



Full length article

Understanding the privacy behavior of adolescents on Facebook: The role of peers, popularity and trust

Bas Hofstra ^{a, *}, Rense Corten ^a, Frank van Tubergen ^{a, b}^a Utrecht University, Department of Sociology/ICS, Padualaan 14, 3584 CH, Utrecht, The Netherlands^b King Abdulaziz University in Jeddah, Department of Sociology and Social Work, Saudi Arabia

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ABSTRACT

We study whether peer influence processes, popularity and trust predict privacy settings on Facebook. We use large-scale survey data from 3434 Dutch adolescents combined with observed privacy behavior on Facebook. The findings show that peer influence processes play a role and that adolescents imitate the privacy settings of their peers in the classroom. Such imitation processes are particularly pronounced for highly connected classrooms. The results show that more popular adolescents in the classroom are more likely to publicly display their Facebook profiles. Furthermore, we find that low-trust groups (ethnic minorities, lower educated and younger adolescents, and girls) more frequently opt for private Facebook profiles.

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1. Introduction

Online social media are increasingly used for the maintenance of interpersonal relations (Boyd & Ellison, 2007). In early 2015, more than one billion people were members of *social networking sites* (SNSs), continuously producing terabytes of information on these platforms (Litt, 2013). This information consists of textual status updates about emotions, opinions and experiences, uploaded photos, videos and music and other highly personal content, which is typically uploaded to the personal SNS profiles of users by users.

Inherent to the unprecedented rise of SNSs is that highly personal content is more easily accessible to an increasingly expanding audience than ever before. Consequently, an unintended byproduct of sharing such personal content has thrived. As a result of sharing photos, hometowns, e-mail addresses, phone numbers, education and employment statuses on SNS profiles, SNSs are highly targeted by hackers (Wu, Chou, Tseng, Lee, & Chen, 2014), which makes it relatively easy to commit identity theft (Javaro & Jasinski, 2014). This type of theft can cause financial damage and huge personal trauma, for instance, by utilizing personal information to obtain

access to credit cards and utility services, make false claims for medical services under stolen social security numbers (Acquisti & Gross, 2009) and evade law enforcement by masquerading under others' credentials (Javaro & Jasinski, 2014).

Therefore, publicly displaying content on SNSs can cause unwanted exposure to third parties, loss of reputation and loss of (job) opportunities (Lewis, Kaufman, & Christakis, 2008). Although most of these consequences are difficult to estimate, users of SNSs must decide on the use of the tools provided by SNS services to ensure protection against such types of harm. Users can typically decide with *whom* to share the content that they upload to their profiles. Facebook, for instance, has a wide spectrum of privacy settings.

Given the potentially dramatic consequences of privacy decisions on SNSs, scholars are increasingly interested in privacy behavior on SNSs. Scholars who have studied privacy behavior have consistently found that women are more likely than men to maintain private rather than public SNS profiles (Acquisti & Gross, 2006; Boyd & Hargittai, 2010; Hoy & Milne, 2010; Lewis et al., 2008; Shin & Kang, 2016; Thelwall, 2008). Younger respondents more frequently maintain private SNS profiles than do older respondents (Litt, 2013; Tufekci, 2008). There also seem to be peer influence effects: those with more friends who have private profiles on Facebook are also more likely to maintain private Facebook profiles themselves (Lewis, 2011; Lewis et al., 2008). Those who are more

* Corresponding author.

E-mail addresses: b.hofstra@uu.nl (B. Hofstra), r.corten@uu.nl (R. Corten), f.vantubergen@uu.nl (F. van Tubergen).

active online (Lewis et al., 2008) and who use Facebook more often (Boyd & Hargittai, 2010) are more likely to maintain private Facebook profiles. In addition, having more Facebook friends (Stutzman & Kramer-Duffield, 2010) and reporting higher Internet skills (Boyd & Hargittai) are related to more private Facebook profiles. Over time, users are also more likely to switch from public to private profiles on Facebook (Stutzman, Gross, & Acquisti, 2013). Finally, those who are concerned with privacy (Litt, 2013; Tufekci, 2008) and who have experienced embarrassing situations on SNSs (Litt, 2013) are more likely to maintain private profiles.

We extend this growing literature both theoretically and empirically. First, we aim to understand why prior work has consistently found that women and younger people more frequently maintain private profiles. We study whether higher levels of distrust among these groups provide an explanation. Trust has previously been linked to online privacy concerns (e.g., Fogel & Nehman, 2009; Thomson, Yuki, & Ito, 2015). To fully investigate the potential role of trust, we also consider the differences in privacy settings among ethnic groups and educational level, given that prior work has suggested that there are lower levels of trust among minorities and at lower educational tracks (Mewes, 2014; Simpson, McGrimmon, & Irwin, 2007). Therefore, we advance theory in online privacy research by unraveling some of the mechanisms that possibly underlie previous findings by specifically considering the role of trust. Are the gender and age findings in social media privacy research a result of the differences in trust within these groups? Additionally, are other well-known trust correlates – ethnic background and education – related to online privacy? Furthermore, we also study peer influence processes and elaborate the role of social networks by considering the potential effect of popularity, given that previous studies have shown that popularity and privacy are related (e.g., Christofides, Muise, & Desmarais, 2012; Utz, Tanis, & Vermeulen, 2012). The present study focuses on adolescents (16–20 years) in high school, and using sociometric information on who are friends in high school classrooms (~23 pupils), we construct the peer status in classrooms. We provide a novel test of the hypothesis that popularity and privacy are related; previous studies have often used the “need for popularity” (i.e., those who want to be popular) (Christofides et al., 2012; Utz et al., 2012), whereas we construct actual peer popularity as judged by the respondents’ peers in class. This approach motivates the main research question of this study: *To what extent are peers’ privacy settings, popularity and trust related to adolescents’ privacy settings on Facebook?*

We also empirically contribute to prior work. We study privacy settings among a large and diverse sample of Dutch adolescent Facebook users in 2014 ($N = 3451$). As shown in the overview of previous studies in Table 1 (these studies are not exhaustive but exemplary), scholars have generally used (potentially biased) self-reported survey data to study privacy settings (e.g., Boyd & Hargittai, 2010; Stutzman & Kramer-Duffield, 2010), and almost all previous studies examine privacy behavior on SNSs with convenience samples of US college students (e.g., Hoy & Milne, 2010; Lewis et al., 2008; Tufekci, 2008).¹ We interpret the term “convenience sample” in the strict statistical sense; that is, instead of a random sample, an easily accessible sample has been used to draw a sample from a target population. Some of the target populations

of the studies in Table 1 resemble our target population (i.e., adolescents/young adults), but most of these studies do not use random sampling. These issues make it difficult to convincingly make generalizable claims on the factors that affect privacy behavior on SNSs. We use stratified sampling to significantly improve the generalizability of our results to the target population of adolescents. Uniquely, we use large-scale survey data (which measure social networks, popularity and trust) and link these measures with observed behavioral data on privacy settings on Facebook. This specific design has been recommended by Tufekci (2014), and we follow this research path. An additional benefit of such behavioral instead of self-reported privacy measures is that they are less prone to underreporting or acquiescence biases (Kuru & Pasek, 2016). Therefore, this study is one of the first attempts to link large-scale survey data – a step forward with respect to the previously used small convenience samples – with the observed privacy behavior of adolescents on Facebook.

Facebook was the most popular SNS in the Netherlands among adolescents in 2014 (Hofstra, Corten, & Van Tubergen, 2015a) and especially adolescents who are highly engaged in SNSs (Corten, 2012). In 2014, Facebook users could choose from a wide spectrum of privacy settings, providing users with several options. For instance, users can choose to hide status updates from specific Facebook friends. Facebook has a long history of changing the tools with which users can decide how public or private their profiles are (see Boyd & Hargittai, 2010), and at each point that Facebook has introduced new privacy tools, the default for Facebook users has been set to “share publicly” (Boyd & Hargittai, 2010). In each case, the privacy setting changes by Facebook users to a more private profile have been a deliberate choice. Many studies examine Facebook privacy in light of whether profiles are visible (e.g., Lewis et al., 2008). Our data allow examining privacy settings more specifically, that is, whether one’s friends are publicly visible to everyone (yes/no) and whether one’s status updates are publicly visible to everyone (yes/no).

2. Theory and hypotheses

2.1. Peers’ privacy and peer status

Following Lewis et al. (2008) and Lewis (2011), we propose that peer influence processes play an important role in adolescents’ decisions to maintain private profiles on Facebook. Behavior depends heavily on the behavior of those with whom one is associated, and in particular, adolescents look to their peers to determine which behaviors are appropriate (Brehwald & Prinstein, 2011). Adolescents seek to gain social approval from their peers and avoid social exclusion by following norms within their groups (Cialdini & Goldstein, 2004). We assume that groups of adolescents hold norms regarding the sharing of information on SNSs and that adolescents conform to these norms; privacy concerns may be more prevalent in one group than in others. If there is a norm within a group that one should be more careful when publicly displaying SNS profile information, then one may be influenced by this norm and choose to maintain a more private profile. A person in a group that is particularly concerned with privacy may be scolded after uploading party pictures of other group members and may be told that he or she must either delete the pictures or set his profile to a more private setting so that not everyone can see the pictures. Hence, due to the actions of one individual, others experience negative externalities and implement a group sanction (Coleman, 1990): scolding or social exclusion when this person does not adhere to the Facebook privacy norm.

Schools constitute a particularly attractive study context for peer influence processes, given that they consist of clearly defined

¹ Our rationale behind choosing these studies is as follows. First, we show what the standard research practices are in this line of research by choosing five highly cited papers on privacy in social media (i.e., Acquisti & Gross, 2006; Boyd & Hargittai, 2010; Lewis et al., 2008; Thelwall, 2008; Tufekci, 2008). Second, we show the research practices of five relatively recent papers in this area (i.e., Hoy & Milne, 2010; Lewis, 2011; Litt, 2013; Stutzman & Kramer-Duffield, 2010; Stutzman et al., 2013).

Table 1

Previous studies on privacy behavior on SNSs (non-exhaustive).

Author(s)	Aim/research question	Data	Type	N	Sampling	Method	Dependent	Predictors	Rel. ^a
The five studies below are highly cited studies on privacy in social media									
Acquisti and Gross (2006)	Investigate why people show more or less information	Self-reported	Cross-sectional	294	Convenience	Correlations; difference tests; multivariate regressions	Privacy concerns	Female	+
Tufekci (2008)	Examine audience concerns and privacy worries and examine disclosure and audience management behaviors	Self-reported	Cross-sectional	704	Convenience	Logistic regressions; difference tests	Private profile	Female	+
								Age	–
								Unwanted exposure	+
Lewis et al. (2008)	Analyze which factors predict privacy	Behavioral	Cross-sectional	1710	Convenience	Logistic regressions	Private profile	Female	+
								Online activity	+
								Friends private	+
								Roommates private	+
Thelwall (2008)	Identify online behaviors that relate to age, network size and gender	Behavioral	Cross-sectional	15,043	Semi-random	Difference tests	Private profile	Female	+
Boyd and Hargittai (2010)	Examine how privacy practices change over time	Self-reported	Two waves	495	Convenience	Difference tests	Privacy tool use	Female	+
								Internet skill	+
The five studies below are relatively recent studies on privacy in social media									
Hoy and Milne (2010)	Examine gender differences in online privacy and use of personal information	Self-reported	Cross-sectional	589	Snowball	Correlations; difference tests; factor analyses	Untagging photos	Female	+
							Selective friending		
							Privacy tool use		
Stutzman and Kramer-Duffield (2010)	Explore the behavior of setting privacy settings to friends-only	Self-reported	Cross-sectional	494	Convenience	Logistic regressions	Private profile	Female	+
								# Facebook friends	+
Lewis (2011)	Analyze the co-evolution of friendships and privacy	Behavioral	Multiple waves	876	Convenience	RSiena	Private profile	Peer influence	+
Litt (2013)	Examine predictors of privacy tool use on social network sites	Self-reported	Cross-sectional	490	Semi-random	Multivariate regressions	Privacy tool use	Female	+
								Age	–
								Embarrassment	+
Stutzman et al. (2013)	Understand how privacy and disclosure changed between 2005 and 2011	Behavioral	Longitudinal	5076	Convenience	Difference tests	Private profile	Time	+

^a Direction of associations found, + means positive association found, and – means negative association found.

social contexts (Corten & Knecht, 2013). We distinguish among friends in class and other classmates in the classroom and assume that correlations between friends' and classmates' privacy settings and respondents' privacy settings may be found in both types of peers. Thus, we propose the following:

H1a. Adolescents who have a larger proportion of friends in the classroom who maintain private (open) profiles are more likely to maintain private (open) Facebook profiles.

H1b. Adolescents who have a larger proportion of classmates who maintain private (open) profiles are more likely to maintain private (open) Facebook profiles.

In addition, we hypothesize that the classroom norm for privacy on Facebook spreads more easily through class networks when more adolescents are friends with one another. That is, when more adolescents nominate each other as friends in the classroom, the

fraction of classmates who maintain a private Facebook profile may be more influential in determining students' privacy settings. Previous research has shown that the density of classrooms (i.e., the fraction of classroom friends who nominate each other as friends) has a moderating effect on peer influence processes (e.g., Corten & Knecht, 2013). The reason may be, in denser classrooms, more pupils interact and, therefore, the initial propensity for a certain behavior will spread more easily through the network. Additionally, in denser classrooms, knowledge on the behavior of others spreads through the network more easily. Therefore, classroom peers can more quickly implement a group sanction when one deviates from a norm. We believe that this is also the case for the classroom norm of privacy behavior, and we hypothesize the following:

H2. The association between having more classmates who have private (open) Facebook profiles and maintaining a private (open)

Facebook profile strengthens as the density of the classroom network increases.

We elaborate the role of peers in the classroom and consider the potential role of peer status. Maintaining a non-private Facebook profile may be driven by the need for distinction, in essence, to differentiate oneself from other peers and to maintain status among one's peers. Research suggests that younger rather than older generations consider post-material values to be more important than material values (Inglehart & Abramson, 1994). Younger people seek means to express themselves, they want to have jobs in which they can be creative, and they value self-expression over high income. Relatedly, younger people increasingly display more narcissism than do older people (Twenge, Konrath, Foster, Campbell, & Bushman, 2008). We assume that self-expression is particularly strong among the most popular peers in the classroom – i.e., those who are recognized by their classmates as popular. They impress their less popular peers by breaking conventional norms, for instance, by using drugs, consuming alcohol, and showing off (Dijkstra, Lindenberg, Verhulst, Ormel, & Veenstra, 2009). Popular adolescents display behaviors that are related to higher status and coolness (Brechwald & Prinstein, 2011). We argue that popular adolescents want to show how cool they are to as many others as possible as a tool for self-expression and to maintain their status among peers. Maintaining a public Facebook profile is a particularly good way of showing status because other peers can see the distinctive friendship choices and/or texts that one uploads when he or she publicly shows a profile. Previous studies also established a correlation between a “need for popularity” (i.e., those who *want* to be popular) and online privacy (e.g., Christofides et al., 2012; Utz et al., 2012). Thus, we propose the following:

H3. More popular adolescents are more likely than less popular adolescents to maintain public Facebook profiles.

2.2. Generalized trust

We also develop hypotheses concerning the role of trust in privacy behavior. Because of the potentially damaging outcomes of displaying personal information online, privacy decisions may be based on trust and expectations about the misuse of personal information disclosed online.

Various definitions of trust can be found in the literature, but a widely used trust concept is that of *generalized trust*, which can be defined as a set of “socially learned and socially confirmed expectations that people have of each other, of the organizations and institutions in which they live, and of the natural and moral social orders that set the fundamental understandings for their lives” (cf. Barber, 1983). This definition captures that trustors form an estimate of the trustworthiness of the average person (Paxton, 2007).

Facebook privacy can be related to generalized trust. A private Facebook profile implies the adjustment of some privacy settings, which means that one closes his/her profile to the *general* audience on Facebook, possibly indicating that one generally thinks he or she “can't be too careful dealing with people”. This concept relates to the trustor's estimate of the average person; Facebook users (trustors) make an assessment of the trustworthiness of generalized others.

Research shows that individual differences in generalized trust are relatively stable (Glaeser, Liabson, Scheinkman, & Soutter, 2000). Furthermore, the findings show the following: men are more likely than women to have generalized trust (Alesina & La Ferrara, 2002; Mewes, 2014); foreign-born persons and minority members are less likely than native-born people and majority

members to have generalized trust (Glaeser et al., 2000; Simpson et al., 2007); lower educated people are less likely than higher educated people to trust (Mewes, 2014); and older individuals are more likely than younger individuals (Mewes, 2014) to have generalized trust.

Women are generally found to be more likely than men to maintain private profiles (Boyd & Hargittai, 2010; Hoy & Milne, 2010; Lewis et al., 2008). Possibly, women are generally less likely to trust others with personal information displayed on SNSs. Tufekci (2008) and Litt (2013) find that younger people are more likely to maintain more private profiles than are older individuals, which may be a result of younger people's being less trustful (Mewes, 2014). Nearly no results exist with regard to ethnic background and its relationship to privacy behavior on SNSs. However, previous studies have shown that those from non-native ethnic backgrounds are less likely to trust (Alesina & La Ferrara, 2002; Glaeser et al., 2000; Simpson et al., 2007) and that those from non-Western countries of origin (e.g., low-trust societies such as Turkey) display significantly lower levels of trust than do those from Western countries (Delhey & Newton, 2005). Following these earlier results, we expect the same for Facebook privacy. Thus, we propose the following:

H4. Girls are more likely to maintain private Facebook profiles than boys.

H4b. Adolescents with a non-Dutch ethnic background are more likely to maintain private Facebook profiles than those with a Dutch background.

H4c. Adolescents who are lower educated are more likely to maintain private Facebook profiles than those who are higher educated.

H4d. Younger adolescents are more likely to maintain private Facebook profiles than older adolescents.

We aim to ascertain that the associations between gender, national origin, education, age and privacy run via the trust mechanism. Therefore, we propose the following:

H5a. The relationship between gender and maintaining a private Facebook profile is (at least partially) mediated by generalized trust.

H5b. The relationship between ethnic background and maintaining a private Facebook profile is (at least partially) mediated by generalized trust.

H5c. The relationship between educational level and maintaining a private Facebook profile is (at least partially) mediated by generalized trust.

H5d. The relationship between age and maintaining a private Facebook profile is (at least partially) mediated by generalized trust.

Finally, Fig. 1 summarizes our hypotheses and the predicted associations with privacy on Facebook.

3. Data

We use survey data on adolescents in the Netherlands originating from the larger project entitled “Children of Immigrants Longitudinal Study in Four European Countries” (CILS4EU) (Kalter et al., 2013, 2015).² CILS4EU followed adolescents 14–15 years of age (third-year high school pupils in the Netherlands), with an oversampling of immigrant minority youth, for three subsequent years beginning in 2010. Each year, the survey was repeated, for a

² The data were collected in Germany, the Netherlands, Sweden and England.

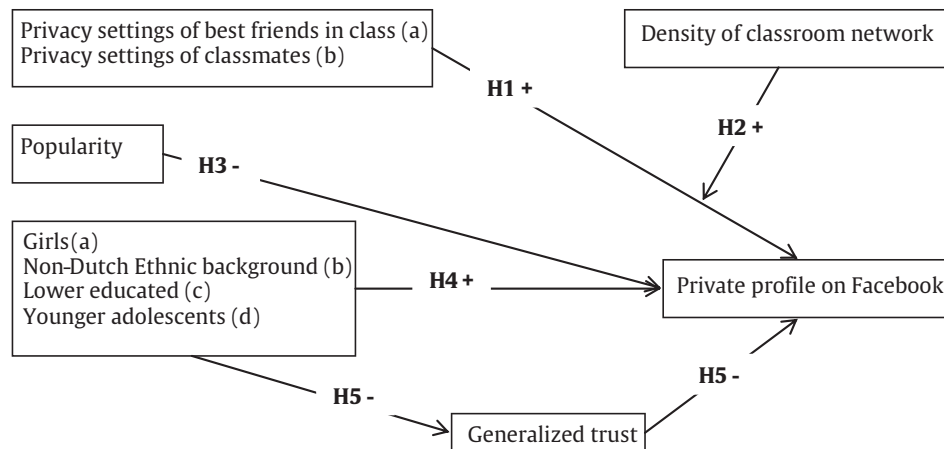


Fig. 1. Conceptual model for the hypotheses as derived from the theory; + = positive effect hypothesized, - = negative effect hypothesized.

large portion with the same questions. The surveys consist of self-completion questionnaires concerning many individual characteristics, attitudes and leisure time activities. The data include information on friends within classrooms. Data collection occurred at high schools.

In wave 1 (2010–2011), high schools were selected according to four strata based on educational track levels and the percentage of non-Western immigrant students in schools (controlling for strata as dummy variables does not change the results of this article). In wave 1, two classes were randomly selected per school, resulting in a total of 118 schools, 252 classes and 4963 students who participated in the survey in the Netherlands.³ Class composition changes between the third and fourth years are common in the Netherlands. Hence, respondents in wave 2 (2011–2012) could be scattered among multiple fourth-year classes that did not participate in wave 1. To interview as many wave 1 respondents as possible, schools were asked to provide more than the two classes initially sampled in wave 1 if the respondents from wave 1 were in classes different from those sampled previously. Consequently, additional students were interviewed: 3803 participants who participated in wave 1 were surveyed again in wave 2 (76.6%), and an additional 2118 new respondents were surveyed in wave 2 (W2 N = 5921).

3.1. Dutch Facebook survey

The Dutch Facebook Survey (DFS) data (Hofstra, Corten, & Van Tubergen, 2015b) were collected to enrich the Dutch part of the CILS4EU survey and consist of observational data from Facebook. The data were collected between June 2014 and September 2014. In waves 3 (2012–2013) and 4 (2013–2014) of the CILS4EU survey, participants were asked about their membership in Facebook.⁴ In waves 3 and 4 combined, N = 4864 respondents indicated being a member of Facebook in at least one of these waves (W3 = 3423, W4 = 3595). For the project, coding assistants tracked down respondents' profiles based on the respondents' names, cities of residence and, if reported in the survey, the URLs of their Facebook profiles. This procedure occurred *after* wave 4 for the respondents

who indicated being a member in wave 3 or 4. The coding assistants were personally instructed, and all followed strict coding procedures; N = 4463 (91.8%) of the profiles were tracked.⁵ Based on the tracked profiles, the privacy settings were coded – whether friend lists were publicly visible and whether timeline posts were publicly visible. We have linked the DFS with wave 2 of the CILS4EU (from which our independent variables are constructed), which is the latest licensed version of the CILS4EU and contains the latest classroom sociometric data. Of the 4463 who were tracked in the DFS, 3864 participated in wave 2 of the CILS4EU, which is the maximum number of observations we can analyze. Fig. 2 graphically displays the number of observations from waves 1 and 2 and how we arrive at N = 3864.

The collected information was publicly visible on Facebook, and we followed a strict procedure with password-protected files. All personal identifiers were removed from the data. The data collection, the coding procedure and the use of these data for scientific purposes were reviewed and approved by an internal review board.

4. Methods

4.1. Measurement of privacy behavior on Facebook

Based on the observational data obtained in the DFS, we code two variables that indicate whether one's Facebook profile settings are private. First, we code whether one's *timeline posts* are private (1) or not (0). Second, we measure whether one's *friend list* is private (1) or not (0). We do not distinguish between the privacy settings *visible to friends* or *visible to friends of friends* or any other custom settings chosen by the respondents on Facebook. For the timeline posts measure, the coding assistants unfold one's complete timeline and code whether *at least one* status update is publicly visible. It may be that a respondent posted publicly in 2012 but no longer posted publicly in 2013 and 2014; these respondents are coded as having a public timeline. With our data, we cannot distinguish between such cases. We capture whether one's timeline posts or relationships are visible to non-friends *in general*. We also code seven variables that indicate whether adolescents choose to disclose personal information on their Facebook profiles' information pages; whether respondents display their family, gender,

³ In the first wave, N = 600 respondents who were not a part of the original sampling frame were sampled because some schools wanted to participate with more than two classes. A random sample of N = 4363 was established in wave 1. We include as many respondents as possible in the sample for analyses, including newcomers (non-random) and the non-random sample of wave 1, to ensure a large sample size.

⁴ As of January 2015, two additional waves of data were collected: waves 3 and 4.

⁵ We cannot distinguish profiles that were not tracked because of privacy settings that were too strict or profiles that we cannot track due to wrong or incomplete information.

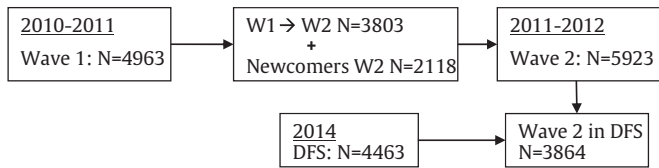


Fig. 2. Attrition rates and maximum number of observations in the analyses.

Table 2
Descriptive statistics of privacy behaviors on Facebook.

	N	%
Timeline posts private: Yes (1)	2437	54.65
Timeline posts private: No (0)	2022	45.35
Timeline posts private: Total	4459	100
Friend list private: Yes (1)	1119	25.07
Friend list private: No (0)	3344	74.93
Friend list private: Total	4463	100

relationship status, romantic interests, hometown, secondary education, and work. We also run all of our analyses described with these privacy decisions, and we do not find qualitatively different results compared with the two privacy settings described above. Table 2 shows that 54.7% of the respondents maintain private timeline posts and that 25.1% maintain a private friend lists on Facebook.

4.2. Independent variables

We operationalize our independent variables by using wave 2 of the CILS4EU data because this wave is the most recent version of the licensed CILS4EU data and because the most recent classroom sociometric data are available in this wave of data.

4.2.1. Privacy settings of best friends in class

The privacy settings of best friends in class are two variables that capture the percentage of classroom friends who have their *timeline posts* and the percentage of classroom friends who have their *friend lists* private. The respondents answered the question, “Who are your best friends in the class (you can write down a maximum of 5 friends)?” We know from these friends (see the measurement of the privacy variables) whether they maintain private friend lists and timeline posts on Facebook. We count the absolute number of classroom friends who maintain a private friend list on Facebook within the respondent's friends, ranging from 0 to 5, divide this amount by the number of classroom friends indicated for this question (also ranging from 0 to 5) and multiply this number by 100. We constructed a similar measure for the percentage of classroom best friends who maintain private timeline posts. Because we limit our respondents to a maximum of five friends in class, we may not capture *all* friends. However, 64% of the respondents indicate fewer than five friends, and the average number of friends is 3.6. Therefore, in most cases, we have captured all of the friends of the respondents in the classroom.

4.2.2. Privacy settings of classmates

For associations between the privacy settings of non-direct classroom friends and respondents, we construct two variables that indicate the *rest* of the class's privacy preferences on Facebook. We measure the percentage of the class that maintains private posts and the percentage of the class that maintains private friend lists, excluding the privacy preferences of the best friends in the class indicated and excluding the respondents' privacy preferences.

4.2.3. Density

We construct a variable that measures the density of class networks, which is defined as:

$$Density_g = \frac{\sum_i X_{ij}}{5N}, \quad (1)$$

where $Density_g$ is the density of classroom g , i is the pupil, X_{ij} is a binary variable that indicates whether a relationship exists between pupil i and pupil j , and N is the total number of pupils in the class. We multiply N by five because respondents could maximally nominate five friends (Valente, 2010). Hence, density is the fraction of the number of ties that could have been realized in the class.

4.2.4. Indegree: popularity in class

We construct a variable to measure respondents' popularity. In the second wave, respondents answered the question, “Who are the most popular students in the class (you can write down a maximum of 5 names)?” The pupils were not allowed to define themselves as popular. We acquire a comparable popularity measure between classes, which is defined as:

$$Popularity_i = \frac{\sum_j K_{ji}}{N-1} * 100, \quad (2)$$

where $Popularity_i$ is the indegree popularity of pupil i , K_{ji} indicates whether pupil j nominates pupil i as popular, and N is the total number of pupils in the classroom. Hence, we acquire a standardized variable between classrooms that indicates what percentage of classroom pupils in a given class indicates the respondent as the most popular pupil (Wasserman & Faust, 1994), and this measure shows sufficient discriminant validity from other dimensions of peer status (Dijkstra, Cillessen, Lindenberg, & Veenstra, 2010).

4.2.5. Gender

We measure whether the respondent is a girl (1) or a boy (0).

4.2.6. Ethnic background

This variable indicates the respondents' ethnic background within one of the six largest ethnic background groups in the Netherlands: 1 “Native Dutch”, 2 “Turkish”, 3 “Moroccan”, 4 “Dutch Caribbean”, 5 “Other: Western (Europe or English speaking)” and 6 “Other: non-Western”. The measure is based on the biological parents' country of birth. When the adolescent has only one native-born Dutch parent, he or she is classified as having the ethnic background of the foreign-born parent. When children have parents from different countries, they belong to the ethnic background of the mother, which is standard practice in research on ethnic background in the Netherlands (CBS, 2012).

4.2.7. Educational track

We create dummy variables to indicate the adolescents' high school tracks. In the Netherlands, when adolescents transition to high school, they are classified into different educational tracks, which differ in terms of the level and type of education. These seven tracks range from “VMBO-basis” (lower preparatory vocational education) to “VWO-gymnasium” (university preparatory education). We combine these classes into three dummy variables: “preparatory vocational education (VMBO)”, “senior general (HAVO)” and “university preparatory education (VWO)”. We combine the four preparatory vocational educational tracks into one category and combine the two levels of university preparatory education into one category because the differences between these educational tracks are not substantially large. We perform robustness analyses in which we separate the highest two levels of

Table 3
Descriptive statistics for the independent variables.

	Range	Mean	SD	N	% Missing
% Best friends' posts private	0–100	37.096	29.858	3529	8.67%
% Best friends' friend lists private	0–100	17.056	22.818	3529	8.67%
% Class timeline posts private	0–100	38.354	16.209	3521	8.88%
% Class friend lists private	0–100	17.555	11.025	3515	9.03%
Density	0.200–1	0.677	0.105	3706	4.09%
Indegree: popularity	0–100	8.873	14.057	3705	4.12%
Girls	0–1	0.546		3719	3.75%
Ethnic background				3864	0%
Dutch	0–1	0.775		2996	
Turkish	0–1	0.030		115	
Moroccan	0–1	0.020		78	
Dutch Caribbean	0–1	0.028		107	
Other: Western	0–1	0.090		347	
Other: non-Western	0–1	0.057		221	
Educational track				3712	3.93%
Preparatory vocational	0–1	0.486		1805	
Senior general	0–1	0.271		1006	
University preparatory	0–1	0.243		901	
Age in months	201–247	223.564	7.173	3668	5.07%
Trust	0–1	0.519	0.500	4433	

vocational education (Dutch: VMBO-T and VMBO-GT) from the lowest two levels (Dutch: VMBO-basis and VMBO-kader). These results are in line with the results presented in the article.⁶

4.2.8. Age in months

This variable measures the age of respondents in months, calculated as the difference in months between the respondent's date of birth and the date when the respondent's privacy variables were obtained.

4.2.9. Trust

We measure generalized trust with the following standard question, which is asked in many other surveys (e.g., GSS, ESS; Nannestad, 2008): “Generally speaking, would you say that most people can be trusted (1) or that you can't be too careful in dealing with people? (0)”. Because this measure is only available in waves 3 and 4, we take answers from wave 3, and if respondents were missing or did not participate in wave 3 but were not missing or did participate in wave 4, then we take the respondents' answers from wave 4. Between waves 3 and 4, trust is relatively stable; 73% of the respondents answer equally when they answer the trust question in both waves. A score of 1 means that the respondent places trust in generalized others.

Table 3 shows the descriptive statistics for the independent variables for the respondents in the DFS data: 3864 respondents participated in W2 and were tracked in the DFS data. This number is the maximum number of respondents who we can investigate. We show the number of respondents who have non-missing values and were tracked in the DFS data, and the % missing column indicates the percentage of missing values relative to the maximum of 3864. A summary table of all of the questions that the respondents were

asked and the constructs used in this article is found in [Appendix A](#).

4.3. Analytical strategy

We perform two sets of statistical analyses to test our hypotheses. First, we estimate two logistic regression models to test whether the privacy behavior of friends and classmates (H1), popularity (H3), gender, educational level, ethnic background and age (H4) affect the tendency to have private Facebook timeline posts or a private friend list. Additionally, we interact the percentage of classmates' privacy settings and class density to test H2. Because adolescents are clustered within classes, we perform a cluster correction for 287 classes and obtain robust standard errors.

Second, we estimate two mediation models by using structural equation modeling (SEM). SEM makes it possible to simultaneously estimate models with multiple endogenous variables. To test H5, our first model estimates whether the relationships of gender, ethnic background, educational level and age with private timeline posts are (at least partially) mediated by generalized trust, and the second model analyzes these same associations with maintaining private friend lists. Generalized trust and Facebook privacy are dichotomous variables, and therefore, we use the *gsem* command in the Stata statistical software package to perform path analysis by using logistic regression (StataCorp, 2013). For both paths of H5, logistic regression is performed. We control for peers' privacy behavior and popularity and perform a correction for 287 classes.

We listwise delete the missing values of all of the variables so that we can generalize our results to the same set of 3434 respondents, leading to an 11.1% loss of observations.

5. Results

Table 4 shows the two logistic regression models for having private timeline posts and private friend lists on Facebook. We report the average marginal effects (AMEs) because they are more intuitively interpreted than are odds ratios; therefore, the effect sizes can be compared across models (Mood, 2010). The odds ratios can reflect unobserved heterogeneity and can therefore be problematic to interpret as substantive effects (cf. Mood, 2010). The AMEs express how $P(Y = 1)$ changes as the predictors change: from 0 to 1 in the case of categorical or dummy variables and with a unit increase for continuous variables. The AMEs are calculated by

⁶ We performed robustness analyses in which we separated the highest two levels of vocational education (Dutch: VMBO-T and VMBO-GT) from the lowest two levels (Dutch: VMBO-basis and VMBO-kader). One may argue that the two highest vocational tracks are significantly different from the lowest two. For “private friend list”, we found no significantly different results, and for “private timeline posts”, we found that those who follow the senior general educational track were significantly less likely to maintain private timeline posts than those in the lowest two vocational tracks. Those in the university preparatory track (although marginally significant, $p = .051$) and the highest two vocational tracks were not more likely to have private timeline posts than those in the lowest two educational tracks. These results are in line with the results presented in the article.

Table 4

Logistic regression: associations between peers' privacy behavior, popularity, gender, ethnic background, educational level, age and Facebook privacy. Average marginal effects are presented.

	Hypotheses	Pr(Private timeline post)			Pr(Private friend list)		
		dy/dx ^a	SE ^b	p ^c	dy/dx	SE	p
% Best friends' timeline posts private	H1 +	0.001	0.000	0.110			
% Best friends' friend lists private	H1 +				0.000	0.000	0.797
% Class timeline posts private	H1 +	0.002	0.001	0.005			
% Class friend lists private	H1 +				0.000	0.001	0.781
Indegree: popularity	H3 –	–0.003	0.001	0.000	–0.001	0.000	0.007
Girls (ref.: boys)	H4a +	0.023	0.017	0.171	0.065	0.016	0.000
Ethnic background (ref.: Dutch)							
Turkish	H4b +	0.105	0.053	0.048	0.363	0.048	0.000
Moroccan	H4b +	0.210	0.055	0.000	0.268	0.071	0.000
Dutch Caribbean	H4b +	0.086	0.052	0.097	0.168	0.051	0.001
Other Western	H4b +	–0.042	0.031	0.173	0.071	0.024	0.003
Other non-Western	H4b +	0.059	0.038	0.115	0.203	0.037	0.000
Educational track (ref.: Voc. educ.)							
Senior general	H4c –	–0.043	0.019	0.026	0.021	0.019	0.260
University preparatory	H4c –	–0.040	0.022	0.063	0.033	0.023	0.159
Age in months	H4d –	–0.007	0.001	0.000	–0.023	0.002	0.000
Constant (log-odds)		6.292	1.139	0.000	29.875	2.753	0.000
N		3434			3434		
Wald χ^2 (df)		104.930	(12)		259.930	(12)	
Prob. > χ^2		0.000			0.000		
Log pseudolikelihood		–2306.452			–1658.212		
Pseudo R ²		0.024			0.147		

^a Average marginal effects.

^b Delta-method standard errors, cluster correction for 287 classes.

^c Two-sided *p*-values.

computing a marginal effect for every observation; all of these effects are then averaged (Cameron & Trivedi, 2010).

We find evidence of the role of peers' privacy behavior in the respondents' privacy settings, but the effect sizes appear to be somewhat modest. With a two-standard-deviation increase in the percentage of classmates who have private timeline posts (32.42), the average probability of maintaining private timeline posts increases by 0.07, whereas classmates' private friend lists are not related to maintaining private friend lists. We find some evidence (borderline significant: p -1sided = 0.055) of the association between best friends' private timeline posts and the respondent's maintaining private timeline posts: with a two-standard-deviation increase in the percentage of friends who maintain private friend lists, the average probability of maintaining a private friend lists increases by 0.06. There is no significant relationship between best friends' private friend lists and respondents' private friend lists.⁷

We find evidence to support H3: popularity in class is significantly related to privacy settings. Again, the magnitude of this association is small: a two-standard-deviation increase in indegree popularity decreases the probability of maintaining private timeline posts by 0.08, and it decreases the probability of maintaining a private friend list by 0.03.

In line with H4a, we find that girls have a 0.07 higher probability of maintaining a private friend list on Facebook than boys have, whereas there is no significant difference in maintaining private timeline posts between girls and boys. In line with H4b, our findings show that Dutch majority adolescents have lower average probabilities of maintaining private timeline posts than do adolescents with Turkish (0.11), Moroccan (0.21) and Dutch Caribbean

(0.09) ethnic backgrounds. Additionally, native Dutch have a lower probability of maintaining private friend lists than do pupils of Turkish (0.36), Moroccan (0.27), Dutch Caribbean (0.17), other Western (0.07) and other non-Western (0.20) backgrounds. Ethnic background has frequently been omitted in prior work, but our study shows that these associations, at least in the Netherlands, are rather large.

The results partly support H4c: those who are in the vocational education track in high school are slightly more likely than those in the senior general track (0.04) and in the university preparatory track (0.04) to maintain private timeline posts on Facebook. We find evidence of the role of age (H4d): adolescents who are 14.37 months older (two standard deviations) have a 0.10 lower average probability of maintaining private timeline posts and a 0.33 lower probability of maintaining private friend lists on Facebook.

We interact class peer influence and class density to test H2 (full results found in Appendix B). As expected, the association between the percentage of classmates who maintain private timeline posts and the respondents' private timeline posts increases when class density increases. This model fits the data significantly better than does the model without the interaction term (LR-test: χ^2 (df) = 6.540(2); Prob. > χ^2 = 0.038). Fig. 3 shows that the AME of the percentage of classmates who maintain private timeline posts on respondents' private timeline posts increases with higher density values.⁸

Table 5 shows the direct and indirect (via generalized trust) relationships of gender, ethnic background, educational track and

⁷ We analyzed the relationship between peers' privacy behavior and maintaining a private Hyves profile (1) or not (0) (a former Dutch SNS, see Hofstra et al., 2015a), where the time lag between the sociometric data and the privacy measure is significantly smaller, finding an AME of 0.002 (N = 1029).

⁸ We estimated a logistic regression model in which we investigated having at least one privacy setting enabled on Facebook; an ordered logistic regression; and a linear regression model, where zero means no privacy settings enabled, one means maintaining private timeline posts or private friend lists, and two means keeping private timeline posts and a private friend list. In none of these analyses did we find qualitatively different results.

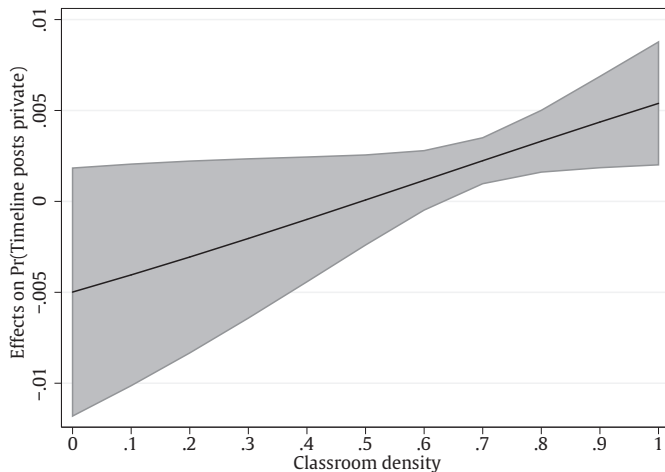


Fig. 3. Average marginal effects of the % class timeline posts private with 95% CIs.

age with maintaining private timeline posts and private friend lists. We once again report the AMEs, based on a self-written program, because AMEs are currently not available for *gsem* in Stata. In this program, we analytically compute the AMEs by elementary calculus and obtain standard errors by non-parametric bootstrapping ($N = 1000$ bootstraps).

Girls trust less often than boys do. Adolescents from a non-native ethnic background trust less often than do adolescents from a native ethnic background. Adolescents in lower educational tracks trust less often than do those in higher tracks. Surprisingly, older adolescents trust less often than younger adolescents do.

We find no significant indirect relationship of gender, ethnic background, education or age with maintaining a private friend list as a result of trust, whereas the direct associations of these variables and the tendency to maintain private friend lists are equal to the associations found in our previous analysis. We do not find a direct relationship between trust and maintaining a private friend list.

Surprisingly, those who place trust in generalized others are significantly more likely to keep timelines private. For the indirect path coefficients, one path coefficient is multiplied by another to obtain the indirect effect. Hence, our indirect associations are in directions opposite to those we expected. For instance, the positive association between trust and private timeline posts multiplied by the negative association between a Turkish ethnic background and trust yields a negative indirect association that is significantly different from zero. Hence, the mediated associations of gender, ethnic background and educational level are in directions opposite to those we expected. Because there is a negative association between age and trust, this indirect association is in the hypothesized direction. However, given the large number of respondents ($N = 3434$), the significance of the indirect associations is somewhat unconvincing, with the smallest p -value being 0.026. Finally, in no case are the relations fully mediated by generalized trust.⁹

⁹ We used the relatively new *gsem* command in the Stata statistical software package to estimate structural equation models with binary dependent variables. Therefore, we were not able to compute fit indices such as the χ^2 , the root mean square error of approximation (RMSEA), and the comparative fit index (CFI). The existing statistical software limits us in the sense that it is currently not able to compute these fit indices.

6. Discussion and conclusions

We investigated which factors are related to the privacy settings of Dutch adolescents on Facebook in 2014. We implemented a theoretical framework consisting of peer's privacy behavior, popularity and trust. We contributed to the previous literature by simultaneously examining *multiple* privacy settings on Facebook while using unique large-scale survey data combined with behavioral data from Facebook.

In line with Lewis et al. (2008) and Lewis (2011), we find associations between peers' privacy settings and respondents' Facebook privacy settings. However, the magnitude of these associations is somewhat small, which may be due to the large time lag between our measure of the class network (in wave 2) and the privacy settings on Facebook (measured at wave 4) – a two-year difference. Interestingly, we find that the density of the classroom friendship network moderates the associations between the influence of peers' privacy settings and the respondents' Facebook privacy settings: in more connected classes, adolescents are more likely to imitate their classmates' timeline post settings.

Why did we find no relationship between peers' and respondents' private friend lists? First, reputational damage or other negative consequences of maintaining private friend lists are not very clear for Facebook friends with public displays: for this setting, norms may be less likely to be enforced. Second, adolescents may be less likely to *know* what their peers' friend list privacy settings are. In timeline posts, with whom a post is shared is visible, whereas with friend lists, this information is not visible, which makes norm enforcement more difficult.

This study also shows that popularity, a previously omitted factor, is related to privacy settings. More popular adolescents are more likely to maintain public Facebook profiles, possibly due to a higher need for self-expression and a need to maintain their status. Popular adolescents display behaviors that are associated with higher risk (Dijkstra et al., 2009), and they are also more publicly visible on Facebook.

Our study finds (further) evidence to suggest that girls, members of ethnic minorities, pupils in lower educational tracks, and younger adolescents more frequently opt for private Facebook profiles. These results are in line with the previously found observation that these groups tend to display lower levels of trust in “most others” (Alesina & La Ferrara, 2002; Glaeser et al., 2000; Mewes, 2014; Simpson et al., 2007) and that girls and younger people also display a higher probability of maintaining private SNS profiles (Boyd & Hargittai, 2010; Lewis et al., 2008; Tufekci, 2008). In particular, we find that the differences across ethnic backgrounds are strong. Those who have an ethnic background from low-trust societies, such as those with a Turkish background (Delhey & Newton, 2005), especially display more privacy on Facebook than do native Dutch. Surprisingly, however, our mediation models do not show that the associations of gender, ethnic background, educational track and age with privacy settings are convincingly mediated by generalized trust. Contrary to our expectations, we find that those who place trust are more likely to maintain private timeline posts, possibly for two reasons. First, one may close his/her profile while generally trusting others because the actual content posted on timelines is much more sensitive. Second, the measure adopted in our study does not fully capture the more complex concept of trust. More refined measures of trust are needed in further research also because not everyone interprets “most others” in the same manner (Delhey, Newton, & Welzel, 2011). One may even speculate that a public Facebook profile that is visible to the general public is an alternative behavioral measure of self-reported trust in “most others”.

Table 5
Structural equation models: direct and indirect associations between gender, national origin, educational level, age and Facebook privacy. Average marginal effects are presented.

Direct associations with privacy	dy/dx ^a	SE ^b	p ^c	dy/dx	SE	p
	Pr(Private timeline post)			Pr(Private friend list)		
% Friends' timeline posts private	0.001	0.000	0.039			
% Friends' friend lists private				0.000	0.000	0.760
% Class timeline posts private	0.002	0.001	0.001			
% Class friend lists private				0.000	0.001	0.700
Indegree: Popularity	−0.003	0.001	0.000	−0.001	0.001	0.012
Girls (ref.: Boys)	0.027	0.017	0.109	0.063	0.014	0.000
Ethnic background (ref.: Dutch)						
Turkish	0.118	0.052	0.024	0.303	0.046	0.000
Moroccan	0.240	0.070	0.001	0.228	0.060	0.000
Dutch Caribbean	0.097	0.055	0.078	0.148	0.040	0.000
Other Western	−0.040	0.030	0.183	0.069	0.022	0.002
Other non-Western	0.068	0.037	0.063	0.176	0.032	0.000
Educational track (ref.: Voc. educ.)						
Senior general	−0.046	0.020	0.023	0.023	0.017	0.190
University preparatory	−0.046	0.023	0.040	0.035	0.019	0.061
Age in months	−0.007	0.001	0.000	−0.023	0.001	0.000
Trust	0.039	0.016	0.017	−0.017	0.014	0.221
<i>Indirect associations privacy (via gen. trust)</i>	<i>Pr(Private timeline post)</i>			<i>Pr(Private friend list)</i>		
Girls (ref.: Boys)	−0.018	0.008	0.031	0.008	0.007	0.242
Ethnic background (ref.: Dutch)						
Turkish	−0.044	0.021	0.038	0.019	0.017	0.258
Moroccan	−0.040	0.022	0.061	0.017	0.016	0.266
Dutch Caribbean	−0.044	0.022	0.042	0.019	0.017	0.268
Other Western	−0.004	0.006	0.430	0.002	0.003	0.561
Other non-Western	−0.036	0.017	0.030	0.016	0.014	0.250
Educational track (ref.: Voc. educ.)						
Senior general	0.014	0.007	0.043	−0.006	0.005	0.258
University preparatory	0.026	0.012	0.026	−0.011	0.009	0.234
Age in months	−0.001	0.000	0.063	0.000	0.000	0.282
N	3434			3434		

^a Average marginal effects.

^b Delta-method standard errors, cluster correction for 287 classes.

^c Two-sided *p*-values.

6.1. Limitations of this study

There are four limitations that warrant acknowledgment, and they pertain to the data that we used. First, our study must be replicated by using an even more representative sample. Second, to substantiate the causal inferences on peer influence, we need dynamic data on social networks and behavior to separate influence from selection effects (Steglich, Snijders, & Pearson, 2010). Third, we did not study whether adolescents oscillate between settings, nor did we study the level of customization of privacy on Facebook. Further research could investigate these dynamics. Nevertheless, we analyzed far more privacy decisions (e.g., romantic interests) than presented here, and these results did not qualitatively differ from the results presented in the article. We went beyond previous studies' findings regarding social media privacy. Finally, we restricted the respondents to a maximum of five best friends in the survey. Therefore, for a small proportion of our respondents, *indirect* friends may be included in the classmates measure. Nevertheless, research shows that, in such questions, respondents indicate their very best friends first (Marsden, 2011), and we found evidence for this phenomenon in our data; 64% of the respondents indicated less than five friends. Furthermore, this limitation did not affect our theoretical intuitions or our conclusions – we expected correlation in peers' privacy behaviors, whether from friends or indirect friends among classmates.

6.2. Conclusion

SNSs are extremely volatile in terms of their popularity (see

Hofstra et al., 2015a), and the privacy tools provided to users by SNS service providers frequently change. Therefore, ongoing research is needed to study the factors that predict (distinct) privacy settings on SNSs.

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Appendices A and B. Supplementary data

Supplementary data related to this article can be found at <http://dx.doi.org/10.1016/j.chb.2016.02.091>.

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