 3.85$ ). Therefore, H2a, H2b, and H2c are not supported.

We further examined the two-way interactions between the blatant benevolence and other post. The interaction effects are significant on relational social capital ( $F_{blatantb \times other_R} = 8.55, p < .01$ ), structural social capital ( $F_{blatantb \times other_S} = 4.93, p < .05$ ), and cognitive social capital ( $F_{blatantb \times other_C} = 4.65, p < .05$ ). Mean comparisons of the moderating effect show that other-post does increase the impact of blatant benevolence on the attainment of relational social capital ( $Relational_{bb-other} =$

5.25,  $Relational_{bnb-self} = 3.94, p < .001$ ), structural social capital ( $Structural_{bb-other} = 4.19, Structural_{bnb-self} = 3.58, p < .001$ ), and on the attainment of cognitive social capital ( $Structural_{bb-other} = 4.14, Structural_{bnb-self} = 3.37, p < .001$ ). Therefore, our H3a, H3b, and H3c are supported.

### **Replication study in China**

To increase the generalizability of the study, we also enrolled 302 respondents from China. In the Chinese experiment, we used the Weibo platform, which is a blog sharing platform similar with Facebook, to replace Facebook, whose usage is blocked in China. We slightly modified the U.S. design to fit Chinese design but kept the 8 conditions similar to the U.S. 8 conditions. All the measurement items were first translated in Chinese by two native Chinese speakers. The Chinese translation was then back translated into English and compared with the original English questionnaire. After several round of iterations, the Chinese questionnaire was finalized. We utilized a similar sampling approach in China and used Sojump, one of the most prominent crowdsourcing companies for online surveys in China (Dong, Li, and Sivakumar, 2019). A total of 416 undergraduate students from a southern city of China were enrolled. The aggregate effectiveness rate on the three manipulation questions is 72.59%, which is consistent with the aggregate effectiveness rate in the U.S. sample. The final number of usable data is 302. We utilized the randomization technique on Sojump to randomly assign the participants into 8 conditions. The MANOVA results reported no significant differences (Wilk's  $\lambda = 0.842, F=1.026, p=0.424$ ) on the control variables (trust propensity, facebook usage, altruism, age, gender, number of Weibo friends, and sociability), indicating the success of the randomization. The CFA results also show edthe satisfactory model fit and factor loadings (see Appendix C for CFA results).



After checking for the CFA results, we went ahead to analyze the differences among the dimensions.

We first conducted MANCOVA on the three dimensions of social capital using the SPSS26. Results showed that the blatant benevolence was significant (Wilk's  $\lambda = 0.82$ ,  $F=21.39$ ,  $p<0.000$ ), the interaction effect between blatant benevolence and frequency was significant (Wilk's  $\lambda = 0.97$ ,  $F=2.72$ ,  $p<0.05$ ), and the interaction effect between blatant benevolence and other post was not significant (Wilk's  $\lambda = 0.99$ ,  $F=0.90$ ,  $p=0.44$ ). We then conducted univariate ANCOVAs test on the main effect and interaction effects on each individual dimension of social capital. See Appendix for the MANCOVA and ANCOVAs results.

Consistent with the U.S. results, we found that blatant benevolence significantly influences relational social capital ( $F_{blatantb_R} = 54.54$ ,  $p < .000$ ) and structural social capital ( $F_{blatantb_S} = 6.52$ ,  $p < .05$ ), in support of H1a and H1b. We found that blatant benevolence did not significantly influence cognitive social capital ( $F_{blatantb_C} = 0.10$ ,  $p < .754$ ) in Chinese sample. We further examined the two-way interactions between blatant benevolence and frequency. The interaction effects are significant on structural social capital ( $F_{blatantb \times frequency_S} = 5.57$ ,  $p < .05$ ) and cognitive social capital ( $F_{blatantb \times frequency_C} = 6.18$ ,  $p < .05$ ), but not significant on relational social capital ( $F_{blatantb \times frequency_R} = 1.86$ ,  $p > .05$ ). Structural social capital ( $Relational_{bb-low} = 4.69$ ,  $Relational_{bb-high} = 4.82$ ) and cognitive social capital ( $Cognitive_{bb-low} = 4.23$ ,  $Cognitive_{bb-high} = 4.40$ ) increased under the high frequency of blatant benevolence condition. Regarding the interaction effect of the blatant benevolence and other post, we did not find any significant results among the three dimensions.

## **Study 2 discussion**

The results from the randomized online experiment show that blatant benevolence increases three dimensions of social capital in the U.S. samples, and relational and structural social capital in Chinese samples. While the frequency positively moderates the effect of blatant benevolence on social capital attainment on three dimensions in the U.S. sample, we found it only significant in structural and cognitive social capital in the Chinese sample. While we found that the moderating effects of other post are significant among the three dimensions in the U.S. sample, we did not find any support from the Chinese samples. The consistent results from both samples showed that blatant benevolence increases relational and structural social capital, and frequency positively moderated the effect of blatant benevolence on structural and cognitive social capital.

Our findings show differences between culture. In the U.S. sample, blatant benevolence leads to the increase of three dimensions of social capital on Facebook setting. U.S. users would want to connect, trust, and exchange opinions with people who display their prosocial nature. However, Chinese users may want to connect and trust. The insignificant finding of the effect of cognitive social capital can be due to Chinese SNSs users usually don't use SNSs as a platform to find common understanding and opinions exchange with others (Ji et al., 2010).

The positive moderating effect of frequency is significant on three dimensions of social capital in the U.S. sample, but only significant on the structural and cognitive dimensions in the Chinese sample. To our surprise, such positive moderating effect is opposite to our prediction, which assumes a negative moderating effect. The results show that when frequency increases, people have more positive opinions toward the posts. It

shows that high frequency of the prosocial post instead brings positive feeling toward SNSs users.

The moderating effect of the others' post is consistent with our hypothesis. The U.S. results show that when the prosocial behavior is posted by others instead of the subject, it increased the three dimensions of social capital. This is consistent with the previous study (Cummings and Dennis, 2018), and shows that ground strengthens the argument of the content in the claim. However, we could not find such significant moderating effect in Chinese sample. One of the potential reasons is that it's rare to post another person's prosocial behavior on SNSs in China. It's not a common post and when the respondents view it, and they feel it unusual. Therefore, the positively moderating effect of other post is supported only by the U.S. sample.

## CHAPTER 5 OBSERVATIONAL STUDY (STUDY 3)

### Design

Study 2 provided preliminary evidence that people are willing to connect, trust, and share opinions with a person who shares the prosocial post online. The finding motivated us to go further to use actual SNS data to test this main effect. Investigating on Twitter platform, we collected public Twitter users' profile data and Tweets to empirically examine the relationship between blatant benevolence and social capital attainment. We selected Twitter as the SNS to test this relationship because humanitarian organizations make use of Twitter for fundraising and to engage donors and potential donors (Schmidt, 2019).

Hofer and Aubert (2013, p2137) discuss that “being followed on Twitter can create a sense of groupness by providing a sense that one is writing for an exclusive supportive audience.” They establish the linkage between the perceived social capital and the number of followers. In the Twitter setting, we operationalized the number of followers as a proxy for social capital, since followers also increase the subject's status and influence. Investigating the growth of followers in the humanitarian settings, Yoo, Rabinovich, and Gu (2020) value the importance of the number of followers on Twitter. Twitter charges an average \$3 for each new follower acquired through follower campaigns. Given the importance of gaining social capital on Twitter, we selected this platform as our focus.

We collected our data through Twitter official API and Twint, a Python library for advanced Twitter scraping (Zacharias & Poldi, 2018). Twint has been widely used for Twitter data collection recently (Bonsón, Perea, Bednárová, 2019; Shao et al., 2019; Freelon and Lokot, 2020). We collected 4,451,647 Tweets from 100,000 randomly selected Twitter users in 9 periods ( 4-30-2020 , 5-07-2020, 5-13-2020, 5-22-2020, 5-26-2020, 6-07-2020, 6-14-2020, 6-26-2020, and 7-05-2020). Keywords, for example “donate”,

“volunteer”, etc., were used to filter the 4,451,647 Tweets and this procedure yields 3,777 unique Tweets for further analysis. We then read through these 3,777 Tweets and coded the Tweets into prosocial and non-prosocial Tweets. At the end of the coding procedure, we identified 118 unique Tweets that are related to prosocial behavior. Examples of prosocial Tweets are provided in Table 15.

Table 15. Examples of prosocial Tweets

Prosocial Tweets
<i>“I just donated a special premature nappy to a UK hospital by tweeting #PampersForPremies - show your support and do the same! “</i>
<i>“Please can people donate to baby lives fundraiser. I have already donated. This poor child”</i>
<i>“What kind of volunteering you do. I volunteer in Charlotte to help the homeless”</i>

### **Dynamic panel analysis**

Given the 118 unique Tweets, we identified the 118 unique public Twitter users who posted these Tweets and downloaded their personal information. These users are public users whose personal information are available to everyone on Twitter. These users are classified into the prosocial treatment group. We created a dummy variable to indicate when a user changes from not posting the prosocial behavior to the prosocial behavior. Since we have 118 users and a time panel in 9 periods, a dynamic panel analysis is suitable here to investigate the effects. Hinz, Spann, and Hann (2015) mention that without a complete set of observable and unobservable user characteristics, it is always possible that omitted variables bias the coefficients. In the dynamic panel model, we swept out the individual unobservable user characteristics by differencing the equations and estimate the coefficients from both models. The dynamic panel analysis considers the lagged dependent variable(s) in the estimation which considers the effect from previous dependent variable (Arellano, 2003). Since following has been shown to affect the attainment of followers (Ye et al., 2012), we included number of following in the model. We also included the number

of likes to control the popularity of the users. *Following* is a continuous variable, which measures the number of following each Twitter user has. *Likes* is a continuous variable, which measures the total number of likes each user receives. Since the variables are skewed, we used the log form of the variables in the equation. A dynamic linear panel data model can be represented as follows (Arellano, 2003) :

$$\text{Log}(\text{Followers}_{it}) = \beta_1 + \rho \text{Log}(\text{Followers}_{i,t-1}) + \beta_2 \text{Treatment}_t + \beta_3 \text{log}(\text{Following}_{it}) + \beta_4 \text{log}(\text{Likes}_{it}) + \mu_i + \epsilon_{it} \quad (1)$$

The main idea behind the difference estimator is to sweep out the individual effect via differencing. Differencing the equation (1) yields:

$$\Delta \text{Log}(\text{Followers}_{it}) = \beta_1 + \rho \Delta \text{Log}(\text{Followers}_{i,t-1}) + \beta_2 \Delta \text{Treatment}_t + \beta_3 \Delta \text{log}(\text{Following}_{it}) + \beta_4 \Delta \text{log}(\text{Likes}_{it}) + \Delta \epsilon_{it} \quad (2)$$

We used Gretl<sup>4</sup> software to estimate the coefficients of the variables. The results of the models are shown in table 16 below.

Table 16. Dynamic panel analysis

<i>DV: Log_followers</i>	Model without time dummy	Model with time dummy
$\Delta \text{Treatment}$	0.009* (0.003)	0.008** (0.003)
$\Delta \text{Log}(\text{Followers}_{i,t-1})$	-0.123* (0.067)	-0.040 (0.066)
$\Delta \text{log}(\text{Following}_{it})$	0.009 (0.008)	0.012 (0.008)
$\Delta \text{log}(\text{Likes}_{it})$	-0.005 (0.006)	-0.006 (0.007)
<i>Period Controls</i>	No	Yes
Constant	-0.002* (0.001)	0.012 (0.003)
$R^2$	0.41	0.38
Number of Twitter users	117	117
Number of observations	584	584

Note. Standard errors in parentheses.

\*\*\* $p < .001$ ; \*\* $p < .01$ ; \* $p < .05$ ; <sup>M</sup> $p < .1$

<sup>4</sup> <http://gretl.sourceforge.net/>

The results show that Twitter users have a higher growth rate of followers after they post the prosocial Tweets. On average, the growth rate of followers increases 0.9% after posting the prosocial Tweets compared with that before posting the prosocial Tweets. After we included the time dummy variables, the effect changes from 0.9% to 0.8% but still remains significant ( $\beta = 0.008, p < 0.01$ ). Our results show that posting the prosocial Tweets lead to increased growth rate of the follower's attainment.

### **Robustness check**

In the dynamic panel analysis, we focused on the within subject analysis. We also checked for the cross-subject analysis. We applied the propensity score matching (Rosenbaum and Rubin, 1983; Hinz, Spann, and Hann, 2015) to create matching pairs between the 118 Twitter users who posted the prosocial behavior and those who did not. To define the matching pairs, we estimated each user's propensity to post the prosocial Tweets, according to observable player characteristics: the initial degree of follower, the initial degree of following, the initial number of likes, the initial number of media, and the initial number of Tweets on 4-30-2020. From our list of randomly selected 100,000 Twitter users, we used Nearest neighbor matching procedure to identify 118 Twitter users who share the same characteristics but didn't post the prosocial behavior. Table 17 depicts the results of the propensity score matching, which shows that propensity to post prosocial behavior increases with the initial number of likes.

Table 17. Propensity Score Matching

Initial number of followers	1.031E-06	(8.7E-06)
Initial number of following	7.9E-06	(1.5E-05)
Initial number of likes	8.7E-06	(3.2E-06)**
Initial number of Media	4.5E-06	(1.4E-05)
Initial number of Tweets	-6.081E-07	(3.0E-06)
Intercept	-2.708	(0.136)

We then compared the initial information between the Twitter users in the prosocial group and the matched group. The MANOVA results reported no significant differences (Wilk’s  $\lambda = 0.999$ ,  $F=0.061$ ,  $p=0.998$ ) between these two groups with the variables collected at the beginning of the data collection period. Table 18 shows the descriptive statistics for the variables in two groups and table 19 shows the correlation matrix of the variables. The correlation matrix indicates no potential multicollinearity among the independent variables.

Table 18. Descriptive statistics and p-values for the variables

	Treatment	Mean	Std. Deviation	Max	Min	N	P-value
followers	Control	6335.91	18147.23	173775	6	118	0.888
	Prosocial	6630.35	13530.45	89392	24	118	
following	Control	4865.94	9108.10	63064	120	118	0.914
	Prosocial	4984.37	7738.80	55166	60	118	
likes	Control	34653.48	49731.39	313210	5	118	0.559
	Prosocial	38413.67	49074.51	251759	0	118	
media	Control	1189.97	2234.29	11900	0	118	0.705
	Prosocial	1315.11	2808.83	23300	0	118	
tweets	Control	25680.95	45919.79	316756	14	118	0.954
	Prosocial	25378.81	33622.86	189828	96	118	

Table 19. Correlation matrix

	followers	following	likes	media	tweets
followers					
following	.580**				
likes	.098**	.140**			
media	.073**	.097**	.120**		
tweets	.143**	.205**	.522**	.472**	

\*\* . Correlation is significant at the 0.01 level

\* . Correlation is significant at the 0.05 level



We created a dummy variable *Prosocial\_group*, where 1 indicates a user is in the prosocial condition and 0 indicates a user is in the control condition. We also controlled the number of following and number of likes to control the popularity of the users. To control for time trends, we included period dummies (T1 to T9) reflecting the range of the date. We ran the model with the prosocial Twitter users and their matched pairs (n=236). The coefficient of the treatment is significant ( $\beta = 0.005, p < 0.01$ ). It shows that users in the prosocial group has 0.5% higher growth rate of followers than the users in the control group. The results show that prosocial Tweets accelerate the rate of follower growth.

Table 20. Regression Results

<i>DV: <math>\Delta \text{Log\_followers}</math></i>	Model – matched (T1-T9)	Model – matched (T5-T9)
<i>Treatment</i>	0.005** (0.001)	0.01** (0.003)
$\Delta \log(\text{Following}_{it})$	0.023** (0.008)	-0.002 (0.013)
$\Delta \log(\text{Likes}_{it})$	0.027*** (0.006)	0.065*** (0.009)
<i>Period Controls</i>	Yes	Yes
Constant	0.009*** (0.002)	0.004 (0.004)
$R^2$	0.11	0.16
Number of Twitter users	236	120
Number of observations	1948	552

*Note. Standard errors in parentheses.*

\*\*\* $p < .001$ ; \*\* $p < .01$ ; \* $p < .05$ ; <sup>M</sup> $p < .1$

For another robustness check, we removed those who posted a prosocial Tweet during T1-T4 from the prosocial group, so the prosocial group only contains who posted a prosocial Tweet during T5-T9. We applied the propensity score matching again to find a new matched group and re-run the regression model on T5-T9 only. The effect of the treatment is consistent with that using T1-T9 ( $\beta = 0.01, p < 0.01$ ). For the users in the T5-T9 period, we still found that prosocial Tweet helps increase the growth rate of

followers. Therefore, we concluded that the main effect of blatant benevolence on follower attainment on Twitter is solid.

### **Study 3 discussion**

Study 3 provides empirical evidence that posting prosocial Tweets does help increase follower growth rate on Twitter. Study 3 results also validate the main effect of blatant benevolence from the second study in study 2 using actual social network data. The result is insightful for SNSs users and charity organizations. First, Twitter users have a higher increased rate on the followers after they post the prosocial Tweets. For users who want to increase followers, posting a prosocial Tweet is a good choice. The finding can also help explain why many YouTubers post donation videos on YouTubes and gains more followers. Second, Charity organizations can encourage their donors to share their prosocial behaviors on Twitter while such action increases the donors' followers. For example, when a disaster happens, charity organization can encourage their donors to post their donation behaviors on Twitter to spread the information. Such action helps increase the users' follower growth rate and helps the charity organization promote relief activities. When the donors post about the charity organization, charity organizations can also gain more followers and more followers lead to increased influence on the public as well (Yoo, Rabinovich, and Gu, 2020).

## CHAPTER 6 - GENERAL DISCUSSION

Across three studies, we identified first, that monetary donation, volunteering, blood donation, attending mission trips, and volunteering at food banks are the most common prosocial behaviors posted on SNSs. In addition, we identified two moderators that change this relationship between blatant benevolence and social capital attainment. Second, selecting the two most mentioned moderators that confirm the literature, we designed an online experiment to validate the main effect and two moderating effects with the three dimensions of social capital. We found that blatant benevolence increases structural and relational social capital. Both moderators, the high frequency of the prosocial post and the other posting the prosocial behavior, increase the positive impact of blatant benevolence on social capital attainment. Lastly, we used Twitter data to examine the relationship between the prosocial Tweets and growth rate of followers. We found that Twitter users who posted prosocial Tweets have higher growth rate of followers than the Twitter users who did not do so. In addition, we found that Twitter users have higher growth rate of followers after they post the prosocial Tweets.

Triangulating results based on three methodologies (interviews, online experiment, and observational data) and four separate datasets; we offer rigorous empirical evidence on the blatant benevolence – social capital attainment link on SNSs. This main effect is significant in two dimensions of social capital in both U.S. and China samples – structural and relational, and it is moderated by two factors – higher frequency of posts (in U.S. and China) and others’ posting the prosocial behavior (in U.S.).

## **Theoretical Contributions**

This study contributes to the literature in several ways. First, we extend the investigation of blatant benevolence to the information systems domain. Since blatant benevolence was introduced (Griskevicius et al., 2007), few studies explicitly focused on it. Griskevicius et al. (2007) define blatant benevolence as a type of prosocial behavior that is useful for publicizing the prosocial nature but not necessarily helpful to provide the aid. In our study, we argue that blatant benevolence online also includes some necessary prosocial behavior, such as monetary donation, mission trips, and food banks. Given the prevalence of these prosocial behaviors on SNSs, we expand the definition of blatant benevolence to include not only the types of inefficient prosocial behaviors but also the types of helpful and beneficial prosocial behaviors. Some of these prosocial behaviors may include altruistic behavior, especially when they are shared by others.

Second, we contribute to the social capital theory by providing the empirical evidence of a new antecedent. Social capital theory has been investigated in the IS domain (Wasko and Faraj, 2005; Chiu, Hsu, and Wang, 2006; Hinz, Spann, and Hann, 2015; Fu, Wu, and Cho, 2017; Cummings and Dennis, 2018). The relationship that social capital causes some types of prosocial behavior, such as knowledge sharing, has been established (Wasko and Faraj, 2005; Chiu, Hsu, and Wang, 2006). Different from previous studies, our study focuses on the attainment of social capital as a consequence of a specific type of prosocial behavior – blatant benevolence. By establishing the casual relationship, we contribute to the literature that a two-way relationship exists between posting prosocial behavior and social capital. While most of the previous studies focus on knowledge sharing

as a type of prosocial behavior, we include a wider range of prosocial behaviors which may not directly benefit the observers.

Third, in addition to examining the social capital attainment as a consequence of blatant benevolence, we also identify and test the moderators that change the relationship. Our studies find the positive impact of the high frequency of prosocial post and that of other posting the prosocial behavior. The two moderators pave a possibility to develop a theoretical framework between the blatant benevolence and social capital.

### **Managerial Implications**

Our results provide evidence of the prevalence of blatant benevolence on SNSs and empirical evidence of the benefit of it on SNSs. The interview, experimental study, and observational study show that blatant benevolence on SNSs benefits the subject. Contrary to people's negative perception of sharing prosocial behavior with others, our study shows the positive effect of blatant benevolence on social capital attainment. The results are insightful to SNSs users, SNSs companies, and COs.

First, we provide evidence that SNSs users can expand their connections or follower bases after posting their prosocial behavior. When SNSs users signal their prosocial nature on SNSs, they can increase their relational social capital, for example, gain more trust from observers and strengthen their relationship with others on SNSs. SNSs users can also increase their structural social capital, for example, have a higher growth rate of followers and thus make more connections on the platforms. According to Nahapiet and Ghosal (1998), potential resources are embedded in the connections. SNSs users can accumulate potential resources with the increase of social capital they have. Also, instead of paying for the network expansion campaign, SNSs users can frequently share some prosocial behavior

they did and expand their network for free while promoting charitable activities. SNSs users are also encouraged to post each other's prosocial behavior since when their prosocial behavior is shared by others, they gain more social capital.

Second, by identifying the potential benefits of blatant benevolence, we provide insights to COs that encouraging their contributors to post prosocial behavior can have a win-win result for both. This evidence provides support to the donation platforms, which will give a choice to the donors to indicate whether they want to share their donation on SNSs. Our results empirically support the benefit of such strategy. COs can also design blatant benevolence promotion programs more often. Our results also explain the fact that many COs promote prosocial behavior by tagging their donors on SNSs (e.g., Fundraisers on Facebook). This strategy can indirectly help COs advertise the campaigns and increase solicitations, while saving costs on advertisement. Our result shows that high frequency of the prosocial posts also helps. COs may encourage their potential donors to post more frequently, as long as the frequency is not exaggerated.

Lastly, we provide insights for SNSs companies on managing users' networks. Users on SNSs are valuable to SNSs. Maintaining users' loyalty is a fundamental task of the SNSs. Realizing that posting the prosocial contents can help build the users' network, SNSs can first create a culture to encourage users to share their prosocial behavior. Even though the decision to post or not to post the prosocial content is up to the users, the culture created will impact individuals' attitudes and behavior on the internet (Calhoun, Teng, and Cheon, 2002). SNSs can also develop new functions to facilitate users to perform and share their prosocial behavior (e.g., GoFundMe page). A collaboration with COs can be another way for SNSs to build the culture and increase the chance for users to behave and share

prosocial behaviors. Through these strategies, SNSs can attract new users and maintain current users.

## CHAPTER 7 - CONCLUSION

Using a multi-method design, we study the blatant benevolence - social capital link on SNSs. The first study explored the various forms of blatant benevolence on SNSs and proved its prevalence. It also found out several factors that moderate the impact of blatant benevolence on social capital attainment. We picked the two moderators that confirm the literature for investigation. In the second study, we designed a 2x2x2 experiment to investigate the causal effect and the moderating effects of frequency and other post and ran the online experiments in the US and in China. Our experimental results show that blatant benevolence leads to the attainment of relational and structural social capital, but not that of cognitive social capital. High frequency strengthens the impact of blatant benevolence on the attainment of relational and cognitive social capital. Consistent with our prediction, other post strengthens the impact of blatant benevolence on the attainment relational and structural social capital. In the third study, we applied an observational study to validate the main effect of blatant benevolence on social capital attainment on a real SNSs platform and find that prosocial Tweets increase structural social capital (higher growth rate of followers).

We admit that this study is with limitations. First, our study does not use a randomized field experiment on social media platforms to investigate the casual effect of the blatant benevolence on social capital attainment. Even though we used an online experiment and an observational study, both methods have weakness. For example, the results from the lab study cannot be generalized to other settings and the observational study cannot establish the casual relationship. These issues can be addressed by a randomized filed experiment on a real social media platform. Second, we only used student



samples in the online study and the samples are thus limited. However, we believe that students are the main users of SNSs, and they provide more reliable insights regarding SNSs research settings. Third, we tested only two moderating factors here. Future studies can investigate the moderating effects of the other moderators found from the interview.

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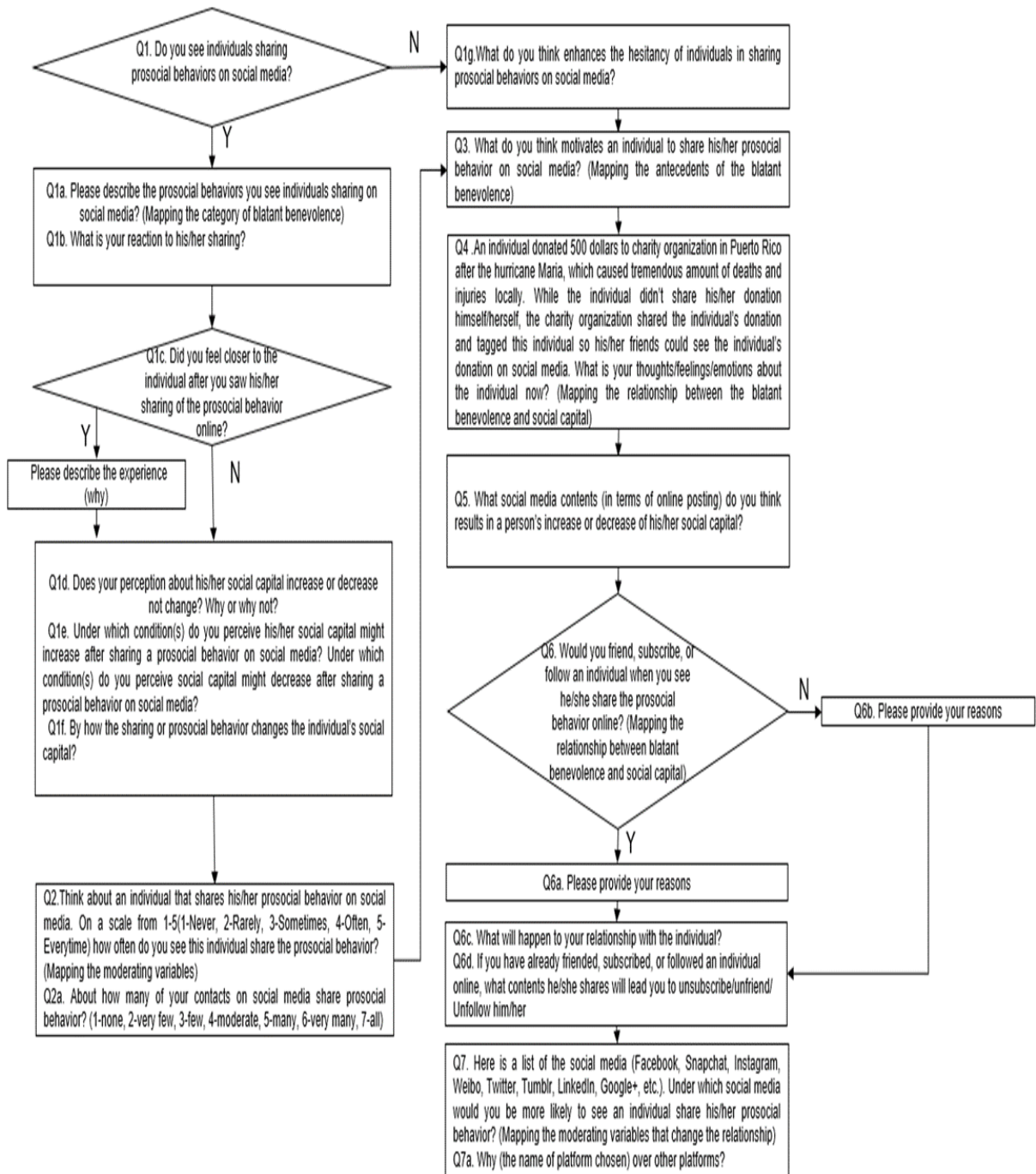
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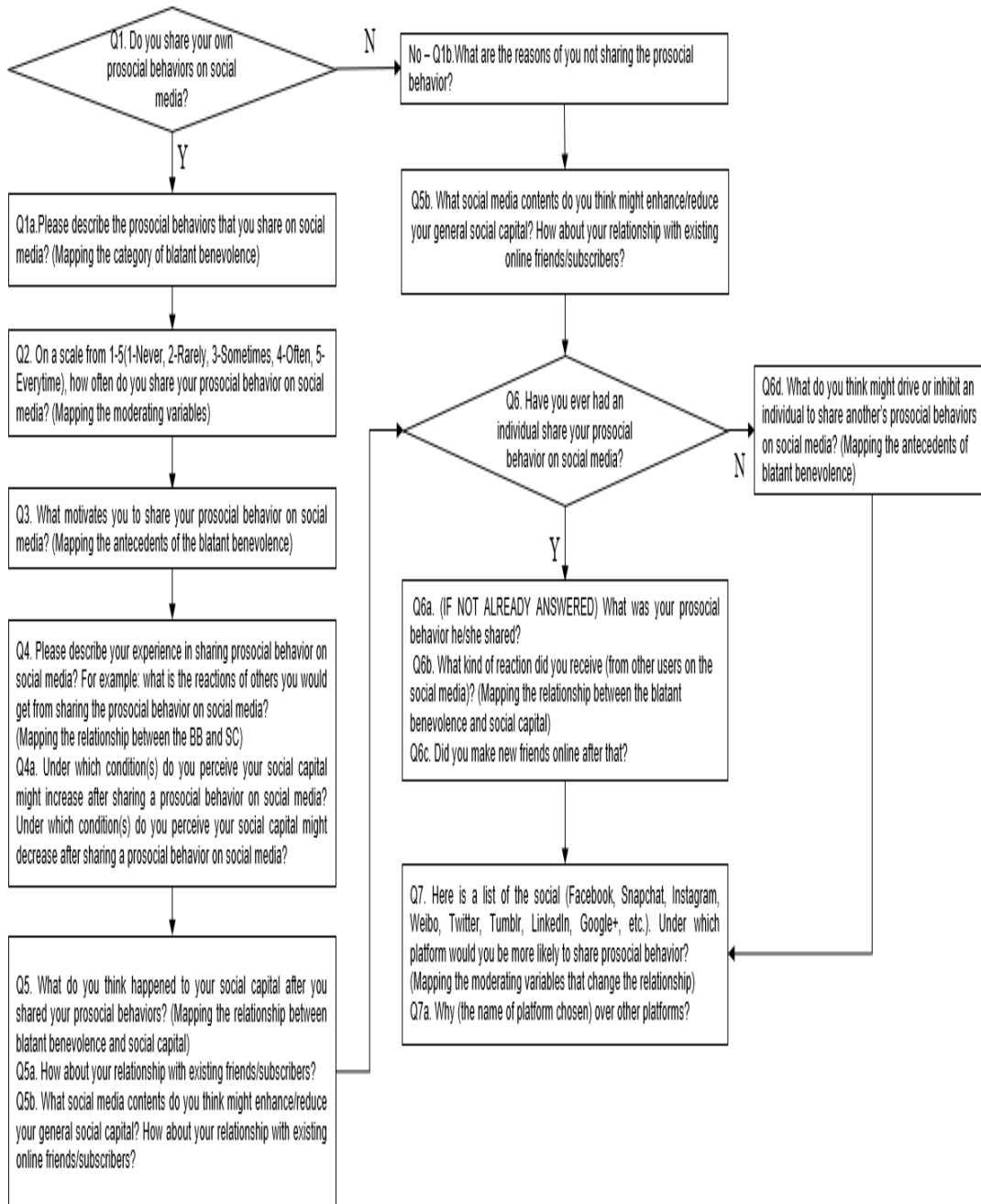
# Appendix A

## Interview Questionnaire – TPP





## Interview Questionnaire – FPP

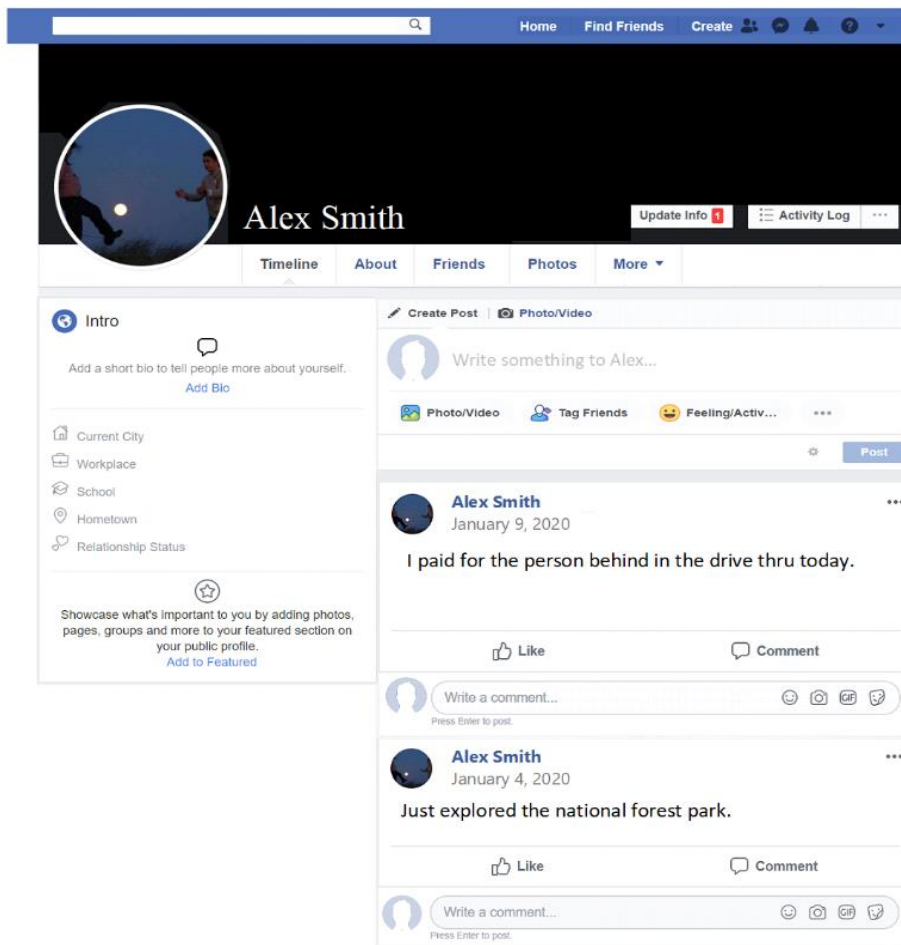


## Appendix B

### Facebook Profile in Eight Conditions

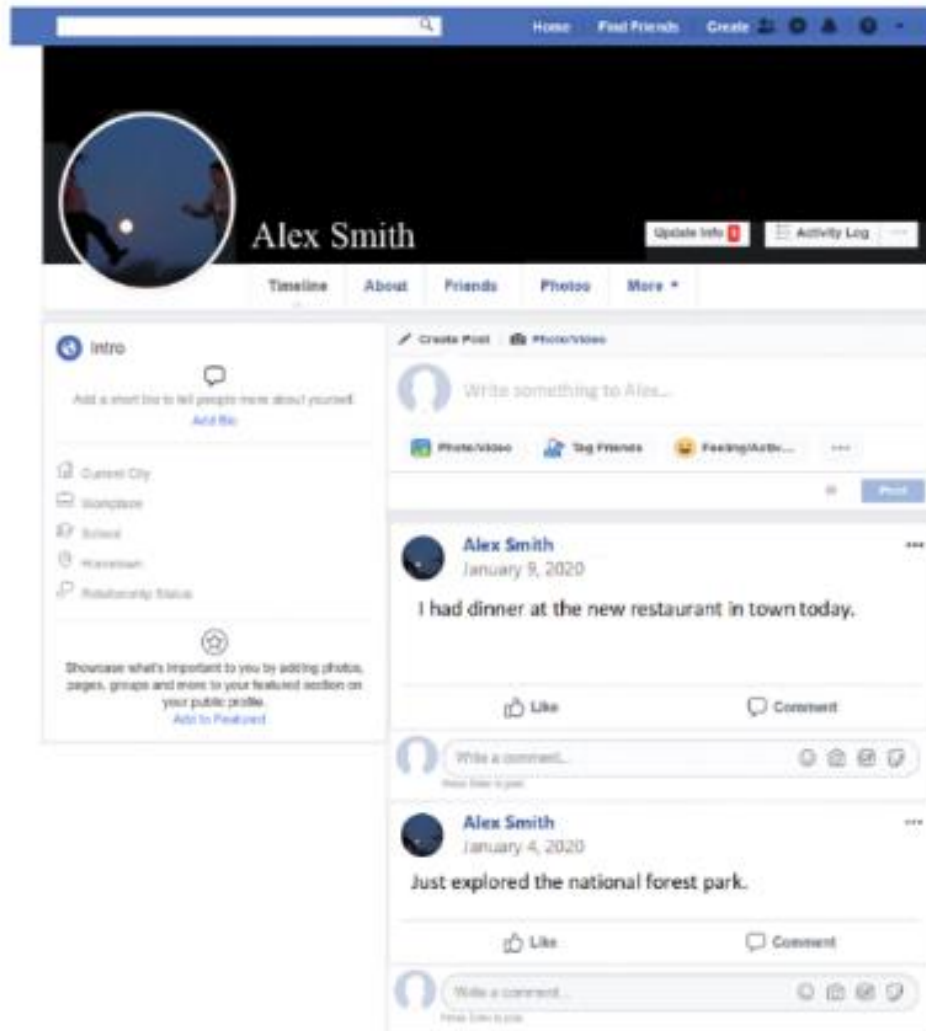
When we designed the Facebook profile, we used gender-neutral names. We discussed with several native speakers to identify the gender-neutral names they usually see. For example, Alex (Alexandra or Alexander) Smith, Sam (Samantha or Samuel) Davis, Pat (Patricia or Patrick) Williams, Chris (Christina or Christopher) Brown, and Eli Johnson. To control the effect of the icon, we selected the icons that do not reflect any personality. In the other-post conditions, we used icons that are plain and don't have any personal pictures involved. To capture the effect of frequency, we manipulated the times of the behaviors posted on the profile within a week. In the low frequency condition, the prosocial behavior/non-prosocial behavior is posted once within a week. In the high frequency condition, 4 different prosocial behaviors/non-prosocial behaviors are posted within a week. This frequency is consistent with the frequency criteria of social media posts on Facebook<sup>15</sup>.

Blatant Benevolence – Low Frequency – Self-post condition

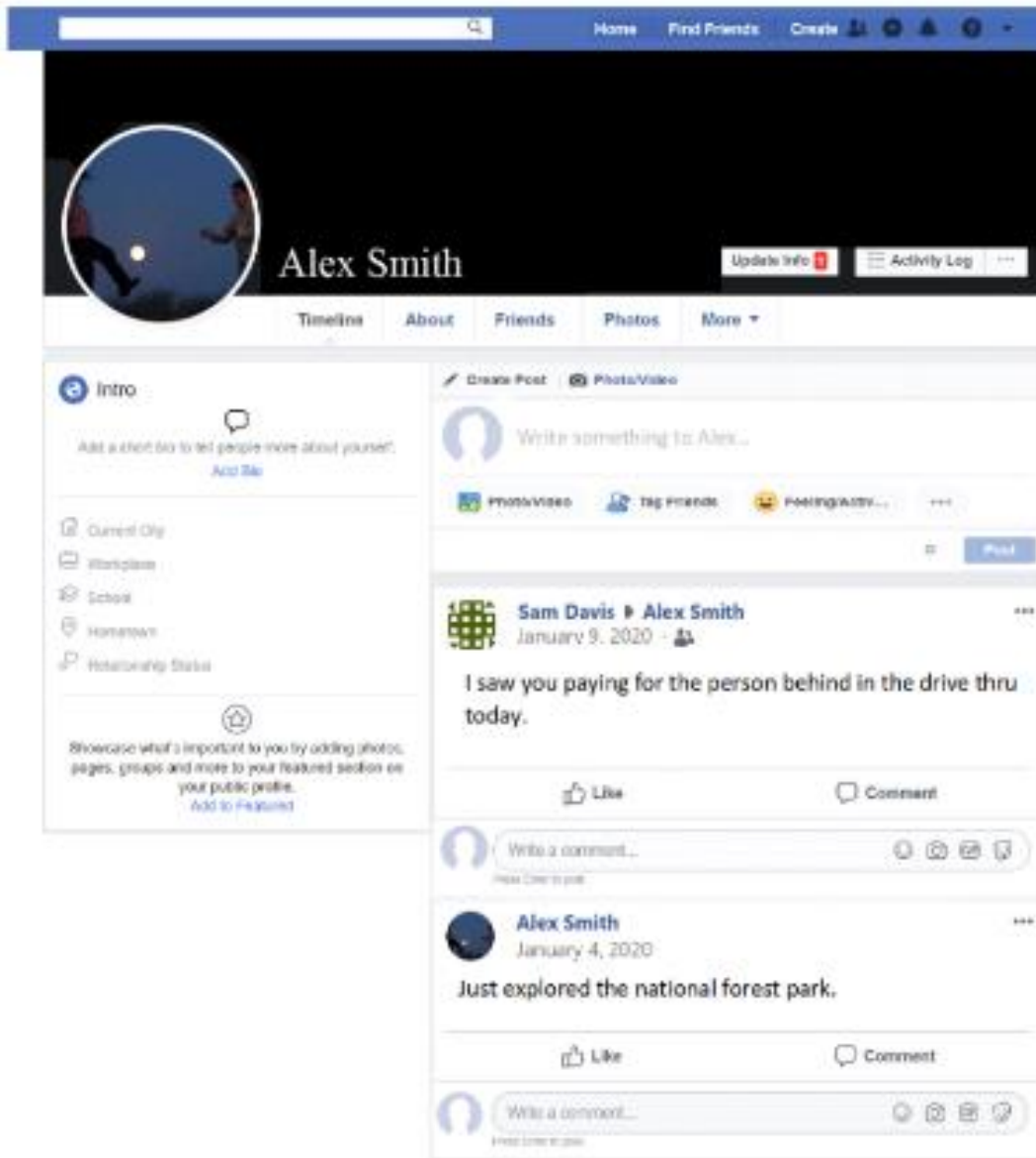


<sup>5</sup> <https://louisem.com/144557/often-post-social-media>

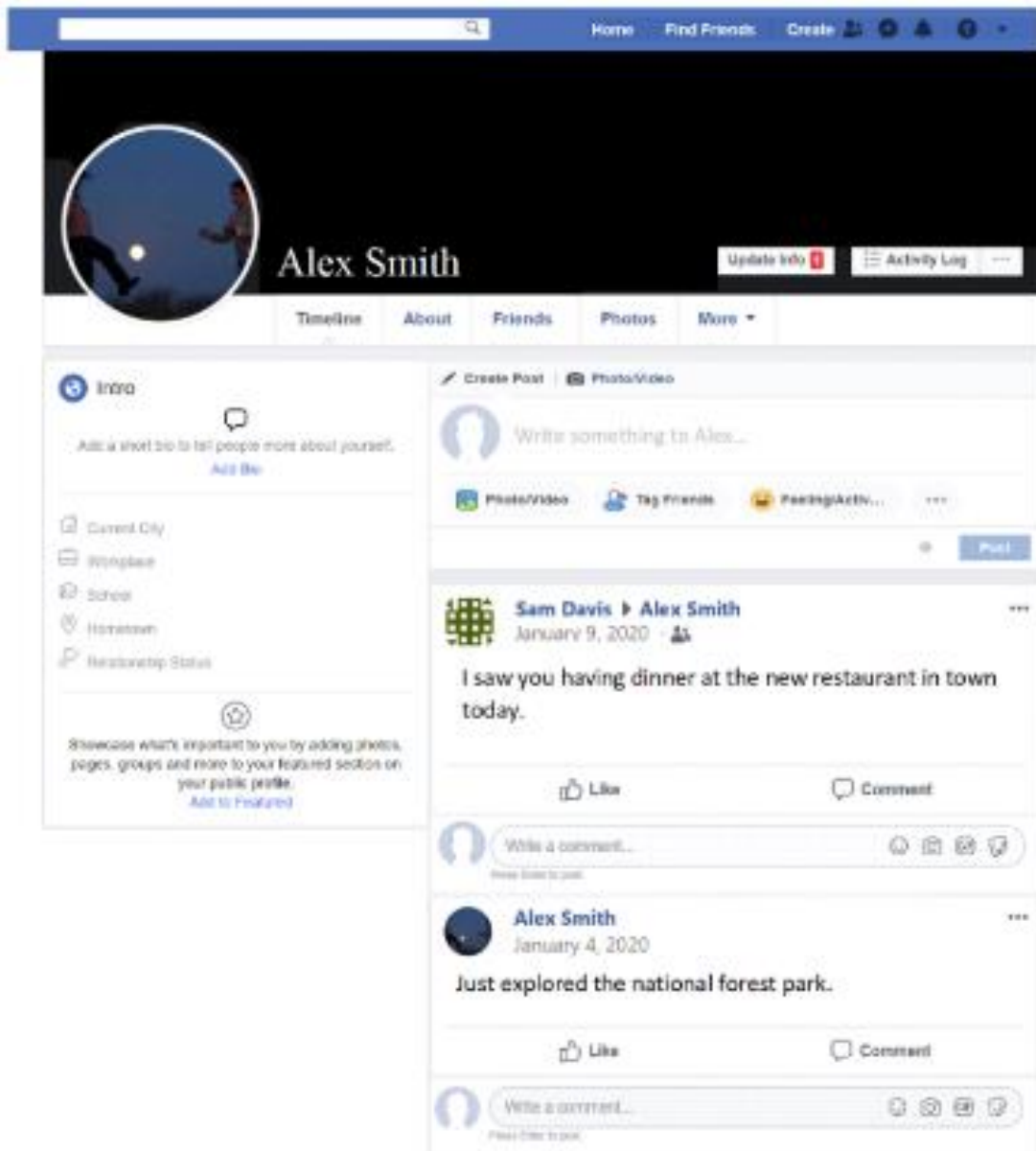
Blatant Non-Benevolence – Low Frequency – Self-post condition



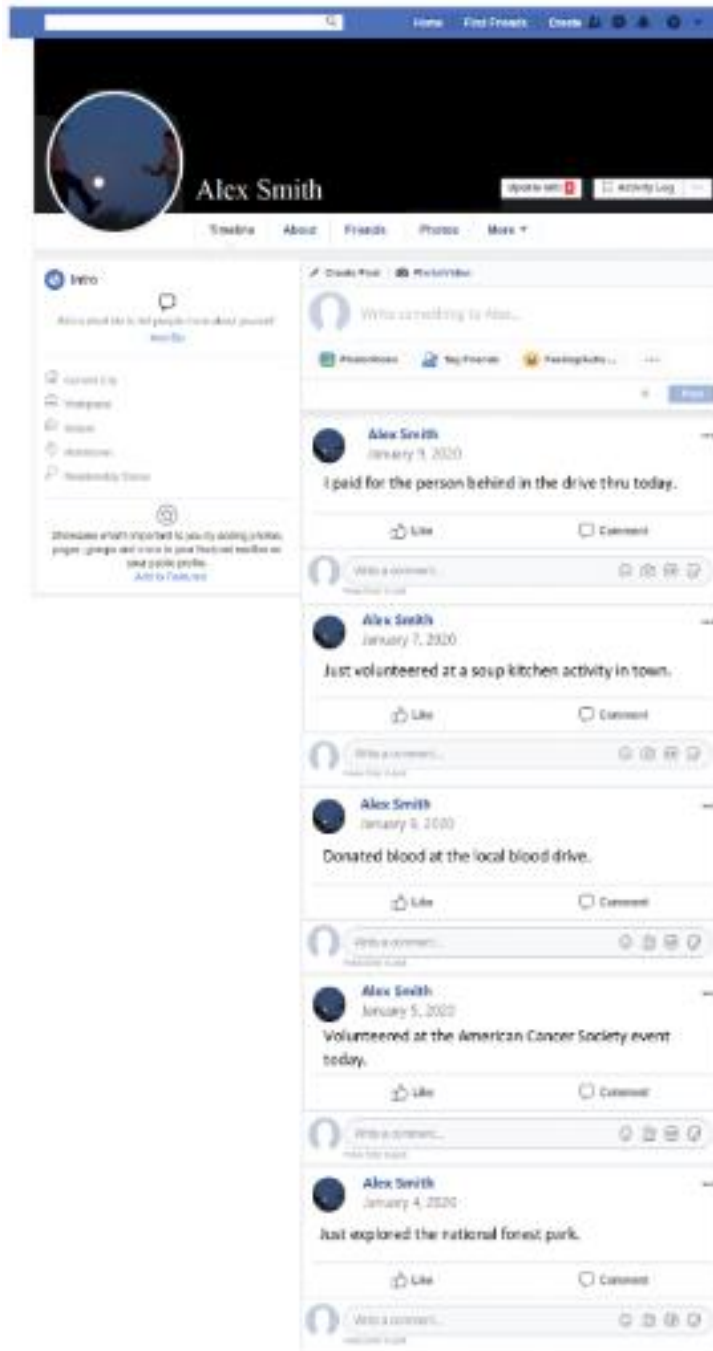
Blatant Benevolence – Low Frequency – Other-post condition



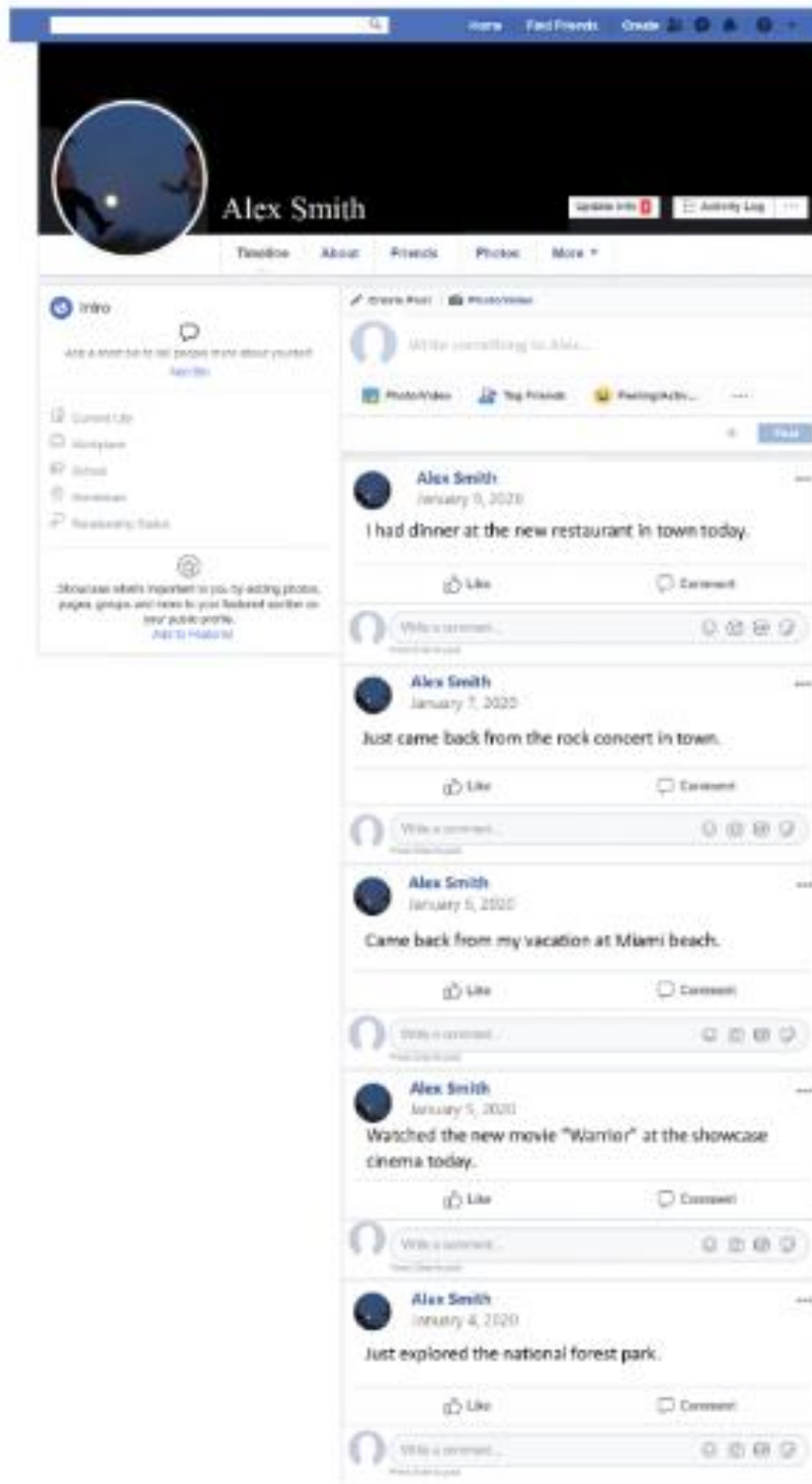
Blatant Non-Benevolence – Low Frequency – Other-post condition



## Blatant Benevolence – High Frequency – Self-post condition



Blatant Non-Benevolence – High Frequency – Self-post condition



Blatant Benevolence – High Frequency – Other-post condition





Blatant Non-Benevolence – High Frequency – Other-post condition



## Appendix C

### Demographics and Control Variables

<b>General Demographic and Usage Questions</b>	
Gender	Male (1) /Female (0)
Age	1-99
GPA	1-4
#Facebook Friends	Text Entry
<b>Disposition to Trust (Cummings and Dennis, 2018)</b>	
DT1	Most people are honest in describing their experience and abilities.
DT2	Most people tell the truth about the limits of their knowledge.
DT3	Most people can be counted on to do what they say they will do.
DT4	Most people answer personal questions honestly.
Scale of items: 1 = strongly disagree to 7 = strongly agree	
<b>Sociability (Choi et al., 2015)</b>	
SO1	I like to be with people.
SO2	I welcome the opportunity to mix socially with people.
SO3	I prefer working with others rather than alone.
Scale of items: 1 = strongly disagree to 7 = strongly agree	
<b>Facebook Usage (Choi et al., 2015)</b>	
FF1	I am familiar with using Facebook.
FF2	I am comfortable with using Facebook.
FUI2	I often use Facebook.
Scale of items: 1 = strongly disagree to 7 = strongly agree	
<b>Altruism (Galizzi &amp; Navarro-Martinez, 2019)</b>	
A1	I have helped push a stranger's car out of the snow.
A2	I have given directions to a stranger.
A3	I have made change for a stranger.
A4	I have given money to a charity.
A5	I have given money to a stranger who needed it (or asked me for it).
A6	I have donated goods or clothes to a charity.
A7	I have done volunteer work for a charity.
A8	I have donated blood.
A9	I have helped carry a stranger's belongings (books, parcels, etc).
A10	I have delayed an elevator and held the door open for a stranger.
A11	I have allowed someone to go ahead of me in a lineup (at Xerox machine, in the supermarket).
A12	I have given a stranger a lift in my car.
A13	I have pointed out a clerk's error (in a bank, at the supermarket) in undercharging me for an item.
A14	I have let a neighbor whom I didn't know too well borrow an item of some value to me.
A15	I have bought 'charity' Christmas cards deliberately because I knew it was a good cause.
A16	I have helped a classmate who I did not know that well with a homework assignment when my knowledge was greater than his or hers.
A17	I have before being asked, voluntarily looked after a neighbor's pets or children without being paid for it.
A18	I have offered to help a handicapped or elderly stranger across a street.
A19	I have offered my seat on a bus or train to a stranger who was standing.
A20	I have helped an acquaintance to move households.
Scale of items: 1 = never to 5 = very often	

Appendix D

Table D1. Correlation matrix (Chinese sample)

	RSC	SSC	CSC	FU	AL	TD	S	G	Age	#WBF
RSC										
SSC	.540**									
CSC	.379**	.451**								
FU	.178**	.182**	.159**							
AL	.108	.281**	.131*	.299**						
TD	.255**	.284**	.228**	.226**	.202**					
S	.032	.189**	.141*	.188**	.334**	.214**				
Gender	.084	.042	-.012	.222**	-.035	.010	.010			
Age	-.007	.049	-.031	.125*	.172**	.099	.048	-.075		
#WBF	-.046	-.019	.001	.062	-.050	.068	-.006	.066	.068	

\*\* . Correlation is significant at the 0.01 level

\* . Correlation is significant at the 0.05 level

RSC= Relational Social Capital; SSC= Structural Social Capital; CSC= Cognitive Social Capital; FU= Facebook Usage; AL= Altruism; TP= Trust Propensity; S=Sociability; G=Gender; WBF=Number of Weibo friends.

Table D2. Descriptive Statistics of the Measures (Chinese sample)

Variable	N	Min	Max	Mean	SD
Relational Social Capital (RSC)	302	1.00	7.00	4.56	1.06
Structural Social Capital (SSC)	302	1.00	7.00	4.66	1.31
Cognitive Social Capital (CSC)	302	1.00	7.00	4.33	1.23
Sociability (S)	302	1.00	7.00	4.91	1.10
Trust Disposition (TD)	302	1.00	7.00	4.41	1.02
Altruism (AL)	302	1.00	5.00	2.70	0.56
Facebook Usage (FU)	302	1.00	7.00	5.28	1.46
Gender	302	0	1	0.63	0.48
Age	302	18	26	21.79	1.88
Number of Weibo friends (#WBF)	301	0	11256	127.06	669.39

Table D3. Scale and measurement properties (Chinese sample)

Scale and Factor Loadings		Standardized Estimates
Construct (1=strongly disagree, 7=strongly agree)		
<b>Relational Social Capital</b>		
Perceived Goodwill		0.82
Perceived Integrity		0.86
<b>F1: Perceived Goodwill</b> (McKnight, Choudhury, and Kacmar, 2002).		
Alex would act in my best interest.		0.46
If I need help, I believe Alex would want to help me.		0.81
Alex would be interested in my well-being, not just his/her own.		0.82
Alex prioritizes others' needs before his/her own work.		0.72
I believe Alex would help an individual in need without expecting any rewards.		0.81
<b>F2: Perceived Integrity</b> (McKnight, Choudhury, and Kacmar, 2002).		
Alex would be truthful when dealing with me.		0.81

I would characterize Alex as honest.	0.85
Alex would keep his/her commitments.	0.77
Alex seems to be sincere and genuine.	0.82
<b>Cognitive Social Capital</b> (Cummings and Dennis, 2018)	
Alex and I would speak the same 'social media' language.	0.85
If I talk to Alex about issues on social media, we would have a common understanding of how things should be handled on social media.	0.64
<b>Structural Social Capital</b> (Lee and Kim, 2014)	
I would be willing to share my interests with Alex on social media.	0.82
I would be willing to express my feelings to Alex on social media.	0.88
I would be willing to express my thoughts to Alex on social media.	0.85
If given a chance, I would like to be friends with Alex on social media.	0.74
<b>Chi-squared &amp; Model Fit Indices</b>	
$\chi^2$ (df=85)	
CFI	163.24
IFI	0.97
RMSEA	0.06
SRMR	0.04

Table D4. Construct Validity, Correlation, and Descriptive Statistics (Chinese sample)

	M	SD	CR <sup>1</sup>	$\alpha$	AVE	MSV	ASV	Correlation Matrix <sup>2</sup>		
								RSC	SSC	CSC
RSC <sup>3</sup>	4.56	1.06	0.83	0.89	0.71	0.41	0.33	0.84		
SSC	4.66	1.31	0.89	0.89	0.68	0.41	0.35	0.64	0.82	
CSC	4.33	1.23	0.72	0.70	0.51	0.29	0.28	0.51	0.54	0.71

Note: 1. CR=composite reliability. 2. Square root of the average variance shared are across diagonal with off diagonal elements being correlations between constructs. Diagonal elements should be larger than off-diagonal elements for discriminate validity. 3.

RSC= Relational Social Capital; SSC= Structural Social Capital; CSC= Cognitive Social Capital

Table D5. Summary of ANCOVA results (*F* statistics) (Chinese sample)

Independent variables	Dependent Variables		
	Relational Social Capital	Structural Social Capital	Cognitive Social Capital
Blatant Benevolence	54.54***	6.52*	0.10
Blatant Benevolence x Frequency	1.86	5.57*	6.18*
Blatant Benevolence x Other post	0.23	0.04	1.49
Frequency	1.61	0.73	1.67
Other post	2.27	0.01	2.15
Frequency x Other post	0.27	2.68	0.04
Blatant Benevolence x Frequency x Other post	0.47	0.14	1.00
<i>F-value</i>	9.89***	2.62*	2.03

Table D6. Main Comparisons of the ANCOVAs (Chinese sample)

A. Mean comparisons of the Main Effects of Blatant Benevolence on Social Capital						
	Blatant Benevolence					
	Blatant Benevolence		Blatant Non-Benevolence			
Relational Social Capital	4.91 <sup>***</sup>		4.06 <sup>***</sup>			
Structural Social Capital	4.81 <sup>*</sup>		4.42 <sup>*</sup>			
Cognitive Social Capital	4.32		4.27			

B. Mean Comparisons of the Moderating Effect of Frequency						
	Relational Social Capital		Structural Social Capital		Cognitive Social Capital	
	Blatant Benevolence	Blatant Non-Benevolence	Blatant Benevolence	Blatant Non-Benevolence	Blatant Benevolence	Blatant Non-Benevolence
Low Frequency	4.76	4.06	4.69 <sup>*</sup>	4.66 <sup>*</sup>	4.23 <sup>*</sup>	4.54 <sup>*</sup>
High Frequency	5.06	4.05	4.92 <sup>*</sup>	4.17 <sup>*</sup>	4.40 <sup>*</sup>	4.00 <sup>*</sup>

C. Mean Comparisons of the Moderating Effect of Other post						
	Relational Social Capital		Structural Social Capital		Cognitive Social Capital	
	Blatant Benevolence	Blatant Non-Benevolence	Blatant Benevolence	Blatant Non-Benevolence	Blatant Benevolence	Blatant Non-Benevolence
Self-post	4.79	4.11	4.78	4.42	4.12	4.25
Other-post	5.02	4.00	4.83	4.40	4.51	4.29

Note: Main comparisons are significantly different across the two conditions with the same subscript: <sup>a</sup> $p < .001$ ; <sup>b</sup> $p < .01$ ; <sup>c</sup> $p < .05$ ; <sup>M</sup> $p < .1$

## Appendix E Weibo Design

Blatant Benevolence – Low Frequency – Self-post condition



# Blatant Non-Benevolence – Low Frequency – Self-post condition



# Blatant Benevolence – Low Frequency – Other-post condition





Blatant Non-Benevolence – Low Frequency – Other-post condition

The image displays two screenshots of a Weibo user profile page, illustrating the 'Other-post condition' in a study. Both profiles have redacted personal information with asterisks.

**Top Screenshot: Profile of 王仕君 (Wang Shijun)**

- Profile picture: A green grid pattern.
- Username: 王仕君
- Buttons: +关注 (Follow), 私信 (Private Message), and a menu icon.
- Navigation: 主页 (Home) and 相册 (Album).
- Left sidebar: 关注 (Followed), 粉丝 (Fans), 微博 (Weibo), and a bio section with redacted text.
- Post: A tweet from 王仕君 (2020-1-9) mentioning @李嘉文: "我今天看见你在市里新开的餐厅吃晚饭了。" (I saw you eating dinner at a new restaurant in the city today.)
- Post actions: 阅读 (Read), 推广 (Promote), 转发 (Retweet), 评论 (Comment), 赞 (Like).

**Bottom Screenshot: Profile of 李嘉文 (Li Jiawen)**

- Profile picture: A circular image of a person in a dark setting.
- Username: 李嘉文
- Buttons: +关注 (Follow), 私信 (Private Message), and a menu icon.
- Navigation: 主页 (Home) and 相册 (Album).
- Left sidebar: 关注 (Followed), 粉丝 (Fans), 微博 (Weibo), and a bio section with redacted text.
- Post: A tweet from 李嘉文 (2020-1-4): "我今天去了森林公园。" (I went to the forest park today.)
- Post actions: 阅读 (Read), 推广 (Promote), 转发 (Retweet), 评论 (Comment), 赞 (Like).

## Blatant Benevolence – High Frequency – Self-post condition



# Blatant Non-Benevolence – High Frequency – Self-post condition





# Blatant Non-Benevolence – High Frequency – Other-post condition

