A Meta-Analysis of the Effects of Sociodemographic Factors on Social Media Adoption

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Focusing on the effects of sociodemographic factors on the social media divide, one of the second-level divides, this meta-analysis finds that individuals who were female, younger, well-educated, well-paid, and urban residents were more likely to use social media. However, race as well as marital status and employment status did not play a role in predicting the adoption of social media platforms. Through moderator analysis, we find that the effect of age was robust without respect to study-level characteristics and that studies conducted in collectivistic countries and random samples demonstrate greater effects for education level.

Keywords: digital divide, social media use, sociodemographics, meta-analysis

According to the Pew Research Center (2018), the Internet penetration rate in the U.S. has amounted to 89% in 2018, but the penetration rate of social networking sites (SNSs[2]) was only 69%. Although policy and academic studies on the digital divide have been abundant and continue to grow, it is intriguing that a substantial portion of the American population with Internet access still does not use at least one social media platform, although social media use is assumed to be able to provide social support, self-esteem, and other types of well-being (for a discussion of the negative effects resulting from social media use, see Valkenburg, Peter, & Schouten, 2006). Many scholars have sought to explore the

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[1] The authors would like to thank the editors (Larry Gross and Arlene Luck) and the three anonymous reviewers for their constructive comments. This research is supported in part by the grant of the National Social Science Foundation of China (Grant No. 18BXW082).

[2] Social media and SNS are used interchangeably throughout the article, although social media may encompass more applications other than SNS.

determinants of the digital divide in social media use or adoption from various perspectives, but these studies have usually had inconsistent findings. More importantly, many studies suffer from numerous problems, two of which notoriously lie in the conceptualization and operationalization of the construct of the digital divide (van Dijk, 2006).

Theoretical Underpinnings of the Social Media Divide

Digital Divide

The term "digital divide" was formulated to reflect the inequalities between those with access to ICTs and those without such access (DiMaggio, Hargittai, Celeste, & Shafer, 2004; van Dijk, 2005; Yu, Ellison, McCammon, & Langa, 2016). Individuals may be involuntarily excluded from using ICTs because of a lack of opportunities or abilities, or they may choose not to use ICTs for other reasons (Eynon & Helsper, 2011; Yu et al., 2016). Even if people have both motivation and physical access to use, they still may not be active in their use (van Deursen & van Dijk, 2014; van Dijk, 2005, 2006). 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; Hargittai, 2002; van Dijk, 2006, 2012) have stated, the divide over time has transformed from the first level (inequalities in Internet access) to the second level (inequalities in skills and usage of specific Internet services; Hargittai, 2002) and to the third level (tangible outcomes; Scheerder, van Deursen, & van Dijk, 2017; van Deursen & Helsper, 2015).

Social Media Divide

There have been many definitions of social media (Carr & Hayes, 2015). Carr and Hayes (2015) define social media as "Internet-based channels that allow users to opportunistically interact and selectively self-present . . . with both broad and narrow audiences who derive value from user-generated content and the perception of interaction with others" (p. 50; for other definitions, see Kaplan & Haenlein, 2010; Obar & Wildman, 2015). Some (Ellison & Vitak, 2015; Xiang & Gretzel, 2010) elaborate on the scope of social media. These classifications are not, however, consistent with Carr and Hayes. These definitions are useful in their own right, but we hope to balance out the theoretical abstraction and functionality by defining social media as online community-based platforms that enable people to engage in networking, messaging, and/or creating (e.g., posting, tweeting, blogging), tagging, exchanging, evaluating (e.g., liking, commenting, voting, rating), and sharing content. This definition includes the most important characteristics of social media applications, tools, and features.

Similar to the construct of Internet use (see Bakker & de Vreese, 2011), social media use is not a unidimensional concept. It may indicate the overall use vis-à-vis nonuse (Pfeil, Arjan, & Zaphiris, 2009), the gradation in usage (Livingstone & Helsper, 2007), usage patterns, and specific use activities, for which the social gap by and large falls into the new phase of the second-level digital divide, or the social media divide. Generally speaking, the social media divide is an extension of the digital divide. The meaningful use of social media has significant social, political/economic, psychological, and cultural implications for users and society as a whole, which might be well explained by some theoretical frameworks.

Theoretical Framework

Many types of determinants of the digital divide and the ensuing consequences in society have been examined, but the underlying theoretical frameworks have been fragmented. Van Dijk and colleagues (DiMaggio, Hargittai, Neuman, & Robinson, 2001; Scheerder et al., 2017; van Deursen, Helsper, Eynon, & van Dijk, 2017; van Dijk, 2006, 2013) lament that most digital divide studies have referred to the same concepts using different nomenclatures that are not guided by theory or by hypotheses derived from theory, and that these discussions remain at a descriptive level of reasoning. Despite the criticism, the effort to provide a sound theoretical framework that can effectively explain the digital divide phenomenon is ongoing.

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, argues 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 Weber's view in some respects, but differs in others (Weininger, 2005). Bourdieu (1986) contends that three forms of capital—economic, cultural, and social—have a close relationship with social class. Unlike Marxists and others, Bourdieu maintains that social inequality results from unequal distributions of economic, cultural, and social resources, which are reflected or mediated through symbolic capital. Likewise, 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).

Weber (as cited in Breen, 2005) argues that individuals who share a common class position tend to behave in similar ways. Some (e.g., Zillien & Hargittai, 2009) have drawn upon Weber (2009) to explain the "status-specific" differential Internet use. Bourdieu (1984, 1986), however, maintains that 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 (i.e., field represents 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).

Therefore, tastes are intercorrelated with capital and field. Choices of any technologies or media platforms are the outcome of the complex synergistic effects among capital, habitus, and field factors (see Bourdieu, 1984, p. 95). For instance, Bobkowski and Smith (2013) find that nonadopters of social media have less economic stability, lower education levels, and weaker social support. This is because individuals can transport their habitus (and capital) from one field to another (Levina & Arriaga, 2014). Consequently, practices in the off-line field (Levina & Arriaga, 2014; van Deursen & van Dijk, 2014) can be reproduced in the online field. Helsper (2012) likewise proposes the corresponding fields model, which posits that social impact factors (access, skills, and attitudes) mediate the effect of off-line resources on digital inclusion and that digital impact factors (relevance, quality, ownership, and sustainability) mediate the effect of digital engagement on off-line inclusion. By the same token, the social media divide may affect social inequalities in areas of psychological well-being (Ellison, Steinfield, & Lampe, 2007), civic engagement (Gil de Zúñiga, Jung, & Valenzuela, 2012), and health benefits (Thackeray, Crookston, & West, 2013), among others.

Unfortunately, the confusing conceptualization and operationalization of the digital divide persists into the research on inequalities in social media use. For instance, many studies have examined the use vis-à-vis nonuse of different social media platforms or engagement with diverse activities on social media (e.g., searching for health information, mobilization of supporters, gaming). Hence, Pearce and Rice (2017) differentiated the social media divide along several dimensions, including the adoption/nonadoption of SNSs, different SNSs, and different capital-enhancing activities (which are able to enhance human capital) used on those SNSs. Furthermore, they find that the divides in SNS usage are much greater than those in activity use (Pearce & Rice, 2017). Similar to the first-level digital divide, the social media divide may result from the systematic differences in socioeconomic and sociocultural backgrounds. We focus the social media divide on overall use versus nonuse and gradation in usage. This specification avoids the complications in activity use, whose determinants may be beyond socioeconomic factors. Moreover, the theorizing of Pearce and Rice (2017) also suggests that choosing one of the dimensions of the social media divide is necessary because the absence of a sufficient number of common outcome variables and consistent measures of these variables has caused extreme difficulties for a meta-analysis, which has been absent so far. Accordingly, this study undertakes this job by focusing on the most studied predictors (i.e., the sociodemographic variables) and the common outcome (i.e., the adoption of social media platforms).

Hypotheses and Research Questions

Many frameworks have been adopted in prior digital divide studies, and various antecedents and correlates of the social media divide have been examined. However, sociodemographic variables appear to be the most popular. In the aforementioned 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) 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 sociodemographics (such as gender, race, age, geographical place of residence, marital status and employment status).

The Pew Research Center (2018) revealed that most social media users in the U.S. are younger (18–24 years) and female with higher education and income levels. A systematic review by Scheerder et al. (2017) identifies seven determinant categories of digital divides: sociodemographic, economic, social, cultural, personal, material, and motivational. However, they found that more than 60% of the studies examined the first two categories (i.e., sociodemographic and economic factors). Additional research has shown that economic and sociodemographic attributes are significant determinants of usage patterns (Büchi et al., 2016). Therefore, the present meta-analysis focuses on sociodemographics not because it is the last resort, but because sociodemographics are, in fact, very important determinants of the social media divide (Chakraborty & Bosman, 2005).

Building on the theoretical framework of Bourdieu (1984, 1986), we argue that social media use, which is mapped onto users' off-line practices, is influenced by resources (capital), tastes, and field. Albeit diverse, sociodemographic factors either directly or indirectly measure or indicate resources, tastes, and field. For instance, some (Correa, Hinsley, & Gil de Zúñiga, 2010; Tannen, 1990) have argued that women place a greater emphasis on forging connections with others and building a sense of community, and social media satisfies these needs. Therefore, understandably, women use more social media than men, primarily because women attach more importance to social capital to satisfy their social needs or desires (Katz, Blumler, & Gurevitch, 1973; McKenna & Bargh, 1999, 2000). For instance, Hargittai (2007) found that when SNS usage is tested in the aggregate, there is a significant relationship of gender to SNS use. Thus, the following hypothesis is proposed:

H1: *Women are more likely than men to use social media.*

Due to fear of being excluded from their peers, most younger people use social media simply to catch up with their friends and to make new ones (Boyd, 2007). Compared with adults, whose social media use results from various needs, it is mainly the need to accumulate social capital that draws young people to social media in light of the paradigm of uses and gratifications (Katz et al., 1973). Indeed, empirical studies have shown consistent findings with respect to the negative effect of age on social media use (Blank, 2017; Braun, 2013; Feng & Xie, 2015; Kuoppamäki, Taipale, & Wilska, 2017; Pfeil et al., 2009; Yu et al., 2016). Consequently, we propose another hypothesis:

H2: *Younger people are more likely than elderly persons to use social media.*

Economic capital is often the root of other types of capital, so it exerts a paramount effect on social media use. Most prior studies (Blank, 2017; Ching, Basham, & Jang, 2005; Hwang & Park, 2013; Straus, Williams, Shogan, & Glassman, 2016) have found that income affects social media use positively. The following hypothesis is thus proposed:

H3: *The higher people's income, the more likely they are to use social media.*

Similarly, most scholars (Feng & Xie, 2015; Hwang & Park, 2013; Schradie, 2012; Straus et al., 2016) agree that education, an important indicator of cultural capital, has a positive effect on SNS use. Education level is also believed to be the source of the knowledge gap hypothesis (Tichenor, Donohue, & Olien, 1970). However, some (Correa, 2016; Pearce & Rice, 2017; Szabo, 2012) have concluded otherwise. Despite the mixed findings, we propose a hypothesis regarding the effect of education level due to the prevalence of the positive effect:

H4: *The higher people's education level, the more likely they are to use social media.*

Urban residents enjoy better cultural capital (more schools and cultural facilities and activities) and job opportunities. This is why most empirical studies have found that urban residents as opposed to their rural counterparts are more likely to obtain Internet access. Many studies (e.g., Pick, Sarkar, & Rosales, 2015; Zhao, 2009) have found that this effect is also channeled into social media. Consequently, the following hypothesis is proposed:

H5: *Urban residents are more likely than their rural counterparts to use social media.*

Race, employment status, and marital status subtly affect overall social inequalities (Yang, 2008), but their effects on the digital divide remain inconclusive. Race has been a complex issue due to the diverse racial and ethnical composition of different countries, and thus it has been operationalized rather distinctly in prior studies. Hargittai (2007) discovered that statistically significant relationships between race and ethnicity and SNS use emerge if specific site usage is examined. However, the direction of the effect of race on the social media divide has been inconsistent. In addition, Blank and Groselj (2014) discovered that unmarried people were more likely to use social media than were married people, a finding similar to Yu et al. (2016), who concluded that SNS users were more likely to be widowed. However, Schradie (2012) presented mixed findings with respect to different types of marital status on social media use. Furthermore, many (Feuls, Fieseler, & Suphan, 2014; McKee-Ryan, Song, Wanberg, & Kinicki, 2005; Zawadzki & Lazarsfeld, 1935) have found that unemployment has profound social, psychological, and health implications. Yu et al. (2016) found that homemakers are more likely to use social media than are employed people, yet many researchers (e.g., Pick et al., 2015; Straus et al., 2016) have not detected a significant relationship between employment status and social media use.

In view of the inconclusive results of prior studies, the following general research questions are raised:

RQ1: *What are the directions and magnitudes of the effects of race (White vs. non-White), employment status (employed vs. unemployed), and marital status (married vs. nonmarried) on social media use across the studies?*

RQ2: *What moderators cause variations in the effects of sociodemographics, and how?*

Method

Sample of Studies and Eligibility Criteria

Our emphasis on the social media divide was the primary basis for selecting journal articles. To maximize the number of relevant studies, we employed various combinations of the following keywords: "digital divide," "digital inequal,"* "digital dispar,"* "digital difference," "digital gap," "digital exclusion," "digital distinction," "digital unfair,"* "social media/network,"* "use of social network sites" (and many specific popular social media platforms), 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. Studies reporting any of the effects of demographics were included. The first round of the search started in December 2017 and yielded 1,559 potentially eligible studies. We then implemented several screening steps for these articles following the procedure in the PRISMA statement (Moher, Liberati, Tetzlaff, & Altman, 2009; see Figure 1).

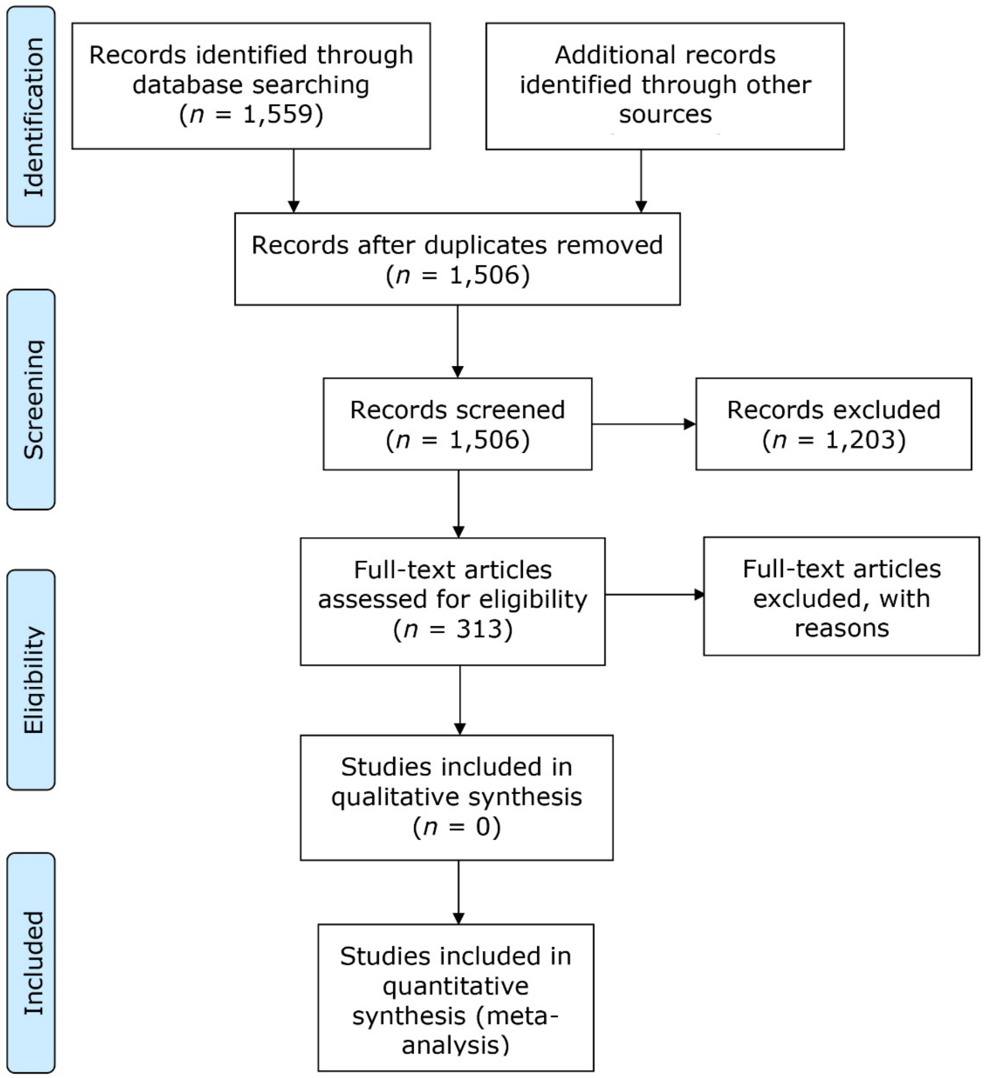

Figure 1. PRISMA 2009 flow diagram.

We searched the reference lists of all located studies and consulted scholars who have conducted research on the digital divide to determine what might be missing from our list. To obtain complete information in relation to effect sizes, 76 corresponding authors were contacted to request key information missing from their studies. Those who did not respond were excluded from subsequent analyses because their studies either lacked statistical details or presented statistical information in a form that did not allow for the computation of effect sizes. The extensive search yielded 1,823 valid effect sizes in 89 articles in relation to all the forms of social media use (cumulative N[3] = 4,553,161). We further selected 627 effect sizes in 71 articles with respect to the adoption of social media (cumulative N = 2,567,218), all of which were included in the analysis—there are 1 (5), 9 (80), 7 (101), 4 (34), 10 (44), 9 (65), 9 (61), 12 (199), 4 (23), 3 (10), and 1 (5) articles from 2006 to 2016, respectively, with the number of effects in parentheses (see Table 1 for the summary of the number of studies).

Table 1. Number of Studies by the Independent Variables and the Moderators.

<table>
<tr><th>IV</th><th>Data type</th><th>Sample type</th><th>Publication type</th><th>Country of origin</th><th>Count</th></tr>
<tr><td rowspan="10">Age</td><td rowspan="8">Cross sectional</td><td rowspan="3">Nonrandom sample</td><td rowspan="2">Journal article</td><td>Collectivistic</td><td>31</td></tr>
<tr><td>Individualistic</td><td>8</td></tr>
<tr><td>Thesis</td><td>Individualistic</td><td>1</td></tr>
<tr><td rowspan="5">Random sample</td><td rowspan="2">Conference paper</td><td>Collectivistic</td><td>3</td></tr>
<tr><td>Individualistic</td><td>2</td></tr>
<tr><td rowspan="2">Journal article</td><td>Collectivistic</td><td>52</td></tr>
<tr><td>Individualistic</td><td>5</td></tr>
<tr><td>Thesis</td><td>Collectivistic</td><td>3</td></tr>
<tr><td rowspan="2">Time series</td><td>Nonrandom sample</td><td rowspan="4">Journal article</td><td>Collectivistic</td><td>2</td></tr>
<tr><td>Random sample</td><td>Collectivistic</td><td>7</td></tr>
<tr><td rowspan="11">Education</td><td rowspan="9">Cross sectional</td><td rowspan="3">Nonrandom sample</td><td>Collectivistic</td><td>9</td></tr>
<tr><td>Individualistic</td><td>4</td></tr>
<tr><td>Thesis</td><td>Individualistic</td><td>1</td></tr>
<tr><td rowspan="6">Random sample</td><td>Book</td><td>Collectivistic</td><td>1</td></tr>
<tr><td rowspan="2">Conference paper</td><td>Collectivistic</td><td>2</td></tr>
<tr><td>Individualistic</td><td>2</td></tr>
<tr><td rowspan="2">Journal article</td><td>Collectivistic</td><td>37</td></tr>
<tr><td>Individualistic</td><td>2</td></tr>
<tr><td>Thesis</td><td>Collectivistic</td><td>3</td></tr>
<tr><td rowspan="2">Time series</td><td>Nonrandom sample</td><td rowspan="3">Journal article</td><td>Collectivistic</td><td>1</td></tr>
<tr><td>Random sample</td><td>Collectivistic</td><td>4</td></tr>
<tr><td rowspan="5">Employed</td><td rowspan="4">Cross sectional</td><td>Nonrandom sample</td><td>Collectivistic</td><td>11</td></tr>
<tr><td rowspan="4">Random sample</td><td>Conference paper</td><td>Collectivistic</td><td>1</td></tr>
<tr><td rowspan="4">Journal article</td><td>Collectivistic</td><td>31</td></tr>
<tr><td>Individualistic</td><td>1</td></tr>
<tr><td>Time series</td><td>Collectivistic</td><td>16</td></tr>
<tr><td>Female</td><td></td><td></td><td>Collectivistic</td><td>47</td></tr>
</table>

[3] Cumulative N is the total sample size by summing the sample size of each effect size (i.e., correlations).

	Cross sectional	Nonrandom sample		Individualistic	9
			Thesis	Individualistic	1
		Random sample	Book	Collectivistic	1
			Conference paper	Collectivistic	3
			Journal article	Collectivistic	55
				Individualistic	4
			Thesis	Collectivistic	3
	Time series	Nonrandom sample	Journal article	Collectivistic	9
		Random sample		Collectivistic	8
Income	Cross sectional	Nonrandom sample		Collectivistic	4
				Individualistic	2
			Thesis	Individualistic	1
		Random sample	Conference paper	Collectivistic	2
			Journal article	Collectivistic	50
				Individualistic	3
			Thesis	Collectivistic	2
	Time series	Nonrandom sample	Journal article	Collectivistic	1
		Random sample		Collectivistic	7
Unmarried	Cross sectional	Nonrandom sample		Collectivistic	5
				Individualistic	2
		Random sample		Collectivistic	35
				Individualistic	2
	Time series			Collectivistic	16
Urban	Cross sectional	Nonrandom sample		Collectivistic	12
		Random sample	Book	Collectivistic	1
			Conference paper	Collectivistic	3
			Journal article	Collectivistic	20
				Individualistic	11
	Time series			Collectivistic	8
Caucasian race	Cross sectional	Nonrandom sample		Collectivistic	43
		Random sample	Book	Collectivistic	1
			Conference paper	Collectivistic	3
			Journal article	Collectivistic	49
			Thesis	Collectivistic	2
	Time series	Nonrandom sample	Journal article	Collectivistic	21
		Random sample		Collectivistic	18

Operationalization of Effect Size

Independent Variables

Corresponding to the hypotheses and research questions, the following demographic variables were chosen for this study: age, gender, income, education level, Caucasian race or White (White vs. non-White; this effect is only applicable to studies conducted in the U.S.), rural residence (urban vs. rural), employment status, and marital status. Moreover, for binary variables, we unified the effect and reference categories across the studies (e.g., because all of the effect categories were unified to female, studies that used the male category as the effect were recoded and the effect sizes were recalculated). In addition, the effect of race was examined by comparing differences among White, Hispanic, Asian, and African American respondents. Because most studies adopted the White category as the effect category, we first changed the names of the effect categories such as Hispanic, Asian, and African American, to non-White, and then reversed the names between the effect and reference category (i.e., changing non-Whites to White), and recalculated the effect sizes. 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 were involved therein, we eliminated those studies that measured the variables with more than two categories.

Dependent Variable

We considered all studies that examined the determinants of the adoption of social media (using either the general term "social media" or the popular social media platforms) to be relevant regardless of whether they mentioned "digital divide" or its equivalents.

Transforming and Imputing the Effect Size

There are multiple types of effect sizes, such as correlations and odds ratios, all of which were transformed to the same type of effect size—that is, Fisher's *z* (which approximately follows the normal distribution; Silver & Dunlap, 1987). For illustrative and interpretative purposes, the resulting weighted mean *z* values were converted back to *r* using Fisher's *z*-to-*r* transformation.

In addition, some studies only reported regression betas. However, articles that only reported regression betas cannot be used directly to estimate the average effect size. Because the number of studies in this category was 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 is negative, and $r = \beta * .98 + 0.05$ if β is nonnegative (a simpler imputation formula, i.e., $r = \beta + 0.05$, can be also used).

Coding Categories of Moderators

Nonartifactual variation in correlations (effects) must be caused by the methods, samples, and interventions of the study—that is, a "moderator" variable (Hunter & Schmidt, 2004; Lipsey, 2003).

Therefore, once the heterogeneity of the effect is detected, the moderator analysis is imperative. In general, differences in the methods and sample characteristics introduce much of the variability ("heterogeneity") among the true effects, so most of the categories were mainly used to examine the methodological influences. In addition, the date of collection was used to examine whether the social media divide has temporal variations. Furthermore, peer-reviewed journal articles usually have better quality control, so the category of publication form was used to examine whether variations in effects were due to this difference. The category of country of origin was used to examine whether the severity of the social media divide is distributed differently across countries. Countries can be classified by some theoretically meaningful criteria, one of which is cultural backgrounds (e.g., individualism vs. collectivism). By doing so, we can determine whether cultural values affect the extent of the social media divide. In light of this reasoning, the following information was coded from each article: (a) date of study (data collection); (b) number of observations; (c) journal name; (d) publication form (journal article, book, conference paper, dissertation, and unpublished document); (e) data type (cross sectional vs. time series including panel data); (f) sampling type (random or probability sampling vs. convenience sampling); (g) country of origin (countries were classified into individualistic—primarily Western Europe and the U.S.—vs. collectivistic—mainly East Asia, such as China and Japan—categories according to Hofstede, 1984).

Two research assistants independently coded studies in accordance with the codebook. We selected 30% of the studies to check intercoder reliability. The results of the intercoder reliability were acceptable (see Table 2). Partial discrepancies were resolved through discussion.

Table 2. Intercoder Reliability Test of Key Moderators.

	Krippendorff's α	% agreement	*S*	Gwet
Data type	0.948	96.20	0.853	0.855
Publication form	0.791	97.90	0.838	0.978
Sample type	0.963	98.70	0.829	0.858
Sample size	0.998	95.80		0.9997
Country of origin	0.977	99.00	0.889	0.892

Note. *S* (Bennett, Alpert, & Goldstein, 1954) is only applicable to nominal variables. Gwet's AC_1 and AC_2 apply to nominal and higher than ordinal levels, respectively. Krippendorff's α can be used across measurement levels. For a review of these indices, see Feng (2013, 2014, 2015).

Procedures of Analysis

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, 1986). The objective of the present study was to identify the effects of sociodemographic predictors as well as possible moderators using meta-analysis. There were four steps in the present study. The first step was to determine the pooled mean effect size of sociodemographic differences in 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 the effects of demographics on 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 (Gleser & Olkin, 2009).

To determine whether each set of effect sizes shared a common effect size, we calculated a homogeneity statistic, *Q* (Higgins & Thompson, 2002; Schmid, Koch, & LaVange, 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 relationship between these study characteristics and the magnitude of the effect sizes, metaregressions were performed. Fitted models were estimated on the basis of the Akaike information criterion (AIC), followed by QE (test statistic of residual heterogeneity) and QM (omnibus test statistic of the significance of moderators).

The compilation of effect sizes showed a clear hierarchical structure because there were multiple effect sizes for many studies. We hence analyzed these data with multilevel mixed-effects modeling, which is generally superior to other approaches, such as robust variance estimation and averaging effects sizes (Moeyaert et al., 2017).

Results

We first report the results of descriptive analysis with respect to each effect size. For the effect sizes of age, 70% were negative, whereas 40% of the effect sizes of education level, marital status, and race were negative. For both gender and urban residence, 30% of the effect sizes were negative; 20% of the effect sizes of income level were negative, and 50% of the effect sizes of employment status were negative (see the forest plots in Figure 2 through Figure 6). To summarize, the effects of age, income level, gender (female), and urban residence were unambiguous, but the rest of the effects are less clear across the literature.

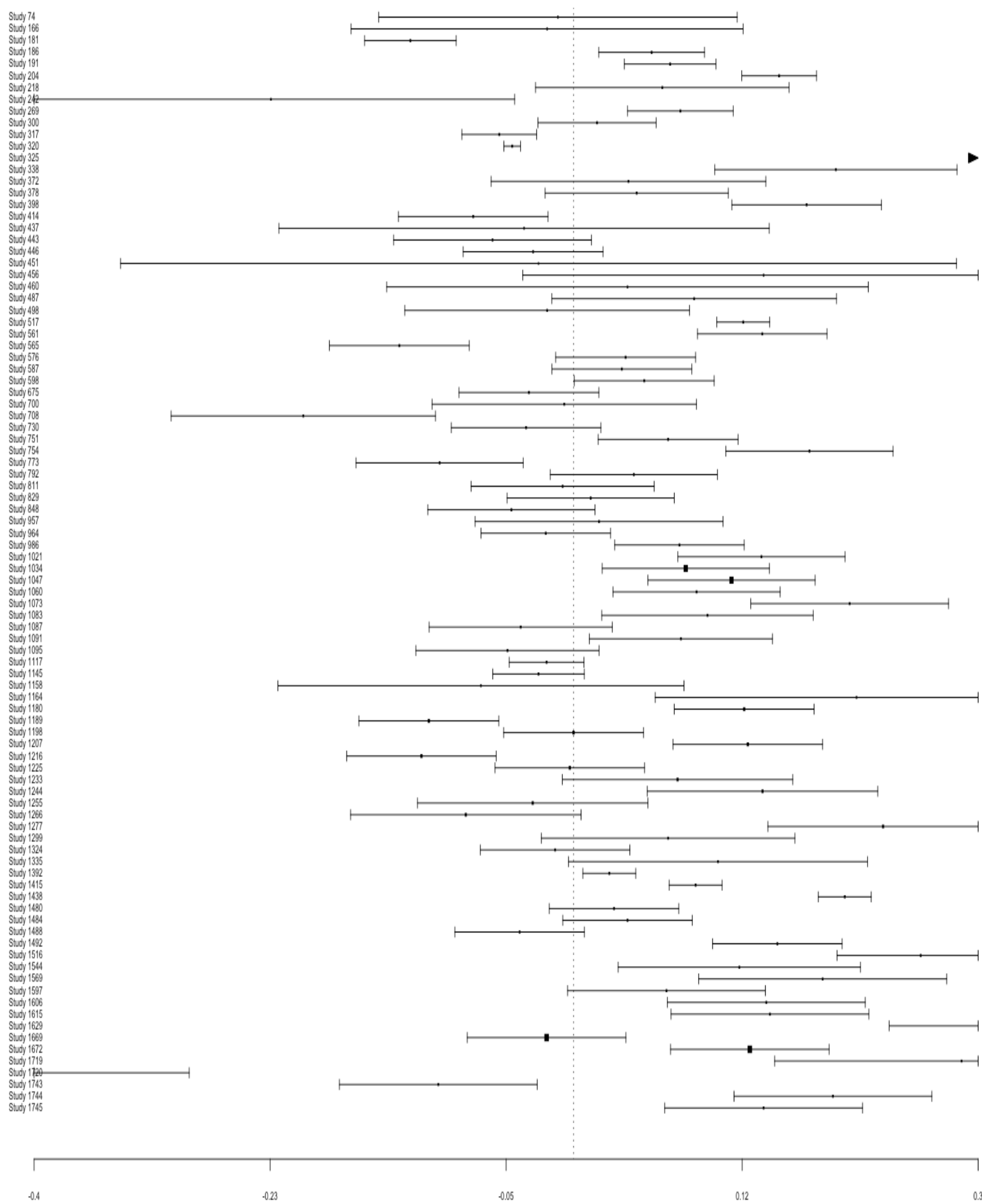

Figure 2. Forest plot of gender.

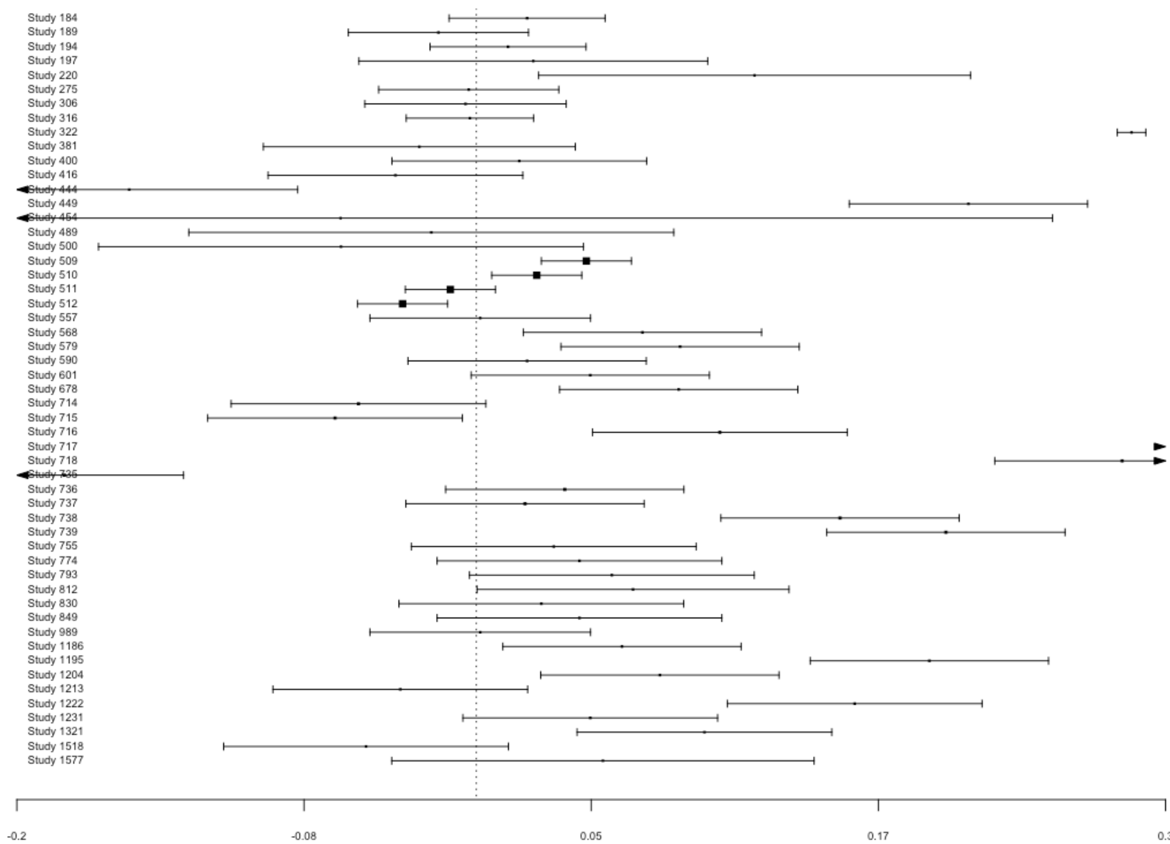

Figure 3. Forest plot of income.

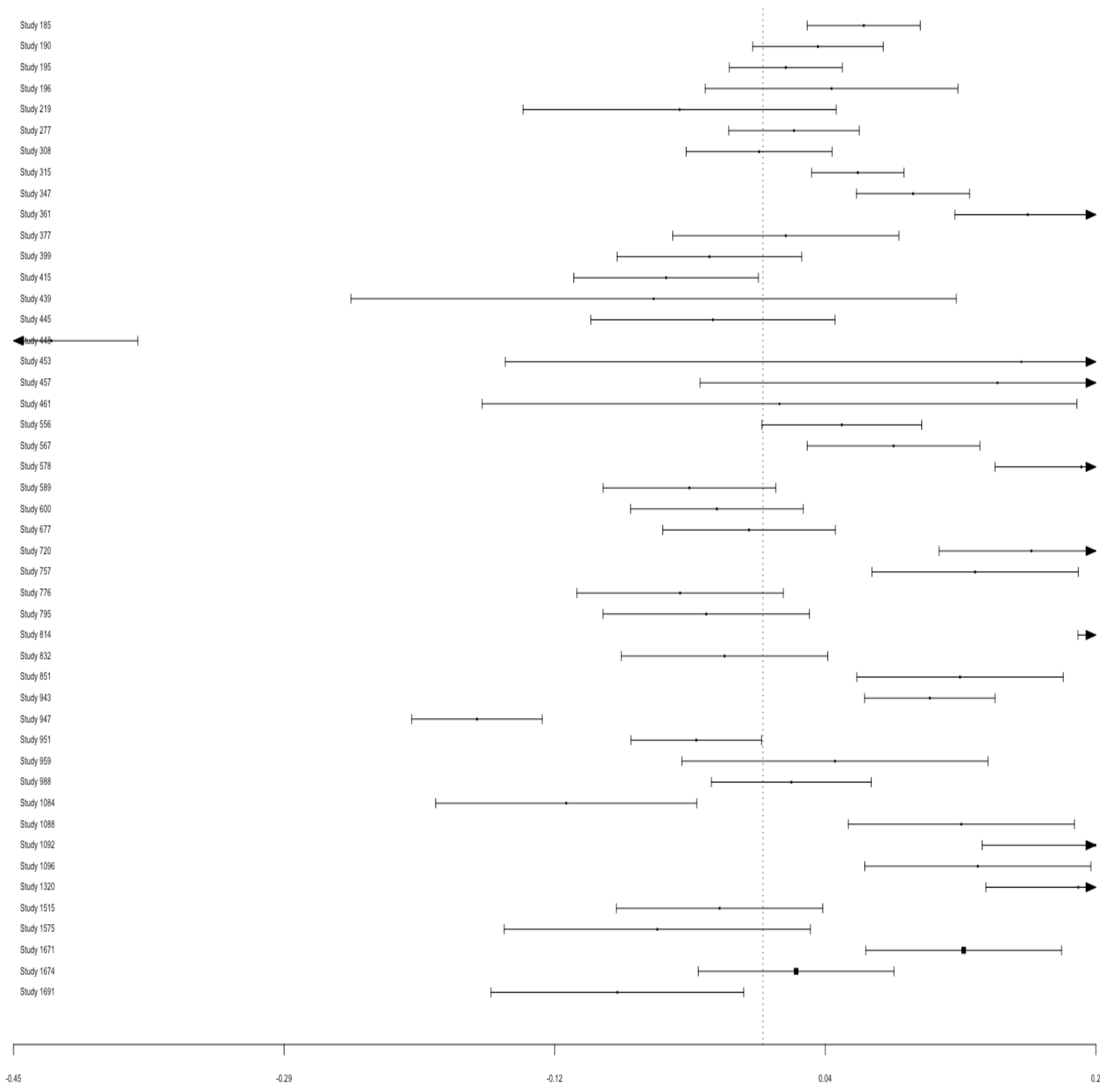

Figure 4. Forest plot of education.

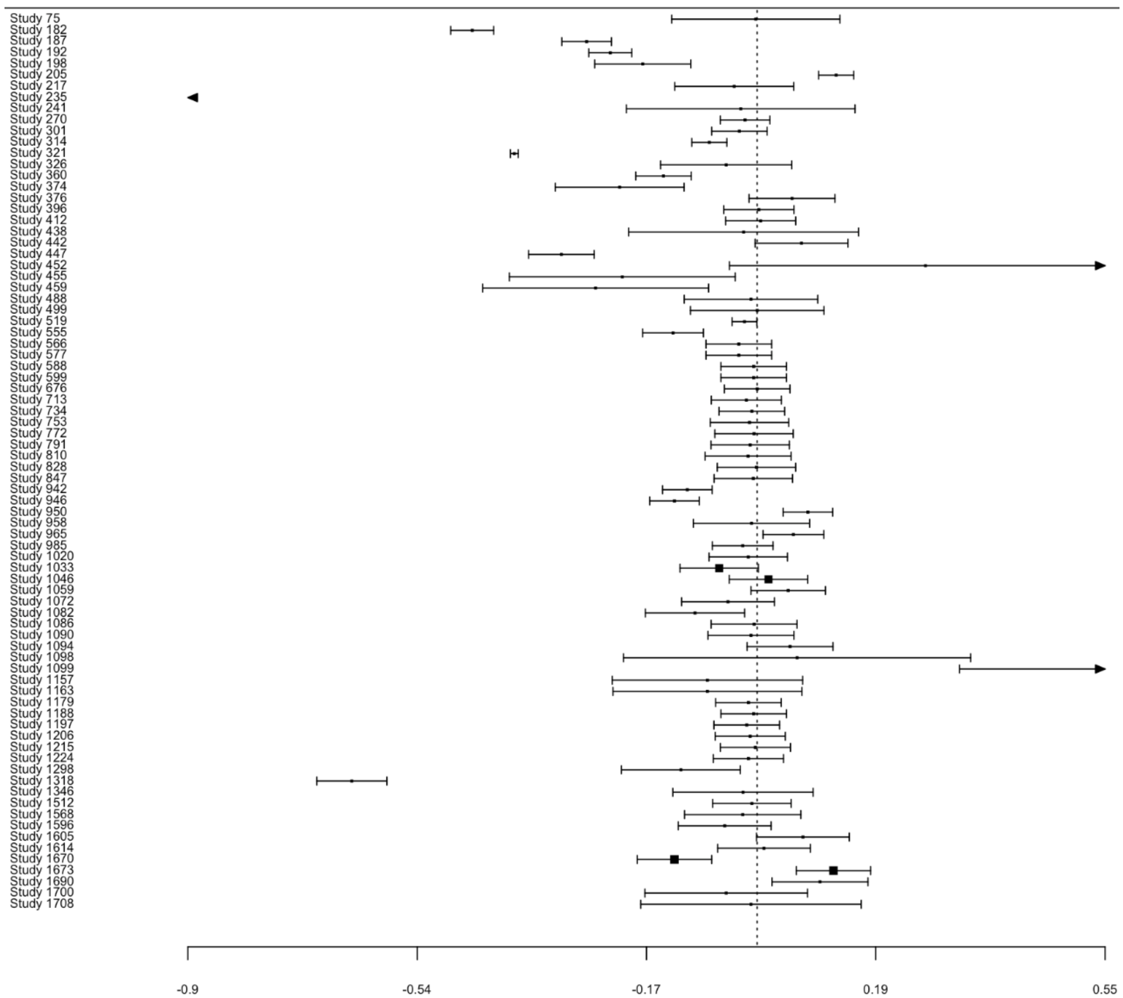

***Figure 5. Forest plot of age*.**

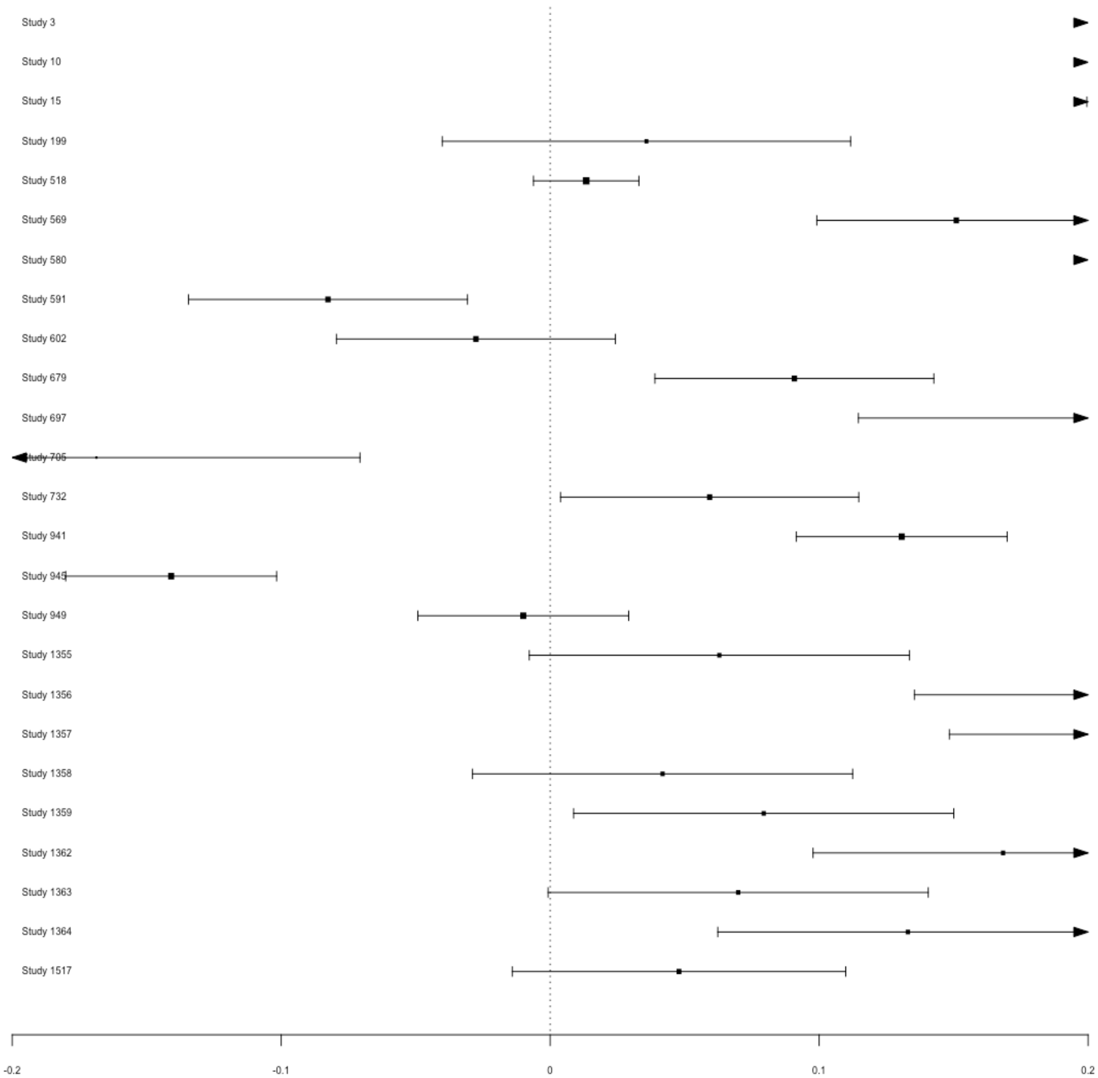

Figure 6. Forest plot of residence.

Subsequently, through a series of intercept-only random-effects meta-analyses, we discovered that females, youths, well-educated individuals, urban residents, the White race (or Caucasians), wealthy people, unmarried individuals, and unemployed people were more likely than their counterparts to use social media. However, the overall effects of gender (female), age, education, income, and urban residence were significant (β = .037, p < .001; β = −.071, p = .005; β = .028, p < .003; β = .048, p = .019; β = .112, p < .001; see Table 3), but the overall effects of the White race, marital status, and employment status were not significant (β = .006, *ns*; β =.03, *ns*; β = −.09, *ns*). That is, a social media divide exists in gender, age groups, education, and income levels and residency, whereas the social media divide in other aspects, such as race, marital status, and employment statuses (RQ1) is not consistent or clear. As a result, H1, H2, H3, H4, and H5 are supported.

Table 3. Model Estimation Results of Major Effects.

IV	Model	Moderator	Beta	*k*	*N*	QE	QM	QMp	τ^2	Rho	AIC
	Null	Intercept	0.04***	141	3,66124	1,918.86	28.144	0.00	0.01	−0.10	−124.56
	One	Intercept	0.06***			1,207.56	0.50	0.48	0.01	NA	−127.33
	moderator	Date of study	0.00			1,207.56	0.50	0.48	0.01	NA	−127.33
		Intercept	0.07**			1,171.46	1.03	0.98	0.01	0.12	−106.89
Female		Random sampling	−0.02			1,171.46	1.03	0.98	0.01	0.12	−106.89
	Full	Time series	0.00			1,171.46	1.03	0.98	0.01	0.12	−106.89
		Conference paper	−0.12			1,171.46	1.03	0.98	0.01	0.12	−106.89
		Dissertation	0.02			1,171.46	1.03	0.98	0.01	0.12	−106.89
		Date of study	0.00			1,171.46	1.03	0.98	0.01	0.12	−106.89
		Collectivistic	0.01			1,171.46	1.03	0.98	0.01	0.12	−106.89
	Null	Intercept	−0.07**	115	2,52834	7,507.30	7.45	0.01	0.03	0.41	−4.23
		Intercept	−0.01			1,157.52	4.75	0.58	0.03	0.32	3.74
Age		Random sampling	0.01			1,157.52	4.75	0.58	0.03	0.32	3.74
	Full	Time series	−0.15			1,157.52	4.75	0.58	0.03	0.32	3.74
		Conference paper	0.06			1,157.52	4.75	0.58	0.03	0.32	3.74
		Dissertation	0.21			1,157.52	4.75	0.58	0.03	0.32	3.74
		Date of study	−0.01			1,157.52	4.75	0.58	0.03	0.32	3.74
		Collectivistic	−0.09			1,157.52	4.75	0.58	0.03	0.32	3.74
	Null	Intercept	0.03**	67	8,8825	764.47	4.89	0.03	0.01	−0.12	−61.35
	One	Intercept	0.02			688.63	4.62	0.03	0.01	NA	−65.81
Education	moderator	Country of origin	0.09*			688.63	4.62	0.03	0.01	NA	−65.81
		Intercept	−0.09*			505.70	14.63	0.02	0.01	NA	−51.17
		Random sampling	0.09*			505.70	14.63	0.02	0.01	NA	−51.17
	Full	Time series	0.03			505.70	14.63	0.02	0.01	NA	−51.17
		Conference paper	0.05			505.70	14.63	0.02	0.01	NA	−51.17
		Dissertation	0.00			505.70	14.63	0.02	0.01	NA	−51.17
		Date of study	0.03			505.70	14.63	0.02	0.01	NA	−51.17
		Collectivistic	0.19***			505.70	14.63	0.02	0.01	NA	−51.17
	Null	Intercept	0.05*	72	2,67470	3,995.67	4.27	0.04	0.01	0.77	208.29
		Intercept	0.05**			3,859.10	4.54	0.10	0.01	0.70	208.03
	One	Conference paper	−0.06			3,859.10	4.54	0.10	0.01	0.70	208.03
Income	moderator	Dissertation	−0.24*			3,859.10	4.54	0.10	0.01	0.70	208.03
		Intercept	0.04			530.34	9.57	0.14	0.00	−0.10	216.75
		Random sampling	−0.01			530.34	9.57	0.14	0.00	−0.10	216.75
	Full	Time series	−0.04			530.34	9.57	0.14	0.00	−0.10	216.75
		Conference paper	−0.01			530.34	9.57	0.14	0.00	−0.10	216.75
		Dissertation	−0.24*			530.34	9.57	0.14	0.00	−0.10	216.75
		Date of study	0.01			530.34	9.57	0.14	0.00	−0.10	216.75
		Collectivistic	0.06			530.34	9.57	0.14	0.00	−0.10	216.75
	Null	Intercept	0.11**	55	2,63068	1,102.84	13.17	0.00	0.02	NA	−21.75
		Intercept	0.08***			489.75	14.77	0.00	0.01	−0.09	−28.60

Urban	One moderator	Conference paper	0.26**	489.75	14.77	0.00	0.01	−0.09	−28.60
		Intercept	0.15	388.15	14.77	0.01	0.01	NA	−10.77
	Full	Random sampling	−0.22	388.15	14.77	0.01	0.01	NA	−10.77
		Conference paper	0.30***	388.15	14.77	0.01	0.01	NA	−10.77
		Date of study	0.04	388.15	14.77	0.01	0.01	NA	−10.77
		Collectivistic	0.10	388.15	14.77	0.01	0.01	NA	−10.77

Note. QE refers to the Q-statistic value, QEp is the p-value for the Qstatistic, QM is the Q-statistic for model fit and QMp is the p-value for QM. QEp is zero in each cell. *k* is the number of effect sizes. *N* is the total sample size.

To address RQ2, each moderator was tested sequentially in a series of meta-analyses. Highly significant heterogeneity was found among effect sizes (see the values of QE and QEp in Table 3 and the forest plots in Figure 7) regardless of whether the overall effects were significant. In summary, among the tested moderators, the country of origin and sample types significantly moderated the average effect sizes of education level, and publication forms significantly moderated the average effect sizes of income level and urban residence. Specifically, studies conducted in collectivistic countries as opposed to individualistic countries and studies using random samples rather than convenience samples had larger effects than those performed to assess the effect of education level (β = .187, p < .001; β = .088, p < .05). In addition, conference papers had a larger effect size than did journal articles for the effect sizes of urban residence (β = .258, p < .001), whereas the thesis publication type had a lower effect size than did journal articles for income level (β = −.237, p < .05).

Publication Bias

Duval and Tweedie (2000) propose a simple trim-and-fill algorithm accounting for the magnitude of the publication bias problem that 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" (pp. 456–457). 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 may not be serious because no missing studies were reported in light of the trim-and-fill analysis for any of the effect sizes. except for employment status, which had only one possible missing study.

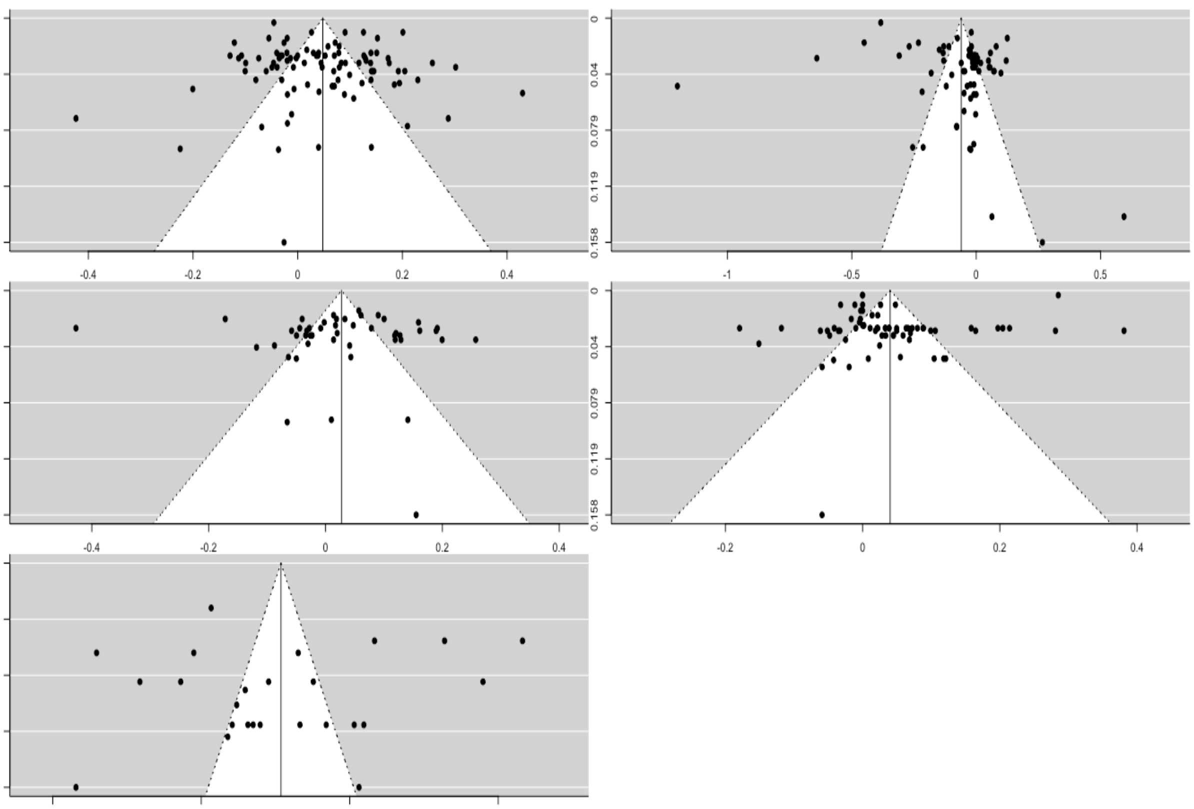

Figure 7. Funnel plots representing gender, age, education, income, and urban residence in the sequence from left to right by row. Solid circles represent the weight of the studies, and empty circles, if any, represent the added studies.

Discussion

With the testing of sufficient effect sizes through a series of meta-analyses, we found that people who were female (vs. male), younger (vs. older), well-educated (vs. poorly educated), well-paid (vs. having low income), and urban residents (vs. rural residents) were more likely to use social media. However, the characteristics of White (vs. non-White races), not married (vs. married), and unemployed (vs. employed) did not play a role in predicting social media use. Our findings are consistent with those of the Pew Research Center (Perrin, 2015). In addition, the effects of gender and age were robust without respect to the study-level characteristics. These results correspond well to the theoretical frameworks reviewed above, particularly that of Bourdieu (1984, 1986). That is, these effects indicate the significance of social (gender and age), economic (income), cultural (education) and symbolic (urban residence) capital, which users either currently possess or pressingly need.

The moderators included in the model played differential roles in affecting the effect sizes. The country of origin for studies has been examined in many primary studies on social media use. For example, many researchers (Choi, Kim, Sung, & Sohn, 2011; Jackson & Wang, 2013; Liu, Ainsworth, & Baumeister, 2016) discovered that the relationship between SNS use and bridging capital was stronger in individualistic countries than in 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 finding is partially consistent with some prior studies. For example, Jackson and Wang (2013) did not find that gender and family income relate to SNS use differently in collectivistic and individualistic cultures.

We found that studies conducted in collectivistic countries demonstrated a greater effect from education level than those performed in individualistic countries, whereas all other effects of demographics transcended cultural differences. Such findings have profound implications, particularly for cross-cultural studies. Hence, we realize the boundary of some effects. That is, some effects are culturally bound, whereas some are universal. In brief, the variations or discrepancies among effect sizes are due to either cultural or methodological differences in the primary studies.

Studies using random samples showed a higher effect size by education level. Convenience samples (e.g., student samples) are characterized by homogeneous participants and hence have lower variance in attributes (i.e., the variable of education level has low variations for student samples). However, if such a predictor (the independent variable) has lower variance in regression analysis, its standard error becomes larger, and consequently the *T* value on the significance test will be smaller (see Neter, Kutner, Nachtsheim, & Wasserman, 1996). Therefore, convenience samples are not ideal, particularly for the test in relation to demographics (such as education level, and age).

Some researchers (e.g., Klümper & Qaim, 2014) have found that conference papers in general have a lower quality than do peer-reviewed journal publications, but does unpublished work therefore have unstable findings? This may be true because strong effects tend to be favored for publication (Ioannidis, 2005), but, surprisingly, null results were also easier to get published (Miles, Vig, Weyant, Forrest, & Rockette, 1996). For instance, Polanin, Tanner-Smith, and Hennessy (2016) and Fuchs and Fuchs (1986) indicate that published studies yield larger effect sizes than those from unpublished studies, but Klümper and Qaim (2014) find that conference papers somehow reported larger effects than journal articles did. The contradictory results of conference papers and theses versus journal articles in this meta-analysis may indicate a lack of determinate conclusions.

The contribution of this study is significant. It is not only the first meta-analysis on the social media divide but also the only formal meta-analysis on the digital divide in general (Scheerder et al., 2017, performed a systematic review). In addition, we found that capital factors, such as gender, age, education level, income level, and urban residence, were real, but weak. Moreover, we discovered that some important moderators, particularly the country of origin of the studies, influenced the variations of some effect sizes. In addition, the effect of age and gender transcended all of the moderators.

This meta-analysis has limitations. First, to have sufficiently large effect sizes for the present meta-analysis, many original independent and dependent variables that had similar or close meanings were renamed to share the same name. Some of these changes may not reflect the initial measurements of the primary studies and thus destabilized the effect sizes of interest. Moreover, different types of effect sizes were converted into the same type (i.e., Fisher's *z*) in the analysis. Although this is a recommended procedure when dealing with inconsistent types of effect sizes (Cooper & Hedges, 1994), it could introduce potential confounding to the results. In addition, although country of origin was found to be a moderator for some effects, the U.S. accounted for 65% of the total number of the studies. The dominance of the U.S.-based studies clearly demonstrates a research gap. Future research could test all of the effects on the U.S. samples and non-U.S. samples separately, to empirically investigate the influences of the dominance. Finally, although we found that the social media divide could be attributed to the effects of various types of capital, the different capitals still lack enough consistent operationalizations, which could produce a series of untested moderation effects.

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