The effects of socio-demographic factors on social media divide:

A meta-analytical review

Abstract

Digital divide has transformed from the early stage unequal access to technologies to a new phase, notably the divergent social media use. Although many determinants of social media divide have been examined, socio-demographics are the most prevalent. Focused on the effects of socio-demographic factors on social media divide, this meta-analysis found that people who were female, younger, well educated, well paid and urban residents were more likely to use social media. However, race, marital and employment statuses did not play a role of predicting social media use. Through the moderator analysis, we further found that studies conducted in collectivistic countries had higher effect than those done in individualistic countries for the effect sizes of education level, and that other moderators had mixed or insignificant roles in influencing the effect sizes. Implications were discussed at last.

Keywords: digital divide; social media use; socio-demographics; meta-analysis; Bourdieu

The term 'digital divide' was originally coined to describe the gaps between those with access to information and communications technologies (ICTs) and those without such access (DiMaggio, Hargittai, Celeste, & Shafer, 2004; van Dijk, 2005). Eynon and Helsper (2011) held that individuals may be involuntarily excluded from using ICTs due to a lack of opportunities or abilities, or voluntarily choose not to use ICTs because of a lack of motivation. However, even if people have both motivation and physical access to use, they still may not be active in use, or use quite differently (van Deursen & van Dijk, 2014; van Dijk, 2005, 2006) , or even cease to use (it was named the fourth divide by Olphert & Damodaran, 2013). Therefore, inequalities of access include multiple successive types of access: motivation, physical access, digital skills and usage (Olphert & Damodaran, 2013; van Dijk, 2005, 2006, 2012). As some (Büchi, Just, & Latzer, 2016; Correa, 2016; van Dijk, 2006, 2012) put, the divide over time has transformed from the first-level (inequalities in Internet access) to the second-level (inequalities in Internet usage and skills). Moreover, many (e.g., Eynon & Helsper, 2011) have argued that the first-level digital divide is more likely due to involuntary exclusion, whereas the second-level digital divide is further caused by personal preferences, tastes and needs. This implies that the driving forces of divide at different levels are distinct.

Instead of simply dichotomizing the level of digital divide, DiMaggio and Hargittai (2001) described five dimensions of digital inequality in usage, i.e., equipment, autonomy of use, skill, social support, and the purposes for which the technology is employed. With the decreasing divide in the basic level of access to and adoption of ICTs, other dimensions of equalities have become more and more salient. As Katy E. Pearce and Ronald E. Rice (2017) contended, with the popularity of Facebook and other such social network sites (SNSs) (for a review, see Ellison, 2007), the digital divide has shifted beyond concerns about access and adoption to more subtle questions of skill, usage, and social capital, and to new venues such as SNSs. Nevertheless, inequalities in social media use not only vary by the types of use, medium and activities, but also are subject to structural influences and individual differences.

Many scholars have sought to explore the determinants of digital divide in social media use from various perspectives. Notwithstanding abundant studies, they usually had inconsistent findings. More important, many suffer from plenty of problems, two of which notoriously lie in the conceptualization and operationalization of the construct of digital divide (cf., van Dijk, 2006).

Conceptualization and Operationalization of Social Media Divide

Social Media Divide

According to Merriam-Webster (2017), social media are "forms of electronic communication (such as websites for social networking and microblogging) through which users create online communities to share information, ideas, personal messages, and other content". Ellison and Vitak (2015) and Xiang and Gretzel (2010) elaborated on the scope of social media, which includes blogs, virtual communities, wikis, social networks, collaborative tagging, and media files shared on sites like YouTube and Flickr (for other definitions, see Kaplan & Haenlein, 2010; Obar & Wildman, 2015). We define social media to be online community-based platforms, which enable people to be networking, messaging, and/or creating (e.g., posting, tweeting, blogging, etc.), tagging, exchanging, evaluating (e.g., liking, commenting, voting, rating, etc.) and sharing information. Such a definition has included the most important characteristic of social media applications, tools as well as features.

Those who have more and less social media usage have had the so-called social media divide (Pfeil, Arjan, & Zaphiris, 2009). The four forms of digital inequality suggested by Pearce and Rice (2013), i.e., access (use vs. non-use), use of different devices, extent of usage, and engagement in different activities are applicable to the sphere of social media, but may still not be conclusive. Some (e.g., Schradie, 2012; van Dijk, 2006) further contended that a distinct difference exists between the consumption and production, which indicates a discrepancy between passive use and active use of social media.

Theoretical Frameworks

Numerous types of determinants of digital divide and the ensuing consequences in a society have been examined, but the underlying theoretical frameworks have been fragmented. van Dijk and his colleagues (DiMaggio, Hargittai, Neuman, & Robinson, 2001; Scheerder, van Deursen, & van Dijk, 2017; van Deursen, Helsper, Eynon, & van Dijk, 2017; van Dijk, 2006, 2013) lamented that most digital divide studies referred to the same concepts using different nomenclatures, which were not guided by theory or by hypotheses derived from theory, and that they remained on a descriptive level of reasoning. Such a situation persists into the research on inequalities in social media use. Despite the criticism, the effort of providing a sound theoretical framework that can well explain the social media divide phenomenon has never stopped.

Digital inequality is rooted in social inequality (DiMaggio et al., 2004), which has been elucidated by many classical sociologists (van Dijk, 2006). Weber (2009), for instance, argued that the primary sources of social stratification are economic class, social status, and political power, which cause people to have unequal access to various types of resources. Moreover, such inequality could translate into differential use of ICTs (Blank & Groselj, 2015).

Bourdieu shares the same view with Weber in some aspects, but differs in many as well (Weininger, 2005). Bourdieu (1986) contended that three forms of capital –economic, cultural (e.g., educational credentials) and social capital – have close relationship with social class. Bourdieu believed that class conflicts are primary pillars of social inequality (Navarro, 2006), but different from Marxists and others, Bourdieu (1986) held that social inequality results from the unequal distributions of economic, cultural and social resources, which are reflected or mediated through the symbolic capital (accumulated legitimatized prestige). Furthermore, these types of resources are interrelated, and convertible between each other (Bourdieu, 1986). In the same vein, the inequality in social media use results from the unequal possessions of economic, cultural, social and symbolic capital (cf., van Dijk, 2005; van Dijk & Hacker, 2003). Only economic capital is needed to possess machines, but to appropriate them and use them in accordance with their specific purpose, both cultural capital and social capital are imperative (cf., Bourdieu, 1986).

Weber (cited in Breen, 2005) held that individuals who share a common class position tend to behave in similar ways. Some (e.g., Zillien & Hargittai, 2009) also have drawn upon Weber (2009) to explain the "status-specific" differential Internet use. Bourdieu (1984, 1986), however, maintained that all actions or practices, which are mainly interest-motivated, are determined by the facets shown in the following formula:

$$[(\text{habitus}) \times (\text{capital})] + \text{field} = \text{practices}.$$

In a nutshell, habitus, which is a set of preconscious dispositions including tastes, translates agents' different class positions in social space specified by different forms of capital into observable practices or behavior in a particular field (it represent a certain distribution structure of some types of capital, and delimits a structure in which habitus operates) (Bourdieu, 1984). That is, the practices that habitus produces vary according to the position in social space (Weininger, 2005). Individuals could transport their habitus (and capital) from one field to another (Levina & Arriaga, 2014). Consequently, the practices in the offline field (Levina & Arriaga, 2014; van Deursen & van Dijk, 2014) could be reproduced in the online filed (digital habitus or information habitus by Robinson (2009)). For instance, Robinson (2009) observed that disadvantaged youths developed a taste for the necessary, and that they do not acquire the same skills and benefits as more advantaged cohorts who were playing seriously (cf., van Dijk, 2005; van Dijk, 2006).

Inspired by Bourdieu (1984, 1986), van Dijk (2005) proposed the concept of information capital (Paino and Renzulli (2013) proposed cultural capital in the digital field, and McConnell and Straubhaar (2015) named it technocapital). van Dijk (2005, 2013) further developed the resources and appropriation theory to explain digital divide. According to van Dijk (2005), the theory consists of five parts, which are (1) a number of personal and positional categorical inequalities in society, and (2) the distribution of resources relevant to this type of inequality are the causes of (3) a number of kinds of access to ICTs. (4) a number of fields of participation in society is the potential consequence of the whole process, and also feeds back upon 1 and 2. Finally, the special characteristics of information and communication technology (ICT) also account for (3). The first part of van Dijk (2005) just indicates demographic characteristics in addition to the personality traits of people. Bolton et al. (2013) offered a similar framework. They are illuminating and useful in their own right, but they have been rarely adopted by empirical research in the field of digital divide.

A number of additional theoretical frameworks, such as the reasoned action theory of Fishbein and Ajzen (1977) (e.g., Hanson, West, Thackeray, Barnes, & Downey, 2014), the theory of planned behavior of Ajzen (1991) (e.g., A. Malik, K. Hiekkanen, & M. Nieminen, 2016), the technology acceptance model of Davis (1989) and its extensions (e.g., Blank & Lutz, 2016; Braun, 2013; Hanson et al., 2014; Hargittai & Litt, 2012; Lu, Hao, & Jing, 2016; Mathiyalakan, White, & Brusa, 2016; McQuiston, 2013; Miller, Mundey, & Hill, 2013), the uses and gratifications approach (e.g., Smock, Ellison, Lampe, & Wohn, 2011), and knowledge sharing model (Kim, Lee, & Elias, 2015), among others, have been adopted or proposed, but applied with varied ways of conceptualization and operationalization.

Due to the inconsistent conceptualization and operationalization of social media use, Katy E. Pearce and Ronald E. Rice (2017) differentiated social media divide on several dimensions including adoption/non-adoption of SNSs, different SNSs and different capital-enhancing activities used on those SNSs, and further found that the divides in SNS usage are much greater than in activity use (Katy E. Pearce & Ronald E. Rice, 2017). The problem of divergent and inconsistent conceptualization as well as operationalization of social media divide has existed since the inception of digital divide research, and have caused extreme difficulties for a meta-analysis, which has been absent all the time. The present study takes on the daunting job by focusing on the common predictors primarily in relation to the economic and cultural capital, specifically, the socio-demographic variables.

Socio-demographic Determinants of Social Media Divide

Many frameworks were adopted in prior digital divide studies, and a variety of antecedents, and correlates of social media divide have been examined, but socio-demographic variables appeared to be the most common ones. In the above reviewed capital theory of Bourdieu (1984, 1986), those forms of capital specifically refer to income and education levels. The volume and composition of the capital are primary factors of social position (class), but most demographic factors (including gender, ethnicity, age, and geographical place of residence, etc.) are the "secondary" factors of position in social space (Bourdieu, 1984; Weininger, 2005). Therefore, social stratification (class in general) or inequality results from the unequal distribution of appropriated resources (capital) in gender, race, age, geographical place of residence, marital and employment statuses.

In addition, Scheerder et al. (2017) identified seven determinant categories through a systematic review: sociodemographic, economic, social, cultural, personal, material and motivational, but found that more than 60 percent of the studies examined the first two categories, i.e., sociodemographic and economic factors. Consequently, no sufficiently cumulative number of studies that include the same or even similar predictors other than demographics are available for a viable meta-analysis. Moreover, a series of studies by the National Telecommunications and Information Administration (cited in ana Rojas, Straubhaar, Roychowdhury, & Okur, 2003) revealed that those in low-income, low-education, minority-racial, and rural location groups have unequal access to the new technologies. Additional research has shown that economic and sociodemographic attributes are significant determinants of usage patterns (Büchi et al., 2016). Therefore, the reason the present meta-analysis is focused on socio-demographics is not because it is the last resort, but because socio-demographics are in fact very important determinants of social media divide. That said, although socio-demographic variables were widely examined in prior studies, the effects of most of these variables have never been conclusive.

Socio-demographics are measured usually with variables such as age, gender, income, education, race, marital status, occupation, religiosity and rural residence, among others. Some demographic variables are combined to form new sub-concepts, such as socioeconomic status (SES), which is defined as a measure of one's combined economic and social status including education, income, and occupation (Baker, 2014). In applied studies on digital divide, examined demographic variables have exhausted almost all of the characteristics of population in question, but were tested in various combinations.

According to Pew Research Center (Perrin, 2015), nearly two-thirds of American adults (65%) use social networking sites, up from 7% in 2005, and younger adults (ages 18 to 29), women, people who have higher education levels and household income and live in urban and suburban communities were more likely to use SNSs, but there were no racial and ethnic differences in SNS use. Despite the fact that the findings were based on large scale national surveys relying on rigorous random sampling procedures, they were contradicted by numerous academic studies to be reviewed below.

Gender difference has been an enduring research interest. Drawing on Bourdieu (1984), Weininger (2005) argued that the habitus is always “gendered”, and some (Huppatz, 2009; McCall, 1992; Skeggs, 2004) contended that gendered dispositions act as cultural capital. Consequently, women and men naturally have different practices. Different than the first-level digital divide studies, which generally concluded that women were less likely to get the Internet access than their male counterparts (Cooper & Weaver, 2003; Katz & Aspden, 1997), many scholars (Cha, 2010; Aqdas Malik, Kari Hiekkanen, & Marko Nieminen, 2016; R. P. Yu, N. B. Ellison, R. J. McCammon, & K. M. Langa, 2016) have found that women were more proficient than men in social media use. Moreover, women self- disclose more (Liu & Brown, 2014), and support each other on SNSs more than men (Ellison & Vitak, 2015). Nevertheless, others (Ching, Basham, & Jang, 2005; Gray, Gainous, & Wagner, 2017; Kuss & Griffiths, 2011; Liu, Ainsworth, & Baumeister, 2016) had opposite findings. E. Hargittai and Y. L. P. Hsieh (2010) elaborated that women pursue more stronger-tie activities than men, yet women engage in fewer weaker-tie activities than men. Furthermore, women use the Internet more for social, while men use it more for instrumental and recreational purposes (Kennedy, Wellman, & Klement, 2003). Consequently, some (E. Hargittai & Y.-l. P. Hsieh, 2010; Liu et al., 2016; Pearce & Rice, 2013) concluded that it is levels of engagement or types of activities that moderated the effect of gender.

There has been almost a consistent finding with respect to the negative effect of age on social media use (e.g., Braun, 2013; Yang Feng & Wenjing Xie, 2015; Hwang & Park, 2013; Pfeil et al., 2009; Rebecca P. Yu, Nicole B. Ellison, Ryan J. McCammon, & Kenneth M. Langa, 2016), although few insignificant and even contradictory effect of age was also reported (e.g., Straus, Williams, Shogan, & Glassman, 2016; R. P. Yu et al., 2016).

Although majority of the prior studies (Ching et al., 2005; Hwang & Park, 2013; Straus et al., 2016) have found that income affected social media use positively, the negative effect of income was also reported by some (e.g., Nam, 2011). Similarly, most scholars (Y. Feng & W. Xie, 2015; Hwang & Park, 2013; Schradie, 2012; Straus et al., 2016) agreed that education had a positive effect on SNS use. Blank (2013) also reports that people with more education are more likely to produce political content in the form of social media posts. Education level is also believed to be the source of the knowledge gap hypothesis (Tichenor, Donohue, & Olien, 1970). However, some (Correa, 2016; Katy E Pearce & Ronald E Rice, 2017; Szabo, 2012) still concluded otherwise. Katy E Pearce and Ronald E Rice (2017) discovered that education played drastically opposite roles in affecting different types of social media use. For example, education negatively affected Meeting new friends, whereas positively influenced Keeping in touch with old friends. That is, the antecedents of bridging and bonding in social capital play out differently (cf., Liu et al., 2016). In addition, Correa (2016) concluded that lower educated young people tended to use Facebook more frequently in general, but more educated individuals tended to use Facebook for informational and mobilizing purposes. Some (Micheli, 2015; van Deursen & van Dijk, 2014) further argued that upper class users (with high SES) spent most of their time online in a capital-enhancing activity, yet working-class users spent more of their online time engaging in social interactions and games. In light of these findings, the type of social media use might be an important moderator of the effect of income, education and gender on social media use.

Race has been a complex issue due to diverse racial and ethnical makeups in different countries, needless to say that it was operationalized rather distinctly in prior studies. Even in the US alone, the effect of race on social media divide has been found inconsistent. For example, Hargittai and Litt (2012) found that African Americans used Twitter more often than white Americans, and yet Asian and Hispanic Americans used less than the white counterparts. However, E. Hargittai and Y. L. P. Hsieh (2010) discovered that Asian Americans engaged in fewer weak-tie activities than white Americans, but both African and

Hispanic engaged in more weak-tie activities than the white Americans. Again, moderators present in each study have caused different conclusions.

Blank and Groselj (2014) discovered that unmarried people used social media more than did married people, a finding similar to Rebecca P. Yu et al. (2016), who concluded that SNS users are more likely to be widowed. Nevertheless, Schradie (2012) had mixed findings with respect to different types of marital status on social media use. With respect to the effect of employment status, Rebecca P. Yu et al. (2016) found that homemakers used social media more often than did employed people, and yet many (e.g., Pick, Sarkar, & Rosales, 2015; Straus et al., 2016) did not detect significant relationship between employment status and social media use.

Meta-analysis is a means of quantitatively determining the real effect and effect size based on findings from previous research on a certain topic, suggesting the existence of moderators if effects are heterogeneous (Glass, Smith, & McGaw, 1981; Hunter, Schmidt, & Jackson, 1982; Rosenthal, 1991). The first goal of the present study was to determine the pooled mean effect size of socio-demographic differences in multiple dimensions of SNS use. Next, the homogeneity of the effect sizes was computed to determine the need for moderator analyses. Moderator analyses were then conducted to determine whether demographic differences in social media use were moderated by study level variables. Fourth, multilevel modeling estimated the relative influence of the moderators taking into account the dependence problem among the effect sizes.

In view of the inconclusive results of prior studies, two general research questions were raised:

1. Are the effects of demographic variables, such as age, gender, income, education level, race (white vs. non-white), rural residence (urban vs. rural), employment status

(employed vs. unemployed), and marital status (married vs. non-married), on social media divide common across the studies?

2. If the answers to RQ1 are not, what moderators have caused the variation of the effects, and how?

Method

Sample of Studies and Eligibility Criteria

Our emphasis on digital divide in SNS use was the primary basis for selection of journal articles. To maximize the number of relevant studies, various combinations of the following keywords such as “digital divide”, “digital inequal*, “digital dispar*”, “digital difference”, “digital gap”, “digital exclusion”, “digital distinction”, “digital unfair*”, “social media/network*”, “use of social network sites”, “facebook”, “twitter”, “youtube”, “LinkedIn”, “blog*”, “friendster”, “Instagram”, “web2.0”, “tumblr”, “whatsapp”, “wechat”, “weibo”, “Skype”, “xanga”, “Myspace”, “pinterest”, “IM”, “instant messag*” and “social media use” in databases such as Web of Science, Communication and Mass Media Complete, SAGE Communication Studies, Communication Abstract, Wiley InterScience, ProQuest, PsycINFO, JSTOR, Scopus and Google Scholar were searched. We additionally searched through the reference lists of all located studies. We also consulted scholars who have conducted research on digital divide about what might be missing in our list. The extensive search yields a valid 1,823 effect sizes in 89 articles [cumulative N = 4,553,161; cumulative *N (social media general use)* =3,820,719], all of which were included for analysis. To obtain the complete information in relation to effect sizes, 76 corresponding authors were contacted to request for the key missing information in their papers. Those who did not return were excluded from the subsequent analyses for they either lacked statistical details or presented statistical information in a form that does not allow for the computation of effect sizes.

Operationalization of Effect Size

Independent variables. After retrieving the summary information regarding the number of each independent variable examined in the relevant studies, we abandoned some socio-demographic variables, which appeared in too few studies such as religiosity, and the immigrant identity, to avoid the unstable meta-analytical results and publication bias (Rosenthal, 1995) (also see Table 1). As a result, the following demographic variables, such as age, gender, income, education level, race (white vs. non-white), rural residence (urban vs. rural), employment status and marital status, were chosen in this study. Moreover, for binary variables, we unified the effect and reference categories across the studies (for example, since all the effect category was unified to female, the studies that used the male category as the effect were recoded and the effect size was recalculated). In addition, the effect of race was examined by comparing differences among White, Hispanic, Asian and African Americans. Since most studies adopted the White category as the effect category, we first changed the names of effect categories such as Hispanic, Asian and African Americans to non-whites, and then reversed the names between the effect and reference category, i.e., changing non-whites to White, and the effect size was recalculated. Some variables, such as education, age and income, were operationalized with both metric scales and the nominal scale of multiple categories in different studies. Because too many inconsistent contrasts therein were involved, we abandoned those studies that measured the variables with more than two categories.

Dependent variable. The outcome variable of interest is social media divide, whose conceptualization as well as operationalization has been rather diverse in the literature. We considered all the studies that examined the determinants of social media use are relevant, no matter whether they mentioned "digital divide" or the equivalents. The categories of dependent variables were finalized by integrating the categories of social media use proposed by Bolton et al. (2013), Pearce and Rice (2013) and Schradie (2012), which include contributing (e.g., posting), sharing and commenting, consuming (e.g., checking information, or searching for content), networking, participating and playing. However, after the final data was collected, only consuming ("social media general use" shown in Table 1) has enough number of effect sizes for a meaningful meta-analysis. To avoid the complexity and low power of estimations, we kept social media general use as the only outcome variable in the following meta-analysis.

Transforming and Imputing the Effect Size

There exist multiple types of effect sizes, e.g. correlations, odds ratios, etc. All the effect sizes were transformed to the same effect size, i.e., Fisher's z, which approximately follows the normal distribution (Silver & Dunlap, 1987), using the compute.es package of R language (Del Re, 2013). For illustrative and interpretative purposes, resulting weighted mean *z* values are converted back to *r* using Fisher's *z*-to-*r* transformation.

In addition, some studies just reported regression betas. However, the papers that only reported regression betas cannot be used directly to estimate the average effect size. As the number of studies in this category is large, the imputation method suggested by Peterson and Brown (2005) was adopted to estimate zero-order correlations from regression betas. According to Peterson and Brown (2005), $r = \beta * .98$ if β_i is negative, and $r = \beta * .98 + 0.05$ if β_i is non-negative.

Coding Categories of Moderators

Differences in the methods and sample characteristics may introduce variability ("heterogeneity") among the true effects. Therefore, once heterogeneity is detected, the moderator analysis is imperative. The following information was coded from each article: (a) date of publication; (b) number of observations; (c) journal names; (d) publication form (journal article, book, conference paper, dissertation, and unpublished document); (e) Data type (cross-sectional vs. time series); (f) sample types (random vs. convenience); (g) country of study (countries were classified into individualistic vs. collectivistic categories according to Hofstede (1984)); (h) number of citations on Google Scholar.

Studies were coded independently by two research assistants, who were briefed on the research prior to the formal start of the work. Inter-coder reliability was estimated via the "irr" package of R 3.4. The results of the inter-coder reliability were acceptable (see Table 3).

Procedures of Analysis

The simplest of the meta-analysis is based on a fixed effects model, which assumes the true effect is the same for all studies, whereas the random effects model allows the true effect to vary across studies, with the mean true effect the parameter of interest (Brockwell & Gordon, 2001; Schwarzer, Carpenter, & Rücker, 2015). It is generally agreed that in the presence of heterogeneity, the random effects model should be used (Brockwell & Gordon, 2001; Council, 1992; Schmid, Koch, & LaVange, 1991).

To determine whether each set of effect sizes shared a common effect size, we calculated a homogeneity statistic, Q (Brockwell & Gordon, 2001; Hedges, 1981; Higgins & Thompson, 2002; Schmid et al., 1991). In the absence of homogeneity, we accounted for variability in heterogeneous effect sizes by relating them to the attributes of the studies. To determine the relation between these study characteristics and the magnitude of the effect sizes, meta-regressions were performed. Fitted models were estimated on the basis of Akaike information criterion (AIC), followed by QE (test statistic of residual heterogeneity) and QM (Omnibus test statistic of the significance of moderators).

Data manipulation and wrangling were performed using regular expressions of both R language and Perl language in addition to the dplyr package of R language (Wickham & Francois, 2015). Data visualization was done using the ggplot2 package of R (Wickham, 2016). In addition, the compilation of effect sizes showed a clear hierarchical structure, as there were multiple effect sizes for many studies. Consequently, to side step the dependence problem among effect sizes, we analyzed these data with multilevel mixed-effects modeling using the metafor package of the R language (Viechtbauer, 2010), which is generally superior to other approaches, e.g., robust variance estimation, and averaging effects sizes (Berkey, Hoaglin, Antczak-Bouckoms, Mosteller, & Colditz, 1998; Moeyaert et al., 2017).

Results

Through a series of meta-analyses, we discovered that females, youths, well educated, urban residents, the white race, wealthy, unmarried and unemployed people are more likely to use social media than their counterparts. However, the overall effects of gender (female), age, education, income and urban residence were significant (β = .041, p < .001; β = -.072, p = .006; β = .025, p < .001; β = .041, p = .031; β = .107, p < .001), but the overall effects of the white race, marital status and employment status were not significant (β = .0002, *n.s.*; β =.06, *n.s.*; β =-.11, *n.s.*).

The pooled effect sizes were very small due to the quite contradictory results present in the primary studies (also see forest plots in Figure 2), so the subsequent heterogeneity test is necessary. Indeed, highly significant heterogeneity was found among effect sizes (see the values of QE and QEp in Table 2), no matter whether or not overall effects were significant. This suggests that effect sizes vary considerably due to the type of effect size differences (the second level) and/or the study differences (the third level). Therefore, the moderator analysis was warranted for all the effect sizes.

Each moderator was tested sequentially in a series of mixed-effects meta-analyses. The number of Google Scholar citations was a significant moderator for the effect sizes of gender and the white race, the publication type was a significant moderator for the effect sizes of income (thesis vs. journal articles) and urban residence (conference papers vs. journal articles), and country of origin was a significant moderator for the effect sizes of education level.

The results of estimated amount of residual heterogeneity suggested that zero amount of heterogeneity can be accounted for by including all of the moderators in the full models ($\tau^2_{\text{difference between the null model and the full model}} \cong 0$). Overall, the moderators are unable to explain the heterogeneity of all of the effect sizes except for those of urban residence based on the omnibus test (QM and QMp in Table 2). Moreover, the QE statistic of residual heterogeneity of all the effect sizes was significant, possibly indicating that other neglected factors determined the heterogeneity.

In summary, among the tested moderators, the country of origin significantly moderated the average effect sizes of education level; the publication type significantly moderated the average effect size of income level and urban residence; the number of Google Scholar citations significantly moderated the average effect size of female and the white race. Specifically, studies conducted in collectivistic countries had higher effect than those done in individualistic countries for the effect sizes of education level (β = .131, $p < .05$). Moreover, studies having more Google Scholar citations had higher effect size for the effect sizes of female (β = .0001, $p < .05$), and yet the lower effect size for the effect sizes of the white race (β = -.0001, $p < .001$). In addition, conference papers had higher effect size than journal articles for the effect sizes of the white race (β = .315, $p < .001$), whereas thesis had lower effect size than journal articles for the effect sizes of income level (β = -.125, $p < .001$).

Publication Bias

For various reasons, studies included in the meta-analysis may not be exhaustive, which likely causes a publication bias, or the "file drawer problem" discussed by Rosenthal (1991). Numerous methods have been proposed in the literature to detect the influence of publication bias (Hedges, 1992). Through a formalization of the qualitative approach using the funnel plot, Duval and Tweedie (2000) proposed a simple trim-and-fill algorithm accounting for the magnitude of the publication bias problem, which is generally superior to the traditional funnel plot proposed by Light and Pillemer (1984). According to Duval and Tweedie, the asymmetric outlying part of the funnel is trimmed off after the estimation of the number of studies in the asymmetric part; the symmetric remainder is used to estimate the true center of the funnel and then the trimmed studies and their missing counterparts are replaced around the center. Both the trim-and-fill analysis and Egger's regression test (Egger, Smith, Schneider, & Minder, 1997) were performed. As shown in Figure 3, publication bias is not a serious issue indeed, as no missing studies were reported for all of the effect sizes except for employment status, which had only one possible missing study.

Discussion

With enough number of effect sizes tested through a series of meta-analyses, we found that people who were female (versus male), younger (versus old), well educated (versus poorly-educated), well paid (versus having low income) and urban residents (versus rural residents) were more likely to use social media. However, people who were white (versus other non-white races), not being married (versus married) and unemployed (versus employed) did not play a role of predicting social media use.

The moderators included in the model played differential roles in affecting the effect sizes. Country of origin of studies has been examined in many primary studies on social media use. For instance, many (Choi, Kim, Sung, & Sohn, 2011; Jackson & Wang, 2013; Liu et al., 2016) discovered that the relationship between SNS use and bridging capital was stronger in individualistic countries than collectivistic countries. This meta-analysis found that country of origin was a relatively important moderator, but that it only influenced the effect size of education level. This is partially consistent with some prior studies. For example, Jackson and Wang (2013) did not find gender and family income relate to SNS use differently in collectivistic than individualistic cultures.

We found that studies conducted in collectivistic countries had higher effect than those done in individualistic countries for the effect sizes of education level. The underlying reason has to do with the family influence. The collectivistic cultures generally cherishes family values (Han & Shavitt, 1994). Urdan, Solek, and Schoenfelder (2007) found that family's influence on children's educational attainment in collectivistic countries is more salient. In addition, all other effects of demographics transcend cultural differences. Such findings have profound implications, particularly for cross-cultural studies. We hence come to realize the boundary of some effects. That is, some effects are culture bound, whereas some are universal. In a nutshell, the variations or discrepancies among effect sizes are due to either cultural or methodological differences in the primary studies.

The number of citations of each article may indicate impact of the study (Fox, Paine, & Sauterey, 2016), and studies with high effect sizes may be cited more often (Lortie, Aarssen, Budden, & Leimu, 2013). However, does impactful research have high effect size as well? There is clearly no easy answer to it. We found that Google Scholar citations had divergent and weak influences in affecting the effect sizes of gender, and the white race. Therefore, we may conclude that the effect size has nothing to do with the impact of the study, specifically, the number of citations.

There is another puzzling question; namely, is unpublished work less rigorous? This may be true because some (e.g., Klümper & Qaim, 2014) found that conference papers in general have lower quality than peer reviewed journal publications. Moreover, does unpublished work hence have unstable findings? Polanin, Tanner-Smith, and Hennessy (2016) indicated that published studies yielded larger effect sizes than those from unpublished studies, but Klümper and Qaim (2014) implied that conference papers somehow reported higher effects than did journal articles. The contradictory results of conference paper and thesis versus journal articles in this meta-analysis may indicate that there have been no conclusive verdict yet.

The contribution of this study is significant. It is not only the first meta-analysis about social media divide, but also the one only formal meta-analysis about digital divide in general as of yet (there was a systematic review by Scheerder et al. (2017)). In addition, we found that some effects such as ethnicity (white vs. non-white), marital status (married vs. non-married) and employed status (employed vs. unemployed) did not exist indeed, and more important, some effects such as gender, age, education level, income level, and urban residence were real, but weak. Moreover, we discovered some important moderators, particularly, the country of origin of studies, the publication type and the number of Google Scholar citations, influenced the variations of some effect sizes.

This meta-analysis without doubt has limitations. Firstly, to have enough number of effect seizes for the present meta-analysis, many original independent and dependent variables, which had similar or close meanings, were renamed to have the same name. Some of the changes may not reflect the initial measurement of primary studies, and thus destabilized the effect sizes of question. In addition, it is still possible to test relevant effect sizes based on the theoretical framework reviewed above, particularly the one proposed by Bourdieu (1984, 1986), although the available effect sizes finally failed such an endeavor. However, this is a promising future research direction for both primary and meta-analytical studies.

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Table 1

Number of effect sizes by independent and dependent variables

	age	edu	employed	sex	immigration	income	married	urban	white	effect sum	article sum
Clout	3	0	2	3	0	0	0	2	0	10	2
SNS health info seeking	1	0	0	1	0	1	0	0	2	5	1
SNS motive SIG	0	0	0	1	0	0	0	0	0	1	1
social media creation	10	4	20	9	1	6	17	11	13	91	10
social media entertainment use	2	2	0	4	0	2	0	2	0	12	2
social media general use	80	48	36	105	5	53	32	25	102	486	61
social media health use	2	0	0	3	1	0	3	0	4	13	3
social media networking business	2	1	0	2	0	0	0	0	0	5	2
social media networking strong	1	3	0	3	0	1	2	5	3	18	4
social media networking weak	6	3	7	10	1	2	4	6	5	44	11
social media political use	9	9	0	6	0	6	0	1	8	39	6
social media privacy setting	0	0	0	2	0	0	0	0	0	2	2
social media sharing	3	1	1	3	0	1	2	2	0	13	4
Yahoo mail use	0	0	0	0	0	0	0	1	0	1	1
sum	119	71	66	152	8	72	60	55	137	740	110

Table 2
Model estimation

IV	model		est	Z	sig.	QE	QEp	QM	QMp	τ^2	rho	AIC
female	null	intrcpt	0.041	4.745	0	1908.898	0	22.516	0	0.012	-0.096	-122.458
	one moderator	intrcpt	0.036	23.277	0	1815.475	0	5.167	0.023	0.011	-0.112	-142.333
		citation Google	0	2.273	0.023	1815.475	0	5.167	0.023	0.011	-0.112	
	full	intrcpt	0.054	2.365	0.018	1244.778	0	4.999	0.544	0.012	-0.084	-112.742
		random sample	-0.013	-0.463	0.643							
		time series	-0.001	-0.042	0.966							
		Conference paper	-0.073	-0.817	0.414							
		thesis	-0.015	-0.219	0.826							
		citation Google	0	1.166	0.244							
		culture	-0.037	-0.897	0.37							
age	null	intrcpt	-0.072	-2.737	0.006	7440.933	0	7.492	0.006	0.034	0.399	-2.614
	full	intrcpt	-0.022	-0.44	0.66	1815.608	0	4.386	0.625	0.035	0.413	6.423
		random sample	-0.069	-1.137	0.256							
		time series	-0.136	-1.126	0.26							
		Conference paper	0.049	0.409	0.682							
		thesis	0.116	1.067	0.286							
		citation Google	0	0.203	0.839							

		culture	-0.071	-0.949	0.342							
edu	null	intrcpt	0.025	6811.606	0	1137.348	0	46397979.94	0	0.013	-0.205	-59.734
	one moderator	intrcpt	0.02	1.107	0.268	1099.426	0	2.978	0.084	0.015	NA	-63.633
		culture	0.087	1.726	0.084							
	full	intrcpt1	-0.089	-1.635	0.102	940.614	0	8.037	0.235	0.014	NA	-59.962
		random sample	0.096	1.803	0.071							
		time series	0.02	0.315	0.752							
		Conference paper	-0.012	-0.133	0.894							
		thesis	-0.025	-0.347	0.729							
		citation Google	0	-0.729	0.466							
		culture	0.137	2.375	0.018							
income	null	intrcpt	0.041	2.153	0.031	3950.665	0	4.635	0.031	0.008	0.759	211.029
	one moderator	intrcpt	0.056	3.065	0.002	3812.346	0	4.786	0.091	0.006	0.683	210.568
		Conference paper	-0.054	-0.652	0.514							
		thesis	-0.125	-2.128	0.033							
	full	intrcpt	0.049	0.741	0.459	743.135	0	7.188	0.304	0.005	0.644	216.757
		random sample	0.003	0.07	0.945							
		time series	-0.043	-0.624	0.532							
		Conference paper	-0.048	-0.585	0.559							

		thesis	-0.122	-2.088	0.037						
		citation Google	0	0.039	0.969						
		culture	0.049	1.125	0.261						
	null	intrcpt	0	0.006	0.995	2825.349	0	0	0.995	0.029	0.092	784.742
	one moderator	intrcpt	0.023	1.289	0.197	2698.084	0	3.378	0.066	0.024	NA	780.41
		citation Google	0	-1.838	0.066						
		intrcpt	0.071	1.323	0.186	2522.526	0	9.491	0.091	0.026	-0.041	785.78
		random sample	-0.077	-1.26	0.208						
white		time series	-0.049	-0.774	0.439						
	full	Conference paper	0.001	0.007	0.995						
		thesis	0.158	0.955	0.34						
		citation Google	0	-2.798	0.005						
	null	intrcpt	0.107	3.629	0	1102.843	0	13.169	0	0.021	NA	-21.746
	One moderator	intrcpt	0.09	4.689	0	489.746	0	14.77	0	0.013	-0.094	-28.6
		Conference paper	0.241	3.843	0						
		intrcpt	-0.044	-0.286	0.775	446.339	0	16.321	0.003	0.012	NA	-26.147
urban		random sample	0.025	0.271	0.787						
	full	Conference paper	0.285	3.884	0						
		citation Google	-0.001	-0.516	0.606						

		culture	0.049	0.912	0.362							
	null	intrcpt	0.06	1.272	0.203	2090.667	0	1.619	0.203	0.07	NA	15.091
unmarried	full	intrcpt	0.171	0.57	0.569	2037.817	0	0.291	0.962	0.068	NA	15.091
		random sample	-0.036	-0.13	0.897							
		citation Google	0.001	0.307	0.759							
		culture	-0.08	-0.41	0.682							
Employed	null	intrcpt	-0.11	-1.372	0.17	6110.217	0	1.883	0.17	0.059	0.877	4622.119
		intrcpt	0.25	0.708	0.479	5880.675	0	2.353	0.671	0.075	0.908	4628.237
		random sample	-0.15	-0.652	0.515							
		Conference paper	0.321	1.067	0.286							
		citation Google	0.003	0.951	0.342							
		culture	0.102	0.339	0.734							

Table 3
Intercoder reliability test

	Krripendorff's α	Scot's π	Cohen's κ	percent agreement	S	Gwet
Journal title	0.976	0.976	0.976	97.90%	0.874	0.874
Data type	0.948	0.948	0.948	96.20%	0.853	0.855
Publication type	0.791	0.791	0.791	97.90%	0.838	0.978
Citations Google	1			100.00%		0.99982
Published year	1			100%		1
Sample type	0.963	0.963	0.963	98.70%	0.829	0.858
Sample size	0.998			95.80%		0.9997
Country of origin	0.977	0.977	0.977	99%	0.889	0.892

Note: Scot's π, Cohen's κ, and *S* (Bennett, Alpert, and Goldstein 1954) are only applicable to nominal variables. Gwet's AC_1 and AC_2 apply to nominal and higher than ordinal levels, respectively. Krripendorff's α can be used across the measurement levels.

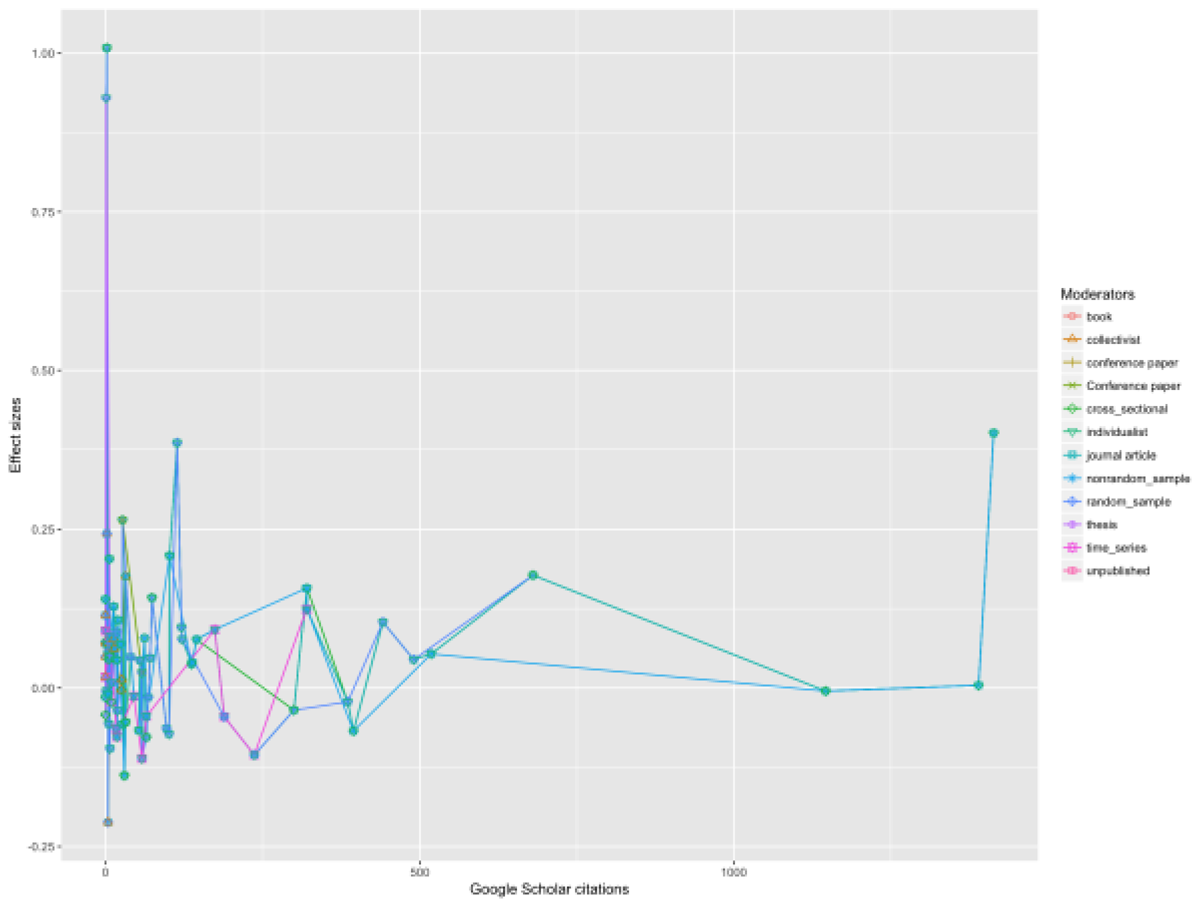

Figure 1 Distribution of effect size (Fisher's Z) by moderators

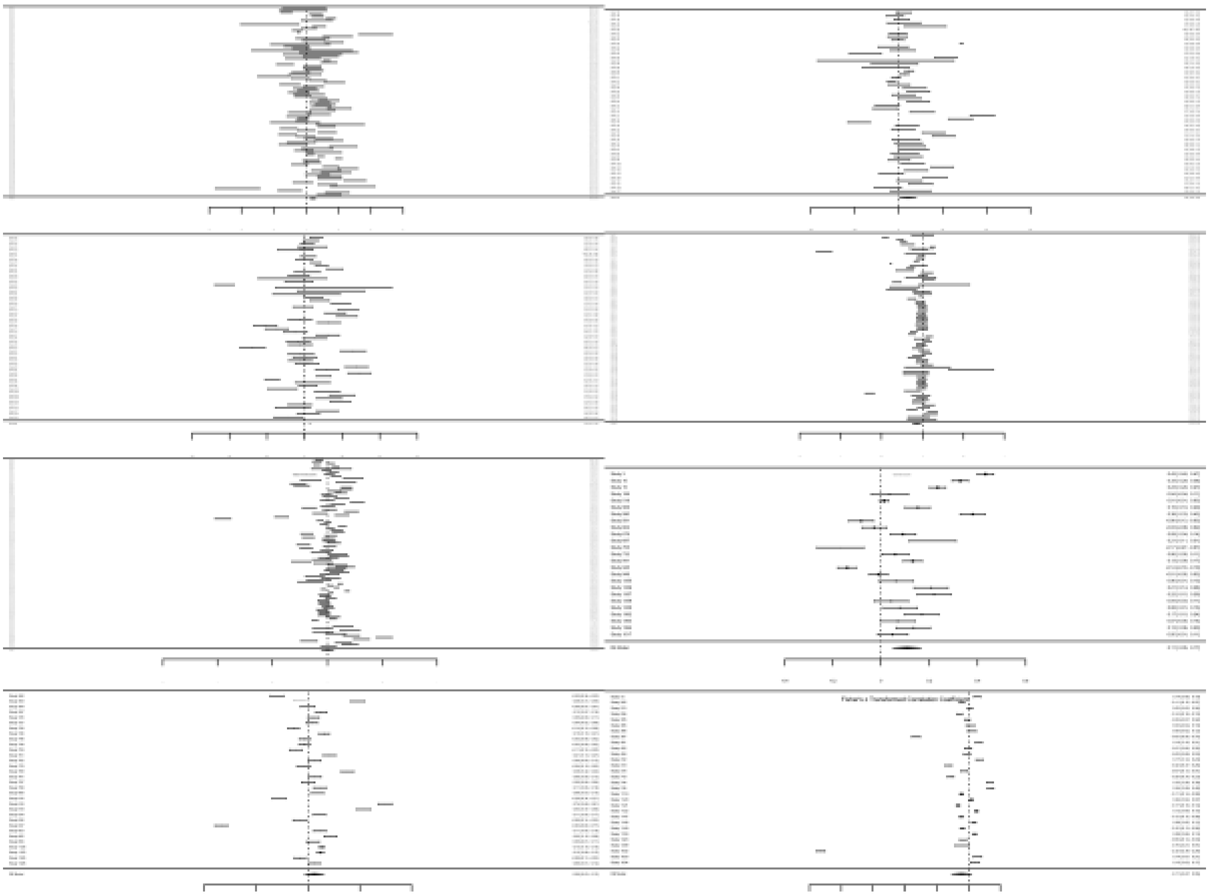

Figure 2 Forest plots

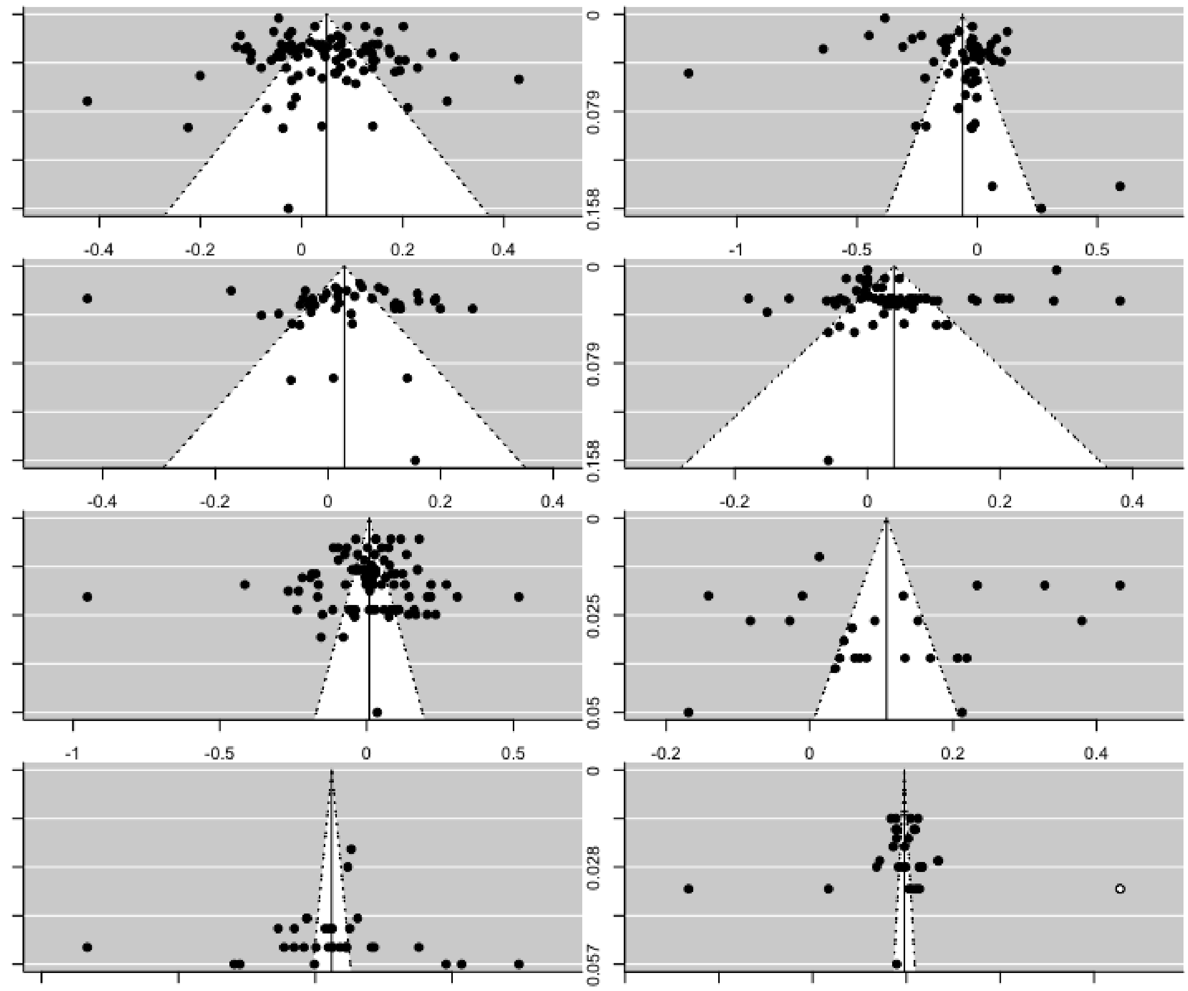

Figure 3 Funnel plots