UNDERSTANDING THE DISCLOSURE OF PRIVATE HEALTHCARE INFORMATION WITHIN ONLINE QUANTIFIED SELF 2.0 PLATFORMS

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Abstract

The quantified self-movement encourages a continuous tracking of data points regarding a person's daily activities through wearable sensors, and thus has important implications for health and wellness. With the advent of sophisticated low-cost wearable computing devices, online communities that facilitate social interaction and exchange of wearable data (Quantified Self 2.0 platforms) have also emerged. Although security and privacy disclosure has been studied within online social networks and online health communities, little has been done to understand how individual and group characteristics influence the disclosure behaviour regarding highly sensitive personal information gathered from wearable sensors (e.g., sleep, nutrition, mood, performance, ambient conditions). Using data collected from 43 Fitbit groups which consist of 5300 Asian users within the Fitbit online community, we examine the influence of group characteristics (size, posts, average steps) and individual attributes on privacy disclosure behaviour. Results from our hierarchical linear modelling analysis suggests that attributes such as group size and individual posts are associated with increased privacy data disclosure, whilst we surprisingly find that when other group members have higher health performance or are more active, individuals are more likely to disclose less healthcare information. Based on these findings, theoretical and practical implications are discussed.

Keywords: Wearables, Quantified Self 2.0, Self-disclosure, Healthcare Online Communities, Self-Presentation Theory, Hierarchical Linear Modelling

1 INTRODUCTION

Wearable computing devices (i.e., *wearables*) represent a class of miniaturized electronic devices worn on top of or beneath a person's clothing (Dibia 2014). These devices have become increasingly sophisticated by incorporating improved processing capabilities and a plethora of sensor arrays that the tracking of physiological and ambient data. A survey of 4556 adults ages 18+ within the USA and Europe showed that 42% were interested in wrist-worn wearables compared to 18% who were interested in head-worn wearables (Gownder 2014). These devices have found important applications in the area of healthcare and health management (Pantelopoulos & Bourbakis 2010) as they are capable of tracking consumer health information and provide insights for improved health behaviour. This information includes health conditions, symptoms, athletic performance, and vital signs such as body temperature, heart rate, and blood pressure. The market value of wearable device was US$5.166 billion in 2014 and is projected to explosively grow to around US$12.642 billion by 2018 (Statista 2014). These devices have increased the ease with which individuals gather data on their personal health, and has contributed to the growing concept of the "Quantified Self".

The Quantified Self movement encourages a continuous tracking of data points regarding a person's daily activities through wearable sensors for the purpose of influencing health behaviours. These data inputs are then usually integrated and displayed in a user-friendly interface, and suggestions are given to the users based on their quantified healthcare information (Swan 2009). The idea of Quantified Self has evolved to a point where quantified healthcare information can be exchanged with social networking friends on online platforms, in a movement known as Quantified Self 2.0 (QS 2.0) (Swan 2012). In traditional online healthcare communities, people share their experiences and seek for informational support to cope with certain diseases (Maloney-Krichmar & Preece 2002) and to make decisions involving the choice of healthcare providers including hospitals and doctors (Liu et al. 2014). Similar to online healthcare communities, QS 2.0 participants may establish or join groups, initiate or contribute to group discussions, make new friends, share their personal health data and also compare their health performance with other members of the platform.

QS 2.0 offers a dramatic change to traditional online healthcare community interactions. First, QS 2.0 members can share objective information on their personal health performance that is measured directly by their wearable devices (as opposed to traditional self-report). The objective nature of information displayed may suggest higher accuracy and credibility, which in turn may drive stronger social influence amongst peers regarding to health behaviour. Extant literature shows that the social interactions in healthcare communities have a significant effect on users' health seeking behaviour and people who are more active in online healthcare communities tend to be healthier (Kamel Boulos & Wheeler 2007). Initial cases have also shown that competition among wearable users significantly motivate users to be more active and are helpful to their fitness (Maryea 2014). These findings support the idea that QS 2.0 communities can motivate users to seek good health and improve their fitness in novel ways not seen before.

Secondly, the benefits of QS 2.0 communities come with privacy and security issues that must be considered. The personal, objective and sensitive nature of data within these platforms necessitate that platforms provide security settings that allow users select various levels of information disclosure. In fact, one of the major obstacles in the adoption of QS 2.0 are the strong privacy issues related to quantified healthcare data (Lindström & Hanken 2012; Morris & Aguilera 2012; Raij et al. 2011; Virkki & Aggarwal 2014). Privacy threats of disclosing such quantified healthcare information are extremely high because they could negatively affect the users financially, psychologically (Raij et al. 2011), and socially. Worse yet, although most users of wearable devices are aware of the existence of the potential threats, they often cannot fully understand the level of privacy risks of disclosing their healthcare information collected by wearable devices (Raij et al. 2011).

Notably most of the scant research done in this area have been largely based on cases or conceptual descriptions of privacy implications. Other studies have also employed survey methodologies that use subjectively reported data to understand privacy disclosure behaviour. Few studies have examined the effect of group-level attributes on disclosure behaviour in QS 2.0 groups. It is important to study group level attributes because the formation of groups within QS 2.0 platforms signal the emergence of smaller social constructs with idiosyncratic social norms (e.g., shared goals, interests, context and rules), all of which can influence individual behaviour.

To address these gaps, our goal is to develop a model that examines the impact of group- and individual-level on privacy disclosure behaviour in QS 2.0 groups. Our model development is guided by insights from self-presentation theory (SPT) as well as social influence theory (SIT) and is empirically tested using objective data collected from a QS 2.0 platform. Results from our hierarchical linear modelling analysis contributes to the literature in two main ways. First, we demonstrate a positive link between two individual factors (group posting behaviour, personal friend network) and privacy disclosure. Group posting behaviour is measured as the number of posts an individual makes within groups where they are members, and personal friend network is a binary value that indicates if an individual has at least one friend within the platform. Secondly, our study excels by identifying the nature of relationships between group attributes and disclosure behaviour. We find that being a member of a large group is related to increased self-disclosure of private healthcare information, whilst increased group performance (average health activity of members in a group) is surprisingly negatively related to disclosure behaviour.

A brief description of the rest of this article is summarized as follows. We begin with a review of our theoretical underpinnings and develop arguments which form the basis of our hypothesis in this study. Next, we provide information on our data context, data collection methodology and results from hierarchical linear modelling. We then conclude with a discussion of findings, limitations and future research work.

2 THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

In this section we develop arguments based on the underlying logic that self-disclosure is influenced by both differences amongst individuals as well as differences across groups to which they may belong. That is self-disclosure is not only determined by individuals' personal traits, but also by the group characteristics which they belongs to. We first introduce SPT and SIT as our theoretical supports to illustrate how these multi-level factors can jointly influence self-disclosure, and then propose our research model.

2.1 Self-presentation and Self-disclosure

SPT, proposed by Goffman (1959) and Leary (1996), suggests that individuals naturally have an inner demands to present "a desired image of themselves to others" (H.-W. Kim et al. 2012, p.1234). According to Ma and Agarwal (2007) identity communication reflects efforts of people to express their identity to others to achieve shared understanding. Goffman (1959) said that people tend to seek specific information about others they can observe. People seek for information about socio-economic status, conception of self, attitude to observer, and so on. This information can help people to make situation clearer, and broadcast their expectations of the results of their communication. According to these expectations, both sides can build their strategies of communication. Based on the acquired information, people often place their counterparts into a stereotype of people they contacted previously. Using this understanding, people try to predict future behaviour of the others. In the context of social networking sites (SNS), it has also been found that users disclose personal information to meet their inner demands of self-presentation (Ellison 2007; Utz 2015).

It is difficult for people to discern important information of others such as attitudes and beliefs, so they usually forced to use some symbolic surrogates that could be interpreted in different ways (e.g., hairstyle, clothes, vocabulary). In such situations individuals have a chance to influence the conceptualization of the situation in others' minds (i.e., managing the presentation of "self"). To do so, an individual can behave in certain ways to present themselves according to their plan. Management of self-presentation can be behavioural or merely through objects such as different clothes, hairstyles, automobiles and so on to make some particular impression on other people in various contexts (Schau & Gilly 2003)

Goffman (1959) says that effectiveness of the influence of the definition of the situation may differ according to awareness of individuals to the responses of their counterparts. For example, in a situation where a person acts according to a tradition of his/her social group, he or she may provide a good impression on the people in this social group, but at the same time, this behaviour might provide negative impressions on people from other social groups (e.g., throwing down gang signs). At the same time, the definition of the situation could be influenced from all the participants. In this regards Goffman (1959) says that people tend to insist on some vital formal rules of communication while remaining silent on less immediately important matters.

Efficiency of self-presentation is important because if a person cannot effectively project a definition of the situation, their counterparts might define the situation wrongly, and some predictions of an individual about the future behaviour of others could thus have an incorrect basis. In such situations, an individual whose self-presentation become discredited by others can feel ashamed, while others can potentially feel hostile to the person.

People tend to employ defensive and protective practices. Defensive practices used by individuals when they would like to protect their own definition of a situation. Protective practices used when individuals tend to protect the definition of the situation projected by others. In this case, protective practices are called "tact." According to De La Ronde and Swann (1998) people rely on their beliefs to predict and control their life; therefore, actions of other people that can challenge these beliefs may break individuals' understanding of their world. Therefore, one of the reasons why people tend to employ protective practices is to keep or restore their perceptions of prediction and control. When people reach understanding about their identities and the identities of their counterparts they experience conformity, which is a key factor of conflict-free social engagement (Ma & Agarwal 2007).

SPT (Goffman 1959) explains the mechanism of situation definition by different counterparts. This theory propose two main motives for self-presentation:

- The first motive could be formulated as willingness of people to influence others and gain rewards through self-presentation (H.-W. Kim et al. 2012). According to Goffman (1959) this motive could be understood as willingness of an individual to control the impression he or she provides to others.
- The second motive is in claiming some personal identity of an individual and using this personal identity to associate with similar people (H.-W. Kim et al. 2012). Goffman (1959) says that if an attempt to control the situation definition and self-presentation was successful an individual has a moral right to expect others to treat him or her in a certain way. At the same time, others expect an individual to have the same behavior style and restrictions that claimed type of people have.

In analysis of social networks H.-W. Kim et al. (2012) assert that online self-presentation as well as offline self-presentation plays an important role. Online identity changes from offline identity of a person in case of possibility to change or hide some attributes of a real person. In order to translate this new identity to others people need to employ online self-presentation. H.-W. Kim et al. (2012) argues that the second motive of self-presentation, which is claiming similarity and association with similar people, is highly coherent with online setting and human behaviour in social networks. They assert that people's willingness to associate themselves with similar people and their need to build relationships causes people to employ self-presentation in virtual communities.

According to Walther (2007) in online communication people cannot rely on traditional physical features like appearance and voice, but they can vary time of writing messages, editing behaviours, different language styles, sentence complexity and so on to provide the required impression. Because not all the traditional features of a person are available online (e.g., lack of nonverbal cues), people tend to present themselves in socially desirable fashion (Walther 2007). The online context allows people to create multiple identities using the manipulation of messages, images, avatars, and so on (Schau & Gilly 2003). Different kinds of media (e.g., images, music, wallpapers) or symbolic tools, like emoticons or text styles, make desired online self-presentation of a person in social networks (H.-W. Kim et al. 2012).

In the IS literature, the privacy calculus model is widely adopt to understand users' disclosure behaviour in SNS, which claims that the more utility users can gain, the more likely they are to disclose private information (Agarwal et al. 2009; Culnan & Bies 2003; Dinev et al. 2006; Keith et al. 2013). Following this logic, if one has higher degree of self-presentation motives, the benefits he or she can gain through disclosing healthcare related private information would be higher; thus, it is more likely for such a user to make private information publicly available.

In the context of online communities of Fitbit groups, there is a mix of available features of offline and online communication. On one hand, Fitbit groups are online communities where all the features of online self-presentation could be employed. However, the Fitbit wristband itself provides actual disclosures of physical body condition like heartrate, physical fitness, or even frequency of physical activity. These features may not be very important in other contexts, such as an online-development community where the main interest is not on the average number of steps of a person. However, in the context of Fitbit groups these features are valid and interesting symbols of similarity/dissimilarity to some group.

Within our study, we identify three variables that can reflect or be related to the self-presentation motives, namely: (1) the amount of posts a user contributes to a group's forums (i.e., *Post*), whether a user has active friends or not using Fitbit (i.e., *Friend*), and the size of the group one belongs to (i.e., *Gsize*). First of all, users who enjoy participating in group discussions and that are more engaged in interactions with other users and who present their daily usage of Fitbit devices, are more likely to disclose more private information. That is, such engaged users are more actively managing self-presentation, and thus are more actively disclosing private information to make the impression they want made (e.g., dedicated fitness buff). Second, according to J. Kim and Lee (2011) and Ellison et al. (2007), with a larger potential audience within an environment (e.g., SNS friends), people are more motivated to make self-presentations to gain social support and social rewards. We thus propose that having more active friends and being in a large group will be positively related with self-disclosure. In summary:

H1: The amount of group discussions posted by Fitbit users in the past is positively related with the self-disclosure of personal healthcare information.

H2: For Fitbit users who have active Fitbit group friends, their self-disclosure of personal healthcare information will be relatively higher when compared with those without any active Fitbit group friends.

H3: The size of the group a user belongs to is positively related with the self-disclosure of personal healthcare information.

2.2 Social Influence and Self-disclosure

Beyond the calculus process, in recent years, more and more IS research has shifted their attention to examine how one's self-disclosure behavior is influence by the beliefs and behaviors of other SNS users. For instance, the online community self-disclosure model proposed by Posey et al. (2010) suggested that users will be more willing to sharing private information to others if they notice that other community members are also engaging in the same kind of self-disclosure behavior (Cialdini 2001; Posey et al. 2010). Thus, disclosure begets reciprocal disclosure. More recently, Cheung et al. (2015) found that impact of social influence and cultural factors on self-disclosure are even more stronger than perceived benefit in the context of SNS; while Chen and Sharma (2015) also regarded self-disclosure as learned behaviors from other social media users.

Per SPT, individuals naturally want to employ some efforts to provide their desired image of themselves to others. In other words, individuals try to control their impression-management in a given situation. At the same time, others also would translate their understanding of the situation and the individual to the group, which could be understood as social influence, from SIT. According to Kelman (2006) this social influence could be understood as three processes: compliance, identification, and internalization.

- *Compliance* occurs when individuals agreed to receive some influence from other people or a group to achieve some favourable reaction from others (Kelman 2006). Compliance could be understood as agreement with some formal rules to obtain a reward or to avoid a punishment (H.-W. Kim et al. 2012).

- *Identification* occurs when individuals agree to be influenced from others to retain or create satisfying self-defining relationship with others. In other words, internalization represents the process of corresponding individual's value system to a group's value system (H.-W. Kim et al. 2012).
- *Internalization* can happen when individuals to accept influence from others to maintain congruence of their actions with their value system (Kelman 2006). H.-W. Kim et al. (2012) explain internalization as person's acceptance of group influence to keep good self-defining relationships with the group to establish emotional involvement with it (i.e., a feeling of group involvement).

For all these different conditions, we are interested in a group's influence on an individual's willingness to disclose the personal information (health condition, weight, some advanced statistics of their progress) to Fitbit website. All of these features, as well as existence of offline friends, can influence group members' self-presentation strategy.

In summary, we argue that disclosure of QS 2.0 healthcare information via Fitbit would also be influenced by the behaviours of other Fitbit activity group members. If an individual feels that all the other group members disclose large amount of private information or are very active in group discussions, it is more likely they will yield to this social influence and thus disclose more private information. Hence, due to different group norms and group cultures, the disclosure level across different Fitbit groups should be different. Moreover, certain group level factors reflecting the activities of group members, would have certain influence on individual's self-disclosure. First, if other group members are more engaged in group discussions (i.e., *Gpost*), then one will feel that as a member of this group that there is an expectations of high participation the group interactions. Second, if other group members frequently use and synchronize their sport activities—e.g., they have higher amount of step performance (i.e., *GAvestep*)—one will be encouraged to disclose more healthcare information in response to other group members. Thus,

H4: The discussion frequency of the group forum is positively related with the self-disclosure of personal healthcare information.

H5: The average steps walked by group members is positively related with the self-disclosure of personal healthcare information.

Finally, as an exploratory study trying to understand self-disclosure in healthcare online communities, we whether interaction effects exist among the individual and group level factors. Thus,

H6: There exist interactions among the individual and group level factors, to be specific, (a) group level factors influence the slope of Friend on Disclosure, and (b) group level factors influence the slope of Post on Disclosure.

Figure 1 depicts the research model proposed in this section.

3 METHODOLOGY

3.1 Sample and Data Collection Procedure

We conducted our study within the Fitbit online community in Asia, an excellent example of a QS 2.0 platform (www.fitbit.com). Fitbit has released a series of wearable activity trackers that daily activity

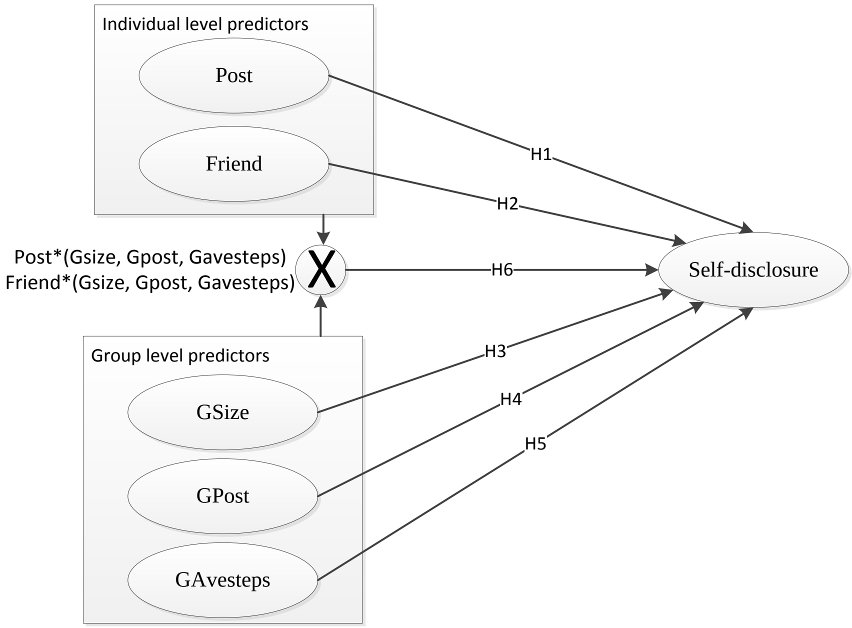

Figure 1. The research model

can collect users' information such as number of steps they walked, daily active minutes, quality of sleep, calories intake, and so forth (Kay et al. 2012). Data collected by Fitbit devices can be synchronized to users' PC or mobile device, and displayed in a dashboard accessible via the web. Fitbit has made great strides in promoting their QS 2.0 services for online healthcare communities. By 2014, more than 15000 Fitbit activity groups (e.g., "Hong Kong Fitbit Group", "Fitbit China User Group") were created voluntarily by Fitbit users, and the creation of these groups is expected to rapidly grow. The structure of the Fitbit QS 2.0 communities are shown in Figure 2 (note that users belong to multiple groups are not reflected in this figure). Fitbit QS 2.0 platform supports social networking features which allow users to exchange their activity information and their healthcare experience with others. First, for users who join any of these groups, they can see the activity and other personal information of all group members that are set to be publicly available. A given Fitbit online group also provides rankings of monthly activity performance of to directly foster competition and social comparison amongst group members. Moreover, group members interact with others by posting new topics or replying to others' posts in the group forums. Finally, Fitbit allows users to import their Facebook account and Facebook friends so that users can also easily get connected with their real world intimate friends.

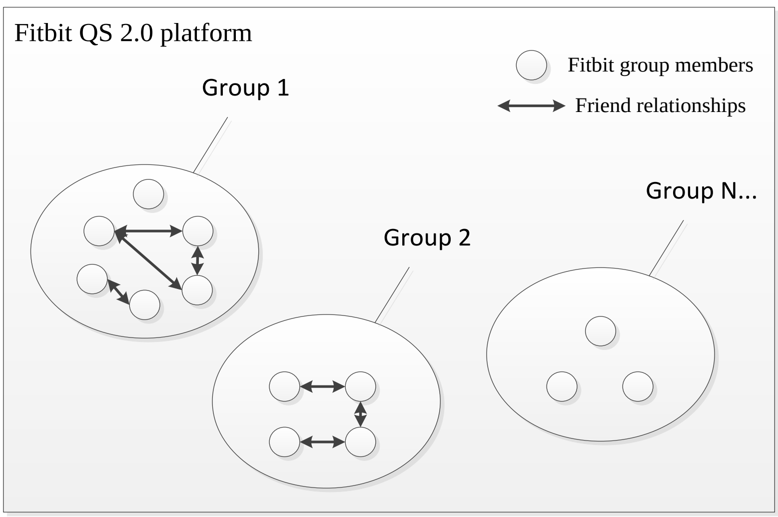

Figure 2. The structure of Fitbit QS 2.0 platform

To empirically test our proposed hypotheses, we develop a web scraping application in Java that crawled the profile pages of 5300 Fitbit users to extract individual level attributes, as well as data from 43 Fitbit activity groups that mainly consist of Asian users. The majority of these users are from China, Singapore, Japan and Korea. Each of these 43 groups contains at least 10 group members. We focus on the Asian users to better control the regional and cultural differences, because they have similar exercise routines and cultural norms. Table 1 providess a summary of the different datapoints which we collected.

HLM was used to understand the influence of both individual and group level factors on the self-disclosure level of personal healthcare information. Notably, these 5300 users belongs to one and only one of the 43 groups to ensure our data is nested to enable a HLM analysis. Users who belonged to more than one of these 43 groups were not included in the analysis. Table 2 provides the descriptive statistics.

Variables (IV/DV)	Level of analysis	Description
Disclosure (DV)	Ind.	A composite measure of an individual's privacy disclosure. This measure is a sum of 11 variables extracted from information fields as displayed on a user's profile page. For each of these 11 variables, a value is assigned based on the privacy setting assigned. 0= Private (Only available by the user itself) 1= Friends (Displayed in their dashboards and available for friends) 2= Public (Displayed in their dashboards and publicly available) The range of the overall disclosure level is 0-22.
Friend (IV)	Ind.	Friend Network: a dummy variable that is coded as follows: 0= User does not have any active friends on his profile page 1= User has at least one active friend on his profile page Active friends refers to their friends who update or synchronize their healthcare information in the last 7 days.
Post (IV)	Ind.	Individual Posts: The amount of posts made by an individual user in the discussion forum of the group they belong to.
GSize (IV)	Group	Group Size: The amount of group members in a group which the individual belongs to[1].
GAvestep (IV)	Group	Average steps of group members: the healthcare performance that on average, how many thousand steps a group member walked in the recent 31 days (i.e. Jan 31st to Mar 2nd 2015).
GPost (IV)	Group	Group Posts: The amount of posts that have appeared in the discussion forum of a group in the last 31 days (i.e. Jan 31st to Mar 2nd 2015).

Table 1. Description of variables used in the research model

Variable	NO. of cases	Mean	SD	Minimum	Maximum
Disclosure	5300	4.11	3.20	0	20
Post	5300	0.30	1.45	0	72
Friend	5300	0.36	0.48	0	1
GSize	43	155.93	281.03	11	1608
GPost	43	2.70	5.20	0	21
Gavestep (thousand)	43	77.50	27.45	6.22	125.74

Table 2. Descriptive statistics

[1] The amount of samples we take into analysis cannot exactly represent the size of each group, because users who belongs to more than 2 groups are excluded from our analysis. This is a requirement for Hierarchical Linear Modelling Analysis.

3.2 Data Analysis and Results

Following the analysis procedure suggested by Woltman et al. (2012), we used four steps to test our proposed relationships. First, we specified the following *unconstrained (null) model* (Model 1), to ensure that the influence of group level factors on the DV was significantly different than zero:

$$\textbf{Disclosure} = \beta_0 + \text{r} \ (1), \text{ in which:}$$

$$\beta_0 = \gamma_{00} + \mu_0 \ (2)$$

Appendix A summarizes the detailed results of testing the unconstrained model. Crucially, the chi-square test suggested that significant variance of the disclosure level is caused by group-level factors (χ^2=3044.6, p<0.001). An intra-class correlation (ICC) value of 0.402 signifies that the between-group variance account for 40.2% of the total variance of our dependent variable. These evidences suggest that there exist both within- and between-group variance in terms of users' self-disclosure level.

Second, a *random intercepts model* (Model 2) was specified to test the relationships between individual level predictors and the DV, while taking into account both the within- and between-group errors (variables in italic indicate they are grand centered):

$$\textbf{Disclosure} = \beta_0 + \beta_1 * \boldsymbol{Post} + \beta_2 * \boldsymbol{Friend} + \text{r} \ (3), \text{ in which:}$$

$$\beta_0 = \gamma_{00} + \mu_0 \ (4)$$

$$\beta_1 = \gamma_{10} + \mu_1 \ (5)$$

$$\beta_2 = \gamma_{20} + \mu_2 \ (6)$$

Again, see Appendix A for details. Notably, both the amount of individual posts (β_1=0.123, T=3.336, p=0.002) and active friends (β_2=2.367, T=6.069, p<0.001) have a positive effect on the disclosure level. Compared to the unconstrained model, σ^2 reduces from 6.55 to 5.22, meaning that 20.3% of the within-group variance can be explained by the two individual level variables. Thus, both H1 and H2 are significant.

Third, a *means as outcomes model* (Model 3) is proposed to test the relationship between group level predictors and self-disclosure:

$$\textbf{Disclosure} = \beta_0 + \text{r} \ (7), \text{ in which:}$$

$$\beta_0 = \gamma_{00} + \gamma_{01} * \boldsymbol{GSize} + \gamma_{02} * \boldsymbol{GPost} + \gamma_{03} * \boldsymbol{GAvestep} + \mu_0 \ (8)$$

The results summarized in Appendix A suggest that all the three group-level factors have significant effects on the intercept β_0. However, the influence of group size is positive (γ_{01}=0.003, T=2.930, p=0.006), while that of the group posts (γ_{01}=-0.193, T=-3.562, p=0.001) and group step performance (γ_{01}=-0.032, T=-3.409, p=0.002) are negative, which is unexpected. τ^2 reduces from 4.41 to 2.11 when three group level factors are added to the model, suggesting that 52.2% of the between-group variance are caused by the three group-level factors. Thus, H3 is supported whereas H4 and H5 are rejected, because two interesting reversed relationships are found.

Finally, to test the interactions among the individual and group level predictors, a *random intercepts and slopes model* (Model 4) was specified as follows:

$$\textbf{Disclosure} = \beta_0 + \beta_1 * \boldsymbol{Post} + \beta_2 * \boldsymbol{Friend} + \text{r} \ (9), \text{ in which:}$$

$$\beta_0 = \gamma_{00} + \gamma_{01} * \boldsymbol{GSize} + \gamma_{02} * \boldsymbol{GPost} + \gamma_{03} * \boldsymbol{GAvestep} + \mu_0 \ (10)$$

$$\beta_1 = \gamma_{10} + \gamma_{11} * \boldsymbol{GSize} + \gamma_{12} * \boldsymbol{GPost} + \gamma_{13} * \boldsymbol{GAvestep} + \mu_1 \ (11)$$

$$\beta_2 = \gamma_{20} + \gamma_{21} * \boldsymbol{GSize} + \gamma_{22} * \boldsymbol{GPost} + \gamma_{23} * \boldsymbol{GAvestep} + \mu_2 \ (12)$$

For the output of final model (See Appendix A), we mainly focus on the interaction terms. We find that all three group level factors do significantly influence the slope of Friend on Disclosure: Friend*Gsize (p=0.016), Friend*GPost (p=0.002), Friend*GAvestep (p<0.001). While the influence of group level factors on the slope of Post are not significant: Post*Gsize (p=0.419), Post*GPost (p=0.317), Post*GAvestep (p=0.695). Thus, H6 is partially supported. The interaction effects are selectively shown in Figure 3.

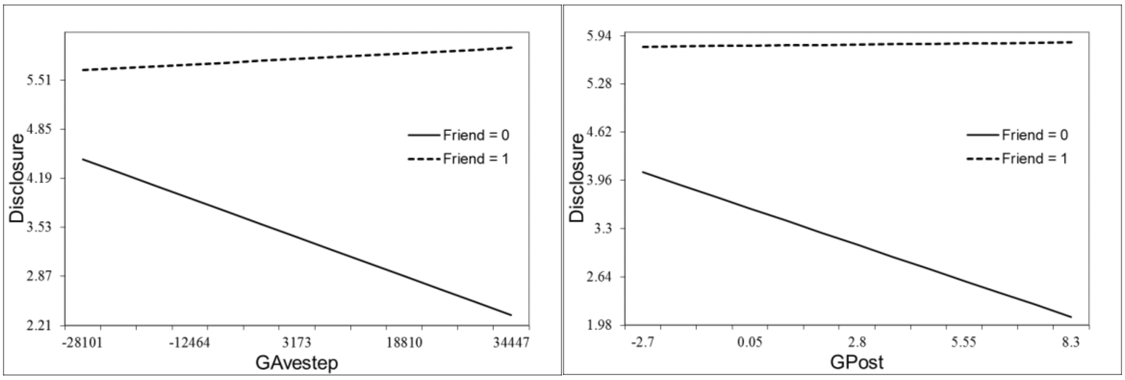

Figure 3. The Moderation Effect of Friend

4 DISCUSSION AND CONCLUSION

This study investigated the self-disclosure level in a quantified-self 2.0 context. The self-disclosure level was found to be significantly different both across different Fitbit groups and among different individual users. Two individual level variables, Post and Friend, were found to be positively related with self-disclosure. Among the three group level variables, GSize was positively related with self-disclosure; whereas the influence of GPost and GAvestep was negative, which was unexpected. Table 3 summarizes the hypotheses testing results.

Hypotheses	Predictors	Supported or not
H1	Post	Yes
H2	Friend	Yes
H3	GSize	Yes
H4	GPost	No (reversed relationship)
H5	GAvesteps	No (reversed relationship)
H6 (a)	Friend*GSize	Yes
	Friend*GPost	Yes
	Friend*GAvesteps	Yes
H6 (b)	Post*GSize	No
	Post*GPost	No
	Post*GAvesteps	No

Table 3. Summarize the results of hypotheses testing.

4.1 Discussion of Results

This section contains a summary of three interesting findings from our analysis. First, individuals tend to disclose more healthcare information as the size of the group increases and as more of their friends belong to the same group. We can explain this relationship from the theoretical point of view that the existence of friendship suggest the establishment of an understanding of their friends' selves. While such friendships may have been formed within the offline or online context, we can assume that individuals have exchanged some form of self-presentation, and this understanding is well established. From this point of view, individuals have less opportunity to form a different presentation of themselves, hence it is easier for them to disclose their healthcare information since some of the group members are already know their self-presentation. Moreover, we believe that if an individual has friends embedded in a group, it is easier to accept the group's influence regarding identification or internalization (H.-W. Kim et al. 2012), which are important stages of social influence within groups. Group size in this case could be important since less attention may be concentrated on a new member of a group, or a larger audience provides more opportunity for self-presentation.

Secondly, when group members are very active and the amount of posts is higher, individuals may tend to keep their healthcare information private. From the point of view of the theory, this behaviour may look unusual. We can explain this behaviour by the fact that in such a situation individuals have more opportunities to form their online self-presentation that could even differ from their offline self. Yet, these individuals can also experience difficulties in socialization with the group norms since they do not have friends among the group members. As mentioned, the online context of Fitbit groups provides individuals a good opportunity to manipulate or even create new self-presentations. Individuals thus can act like someone they would like to be. Therefore, additional information about their real physical condition or state of health can conflict with their online self. For this reason, people may tend to hide information. The second reason is connected with the potential conflict between individuals and the group when individuals provide insufficient information about themselves and the group cannot recognize the pattern of their behaviour, or in other words the individuals are inefficiently presenting themselves. In such situations, individuals could choose the "wrong" behavioural pattern and as a result feel ashamed or discomfort to disclose their information. For example, individuals may be ashamed to provide their performance results in a group of accomplished athletes if their personal results are mediocre.

Third, such kinds of negative social influence is not absolute, and can be moderated by intimate friends: for users who have friends in Fitbit website, the negative influence of active others will be no longer significant, and can even become positive, as shown in Figure 2.

4.2 Theoretical Implications

This research work provides empirical evidence in support of the premise that individual level factors and group level factors play an important role in determining disclosure behaviour withing QS 2.0 platforms. In exploring the impact of these different factors, our study makes several important contributions to the theoretical discuss in the area of online QS 2.0 platforms as well as privacy disclosure.

First, this work improves on previous methodological approaches by using objective measures rather than subjective measures. We advance the literature on healthcare privacy disclosure by empirically measuring actual disclosure behavior using a composite variable. Related studies have captured the notion of privacy disclosure (intention to disclose or subjectively reported disclosure) through subjective self-report, which is more prone to error. This is in light of findings from the privacy paradox literature that mentions that although IT users claim that they are concerned about privacy, a large amount of private information is disclosed. This suggests that there exists some possible gaps between the intention to disclose and the actual disclosure (Smith et al. 2011). Actual behaviors are thus more meaningful. Notably, we model individual attributes using actual posting behavior, friend lists and group attributes using actual group size, group performance and group posting metrics.

Second, our study introduces the Online QS 2.0 Context to healthcare communities. Existing research in the area of health care information has mainly focused on utilitarian healthcare systems, or online health care communities that simply facilitate the exchange of disease information (Liu et al. 2014; Maloney-Krichmar & Preece 2002). Little research has addressed the context of QS 2.0 communities.

Third, our study captures the impact of sub groups within an online platform, on disclosure behaviour.In understanding the disclosure behavior of individuals, extant research have customarily examined the influence of individual attributes on disclosure behavior. For example personal characteristics(Korzaan & Boswell 2008), protection beliefs (Lowry et al. 2011) and the benefit-cost privacy calculus process (Agarwal et al. 2009; Keith et al. 2013; Xu et al. 2011) have been shown to influence disclosure behavior. However, QS 2.0 communities inherently support the formation of groups, which could be seen as sub-communities in the platform and can exert an influence on disclosure behavior. We move beyond this individual-modelling by incorporating the effects of group-level attributes, and perform a multi-level analysis using hierarchical linear modeling that yields individual- and group-level results.

4.3 Practical Contribution

To understand the managerial implications of this study, it worthwhile to breifly examine how disclosure behaviour may impact objectives of QS 2.0 platform owners. Individual platform members who disclose more information about themselves are more likely to engage in social interactions such as making friends, as compared to individuals that disclose little information (private profiles). This is because the disclosure of more information allows other members form a richer understandng of a person and aids the process of identifying shared values which shape social interactions. In turn, increased social interactions and continued usage is critical to the health and long term sustainability of the platform (Cheung & Lee, 2009). Given this potential impact of disclosure on platform health, our study holds important implications especially for the design of such platforms to ensure sustainability. Given the relationships we identify between friend, network, group size, and disclosure behaviour, we beleive QS 2.0 platform designers should incoporate platform features that encourage formation of friends and joining of groups within the platform. An example would be the incoporation of badge based incentivizes such as virtual badges awarded for having a certain number of friends or virtual badges awarded for being a member of a certain number of groups.

4.4 Limitations and Future Work

Finally, this study has several limitations that yield future research opportunities. First, we selectively choose Fitbit users from East and Southeast Asia groups, whose results may not generalize to those from other cultures. In addition, members who belong to two or more Fitbit groups were excluded from the analysis due to the restriction of HLM. Second, users' self-disclosure may change along with the usage of Fitbit devices; however, we did not control for the different stages of use or for longitudinal changes in disclosure behavior. We believe these ommisions represent exciting future research.

APPENDIX A: MODEL ESTIMATION RESULTS

	SD	Variance component	Df	χ^2	P-value
r(within-group)	2.099	τ^2_{null}=4.406	42	3044.59	0.000***
μ_0(between group)	2.560	σ^2_{null}=6.552			
ICC (group variance/total variance)=$\tau^2_{null}/(\tau^2_{null}+\sigma^2_{null})$=0.402.					

Table A1. Chi-square and variance component for the unconstrained null model (Model 1)

Fixed effect	Coefficient	SD	T-ratio	P-value
Intercept (γ_{00})	3.574	0.367	9.742	0.000***
Post (γ_{10})	0.123	0.037	3.353	0.002***
Friend (γ_{20})	2.367	0.390	6.068	0.000***
σ^2_{model2}=5.228, r^2_{level1}(within group variance)=$(\sigma^2_{model2}-\sigma^2_{null})/\sigma^2_{null}$=0.203.				

Table A2. Estimation of the random intercepts model (Model 2)

Fixed effect	Coefficient	SD	T-ratio	P-value
Intercept (γ_{00})	4.051	0.237	17.101	0.000***
GSize (γ_{01})	0.003	0.001	2.930	0.006***
GPost (γ_{02})	-0.193	0.542	-3.562	0.001***
GAvestep (γ_{03})	-0.032	0.009	-3.409	0.002***
τ^2_{model3}=2.111, $r^2_{level2}(between\ group\ variance)$=$(\tau^2_{model3}-\tau^2_{null})/\tau^2_{null}$=0.522.				

Table A3. Estimation of the means as outcomes model (Model 3)

Fixed effect	Coefficient	SD	T-ratio	P-value
Intercept (γ_{00})	3.516	0.257	13.686	0.000***
Gsize (γ_{01})	0.003	0.001	2.632	0.012**
GPost (γ_{02})	-0.186	0.057	-3.227	0.003***
GAvestep (γ_{03})	-0.038	0.000	-3.717	0.001***
Post (γ_{10})	0.135	0.080	1.687	0.099
Post*Gsize (γ_{11})	0.000	0.000	0.818	0.419
Post*GPost (γ_{12})	-0.011	0.010	-1.014	0.317
Post*GAvestep (γ_{13})	-0.001	0.003	-0.394	0.695
Friend (γ_{20})	2.402	0.269	8.930	0.000***
Friend*Gsize (γ_{21})	-0.003	0.001	-2.535	0.016**
Friend*GPost (γ_{22})	0.194	0.058	3.325	0.002***
Friend*GAvestep (γ_{23})	0.045	0.011	4.234	0.000***

Table A4. Estimation of the random intercepts and slopes model (Model 4)

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