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Self-Disclosure in Online Interaction: A Meta-Analysis

Christine Bauer
Vienna University of Economics and Business,
Department of Information Systems and Operations
chris.bauer@wu.ac.at

Michael Schiffinger
Vienna University of Economics and Business,
Interdisciplinary Institute for Management and
Organisational Behaviour / Center for Empirical
Research Methods
michael.schiffinger@wu.ac.at

Abstract

Using the Internet increasingly requires people to disclose personal information for various reasons such as establishing legitimacy, authentication, or providing personalized services. An enormous amount of literature analyzed various influencing variables that shape self-disclosure in online interaction. However, the range of studies considers very specific variables and therefore provides merely puzzle pieces of the field. This paper puts the pieces together by combining extant evidence into a meta-study. Results suggest that, while the overall effects of demographic, environmental, person- and system-based predictors are rather weak, self-disclosure can to some extent be influenced by system design.

1. Introduction

Using the Internet increasingly requires people to disclose personal information for various reasons. In personal online interaction, disclosure may contribute to reducing uncertainty between the communication partners [1]. When joining an online group, it serves to establish legitimacy [2]. Frequently disclosure of name and e-mail address is a prerequisite to access certain services on the Web via registration [3]. To make online purchases, further information such as name, address, and credit card details are required for invoicing and payment [3, 4]. Furthermore, users highly value personalized services on the Web [5] (such as personalized recommendations or "one click" purchasing [6]), which also seems profitable for companies engaging in business-to-consumer electronic commerce [7]. This potential win-win situation is, however, marred by the fact that companies need detailed user information in order to tailor products and services to the individual's needs. However, users seem increasingly reluctant to disclose personal information [8]. Consequently, companies are eager to find ways to encourage users to reveal personal information.

The research thread on self-disclosure is not a new one. Considerable psychological [e.g., 9, 10, 11, 12] and marketing research [e.g., 13, 14, 15, 16] has examined the phenomenon of self-disclosure.

Basically, we can identify three main research trajectories adopting different perspectives to explain the self-disclosure phenomenon: similarity theory [17], self perception theory [18], and social exchange theory [9, 19, 20]. Similarity theory posits that people disclose more when they perceive that similarity exists between them and their counterpart [21]. Self perception theory suggests that individuals may infer people's attitudes from their behaviors and, thus, self-disclosure contributes positively to relationship building [18]. Social exchange theory postulates that users' willingness to disclose personal information is based on their assessments of the costs, risks, and benefits [22, 23].

The enormous amount of literature in the field of self-disclosure analyzed various influencing variables that shape disclosure. The scope of the investigated variables is tremendous. Among them are gender [e.g., 24, 25], education [e.g., 26, 27], social anxiety [e.g., 28], reward [e.g., 22, 27], anonymity [e.g., 29, 30], trust [e.g., 31, 32], and privacy [e.g., 3, 33, 34].

Besides influencing factors that are inherent to a person and cannot be easily changed (e.g., demographics [27] or personality traits [10]), studies have also revealed determinants of self-disclosure that may be influenced by system design (e.g., introducing privacy seals [35], rewards [23], considering the questions' sequence [20]). But how effective are these variables? And can an organization influence a user's self-disclosure? The range of studies considering very specific variables provides merely puzzle pieces regarding these issues. This paper aims at putting the pieces together by combining extant evidence into a meta-study in order to provide better-founded answers to these questions. In this paper we provide two main

contributions: First, we develop a categorization of the heterogeneous scope of self-disclosure predictors in online settings, as investigated in existing studies. Second, we examine the effects of these categories on self-disclosure.

The next section outlines the foundations of the concept of self-disclosure and discusses literature on possibilities for altering user's disclosure. Section 3 describes in detail how we carried out the meta-analysis, including details on data collection, coding, and computation. Section 4 presents the results of the meta-analysis, which are then discussed in Section 5.

2. Conceptual foundations

2.1. The concept of self-disclosure

Self-disclosure is defined as what individuals verbally communicate about themselves [19], including thoughts, feelings, and experiences [36]. People disclose information for a variety of purposes, in part dependent on the context in which disclosure occurs [37]. In dyads, it serves to increase mutual understanding [38]. In groups, disclosure may enhance trust between group members, act as legitimization for group membership and strengthen group identity [2]. Disclosure towards an organization may serve authentication purposes, for instance, to allow authentication of a claim to identity [37]. Organizations may also ask for personal information to allow tailoring of products and services to an individual (e.g., personalized recommender systems) or for marketing purposes (e.g., personalized advertising) [37].

An important aspect of self-disclosing behavior is reciprocity. This concept refers to the mutual exposure of communication partners, where – particularly in dyads – a disclosure of one communication partner follows a disclosure of the other [39].

Self-disclosure is of particular interest in the domain of human-computer interaction for many reasons [37]. It is critical for a scale of Web-based services that are tailored to an individual such as personalized recommender systems, "one click" purchasing [6], or applications such as e-recruitment [40]. Furthermore, when people disclose personal information they signify that they trust an organization and accept the privacy assurance [37]. As concerns electronic commerce and online relationship building, both is in the interest of an organization [37] because

in the absence of face-to-face interaction companies have to rely on such feedback behavior.

2.2. Altering self-disclosure

Not all users are willing to disclose personal information. As a result, many generally shy away from electronic commerce and online services [4]. One of the major barriers is people's privacy concern. And those objections appear to be well founded, given that in the beginning of the millennium many commercial Web sites did not entitle users to much privacy [4, 23]. Consequently it does not come as a surprise that many users are reluctant to disclose personal information because of privacy concerns [4, 8]. However, there are also many users that appear to provide personal information abundantly and freely in the online setting, particularly in the context of online social networks.

While organizations that build their business model entirely on users' personal information (e.g., online social networks) look for ways to encourage people to disclose (more) personal information on their platforms [41], organizations dedicated to protecting consumer rights (e.g., privacy organizations) aim at minimizing online self-disclosure.

Social exchange theory suggests that altering users' cost-benefit trade-off for self-disclosure may either encourage or discourage people to disclose personal information [22, 23]. For instance, organizations may offer rewards in exchange for disclosing personal information to increase users' subjective benefits of self-disclosure [23, 42]. Offering high rewards, however, may also intensify users' self-disclosure concerns because they may become suspicious and think that the organization offers the reward as a decoy used to inveigle individuals to reveal sensitive data [22].

Besides opportunities to alter people's disclosing behavior by manipulating influencing factors, other variables are inherent to a person and can therefore not be changed. Whether and to what extent a user's self-disclosure can be manipulated is therefore one of the central questions of this paper.

3. Materials and methods

The specific objective behind this central question is to identify the most influential factors that shape self-disclosure. We address this problem by exploiting existing research findings in the field through a meta-analysis of 48 studies on self-disclosure. Put simply, a

(statistical[1]) meta-analysis represents a systematic aggregation of the findings of previous studies regarding the extent to which one or several predictors affect a dependent variable, based on so-called effect sizes [43].

3.1. Literature search

To develop an effective search strategy, we made a scoping review of the published literature. Two procedures were used to locate studies to be included in the sample.

First, we searched for scientific studies on electronic databases. The following databases were included in our search: Web of Science, IEEE Xplore Digital Library, ProQuest Computing, EBSCO Business Source Premier, PsycARTICLES, PsycInfo, ABI/INFORM Global and ABI/INFORM Trade & Industry. In all databases and search engines, we searched for journal articles, conference contributions, and theses.

The search terms comprised *disclosure* or *self-disclosure* or *disclose or disclosing* in combination with either *online* or *Internet* or *Web*, within the title and/or the abstract.

Second, the reference lists of identified publications were examined for relevant sources. In doing so, we analyzed both, publications that we finally included in the sample and also those that were excluded (cf. Section 3.2).

If the full paper was not accessible via databases and the libraries in town, the authors were contacted via e-mail. Such a request was sent out to the authors of three studies. One of them provided the full paper; no reply was received from the authors of two studies.

3.2. Criteria for inclusion

Based on a review of the full-text of a publication, a study was *included* if it fulfilled the following criteria: (1) It investigated disclosure as a result of one or more influencing factors; (2) self-disclosure was analyzed in an online setting; (3) it was an empirical study; and (4) the authors provided adequate data for the computation of effect sizes.

A study was *excluded* if at least one of the following criteria were met: (1) The study investigated solely the effects of disclosure on other factors or outcomes; (2) it investigated the disclosure of health

issues; (3) the study investigated disclosure in the field of dating; (4) it analyzed privacy disclosure; or (5) corporate disclosure; (6) the study covered disclosure merely in offline settings; (7) it was a qualitative study; (8) data necessary for computing effect sizes were not available in the publication.

For studies where the decision was not clear-cut, inclusion and exclusion was discussed among the three literature researchers until they reached common agreement. The included sources are presented in Appendix 1.

3.3. Coding from publications

We coded inductively from raw data (the studies). For each study, we obtained the following information: (1) meta-information on the publication (citation information), (2) total sample size, (3) for experiments: sample size of experiment groups and control groups, (4) dependent variables used, (5) independent variables used, and (6) test method and respective data reported.

3.4. Categorization of independent variables

As the studies in the sample analyzed a wide scope of different independent variables, we had to reduce the complexity of the data. As a result, we set up a categorization scheme with four categories (demographic, person-based, environmental, or system-based predictor). Informed by this categorization scheme, we assigned each of the independent variables (as coded in step 5 of the coding procedure as described in Section 3.3) to one of the following categories (*no* multiple assignments):

- Demographics: Variables that were coded as demographics include, for instance, sex, age, or education.
- Person-based variables: Person-based variables are inherent to a person and his or her perceptions. Examples are self-esteem, personality traits, or perceived risk.
- Environmental factors: Environmental factors include peer-related variables (such as peer pressure) and provider-related variables (such as reputation of a company).
- System-based variables: Variables that may be controlled by a system or are inherent to system design were coded as system-based variables. Examples for this category are privacy priming or reward provided in exchange for disclosed information.

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[1] Sometimes literature reviews are also presented under the label of "meta-analysis".

Three coders perused each study and built the categorization scheme. Computing initial intercoder agreement values (using the irr package [44] for R [45]) resulted in an overall agreement of 81% and a Fleiss-Kappa [46] of .77, which represents "substantial agreement" according to Landis and Koch [47, p. 165]. Except for environmental factors with a lower Kappa (.43), all other categories even achieved "almost perfect agreement" with Kappa values higher than .80. In the instances where some disagreement emerged, the coders discussed the study in question until *complete* consensus could be established.

Frequently, one publication involved more than one sample and/or one study more than one predictor variable. The data set therefore consists of 92 effect sizes of a demographic, person-based, environmental, or system-based predictor on self-disclosure.

3.5. Computation

Since the effect of interest refers to a relationship between two variables, the chosen effect size is the correlation coefficient r. When findings in the included studies were not reported as r coefficients, they were converted into r (for formulas, see, e.g., Lipsey and Wilson [48, p. 201]). Following a standard procedure for easier calculation of confidence intervals, the r coefficients were converted into Fisher z values and weighted with the sample size of the respective study [e.g., 49, pp. 41-43], before being transformed back into the more familiar r coefficients shown in the following plots. Assessment of the strength of the reported effects can be based on the classification by Cohen [43]. An r coefficient of .1 would thus represent a weak effect, $r = .3$ a medium and $r \geq .5$ a strong effect. Analyses were conducted with the metafor package [50] for R [45], the random-effects models (see top of Section 4) using a Restricted Maximum Likelihood (REML) estimator [e.g., 51].

4. Results

The following plots (Figures 1 to 4) show the effect size r of each study (including the 95% confidence interval) for the four categories (demographic, person-based, environmental, or system-based predictor) and the estimated mean effect size calculated for both random- and fixed-effects models (RE and FE, respectively). Index numbers after the study identifier stand for multiple samples and/or categories within one study. Simply and roughly spoken, fixed-effects models regard the included studies as the population representing the true effect whereas in random-effects models the included studies are seen as a (random) sample of studies. Generally speaking, a random-effects model is considered as more appropriate in most instances. From a "practical" perspective, the random-effects models give relatively more importance to studies with a smaller n and yield effect estimates with larger standard errors and confidence intervals. For a more detailed discussion of fixed- versus random-effects models, see, e.g., Hedges and Vevea [52].

According to the above-mentioned classification for r in terms of effect strength, the results for the mean effects therefore suggest that the demographic predictors have almost no effect on self-disclosure[2], and the environmental factors merely a weak effect. These two sets of predictors are also potentially non-significant as the 95% confidence interval for the random-effects models includes zero, even though on the other hand the RE effect estimate for environmental predictors ranges towards a medium effect strength with an upper bound of .27. This does not apply to person- and system-based predictors, which are significantly different from zero in both the fixed- and random-effects model, albeit without suggesting notably stronger effects. According to the results, the importance of these two predictor sets is weak to medium and slightly stronger for person-based factors (considerably so in the fixed-effects model); however, this may partly be a result of method variance (cf. Section 5).

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[2] This could be at least partly explained by the rather homogeneous samples across the included studies, mostly consisting of rather young and well-educated persons and therefore presenting comparatively little demographic variability. Our thanks go to an anonymous reviewer for pointing this out.
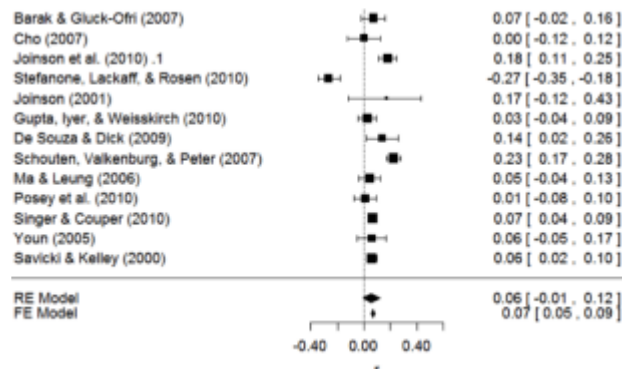
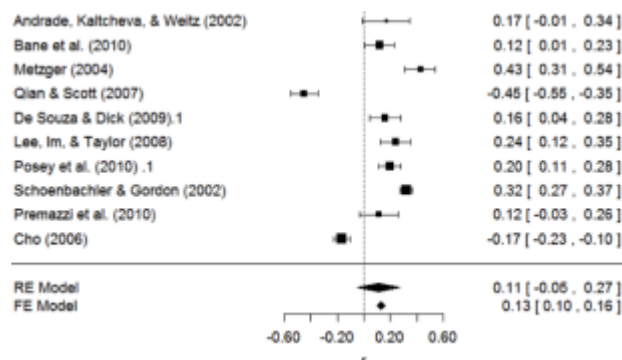Figure 1. Forest plot: demographic predictors

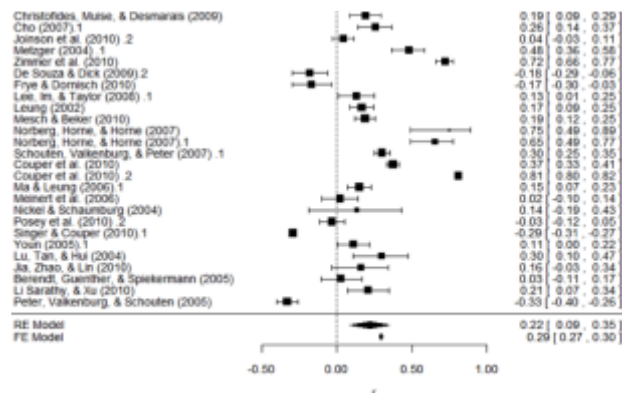Figure 2. Forest plot: environmental predictors

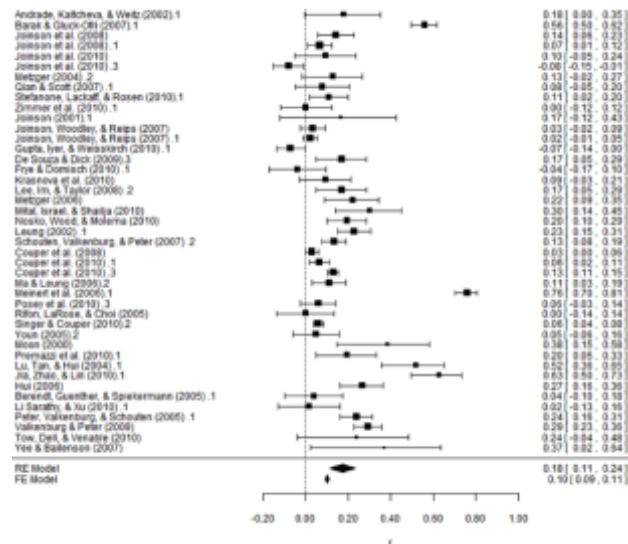Figure 3. Forest plot: person-based predictors

Figure 4. Forest plot: system-based predictors

Furthermore, the forest plots show that there is considerable heterogeneity among the effect sizes in each category, least so for the demographic predictors. This impression is confirmed by the analyses. Table 1 presents heterogeneity statistics for the random-effects models for each category.

According to, for example, Higgins and Thompson [53, p. 1550], these figures hint at a rather large degree of heterogeneity among the studies' findings for each predictor category. For instance, the I^2 values indicate that almost the entire identified variation in effects on self-disclosure is due to heterogeneity between studies. This raises the question whether the differences in mean effect size per predictor category are meaningful and/or statistically significant. Again, the answer is strongly influenced by the chosen model. In a fixed-effects model, category as moderator captures a significant amount of heterogeneity in results ($p < .001$). This is not surprising given that the mean effect sizes depicted under the "FE model" label in the forest plots (Figures 1 to 4) have quite different values, especially the estimate for the person-based predictors. Comparing the amount of heterogeneity accounted for by the moderator versus residual heterogeneity by H values yields a "moderator H" of 15.06 and a "residual H" of 9.91[3]; this suggests that a predictor category makes a considerable difference for the effect on self-disclosure based on a fixed-effects model.

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[3] The underlying formula is $H^2 = Q/df$, see, e.g., Higgins and Thompson [53, pp. 1545-1546]. Q(moderator) = 680.5 (df = 3), Q(residual) = 8636.7 (df = 88).

Table 1. Heterogeneity statistics for each predictor category

	demographic	environmental
Q (df)	99.8 (12) **	251.8 (9) **
τ^2 (s.e.)	.013 (.006)	.068 (.033)
H	3.65	5.25
I^2	92.5%	96.4%
	person-based	system-based
Q (df)	7658.5 (25) **	626.5 (42) **
τ^2 (s.e.)	.125 (.037)	.041 (.010)
H	9.89	5.79
I^2	99.0%	97.0%

** $p < .01$

For the random-effects models, the differences in mean effect size between predictor categories appear a lot less conspicuous, and indeed predictor category as an overall moderator fails to reach statistical significance ($p = .28$). The "moderator H" is reduced to 1.14 (residual heterogeneity is unchanged), suggesting that under a random-effects model the different predictor categories account for little heterogeneity. Allowing for the fact that some studies included more than one effect size does not alter these results a lot; with a corresponding nested model $p = .34$ and "moderator H" is 1.05.

Especially when considering the results for the random-effects models (which appear more appropriate for the present data after all, not least because of the pronounced heterogeneity), these results seem to suggest that based on extant research the answers to the question "how strongly is self-disclosure influenced by various predictors" are quite varied and that the categorization into demographic, environmental, person-based and system-based factors in its present form might not be the "golden nugget" for explaining this heterogeneity. However, using a more fine-grained categorization of predictors is no straightforward remedy either. Besides representing a change of focus from the intended "overview" nature to a more detailed analysis, it would weaken the data foundation per category, sometimes considerably so, even though it would obviously increase the amount of heterogeneity accounted for by the different categories. Still, re-evaluating the scope and dimensionality of the predictors of interest is arguably an avenue for further research.

Another issue with potential for further analyses regards the criterion variable of this meta-study. We examined self-disclosure at large, including studies referring to both attitude and behavior. However, research indicates a potential mismatch between people's (reported) intentions to disclose personal information and their actual disclosure behavior, known as "privacy paradox" [54]. Finally, whether or not all these categories interact in their effect on self-disclosure could not be examined here and is another potential field for further research.

5. Discussion and conclusion

Focusing on the mean effects for the four categories rather than on the variability in results, two main conclusions can be drawn from this meta-analytic study.

On the one hand, from a research perspective regarding the predictability of user self-disclosure, the identified effect sizes appear rather low. For instance, with all due caution regarding such comparisons, several meta-analyses on other aspects of (online) user attitudes and behavior [e.g., 55, 56] by and large report stronger effects. Nevertheless, the results quite clearly suggest that person- and system-based variables do influence user self-disclosure to some extent. Regarding the relative importance of the two former categories, person-related variables appear to have both a marginally stronger effect (depending on the model), but a larger variation, too. In addition, the effect estimates for person-based predictors might be artificially inflated by a so-called single-source bias; i.e., correlations solely owing to the fact that predictor and dependent variable are subjective constructs ascertained from the same source at the same time [57]. System-based criteria are mostly directly observable "hard" variables and are typically assessed independently of the person who rates his/her self-disclosure tendencies; accordingly the findings for this effect arguably suffer much less – if at all – from such bias.

The second conclusion is more encouraging from an organizational and system design perspective, regarding the question whether self-disclosure is haphazard or can be manipulated by organizations. Our results suggest that system-based variables, which can be purposefully designed by organizations, are at least a moderately effective key to "shape" user self-disclosure. For instance, system functionality and usefulness have a substantial impact on self-disclosure. The same applies to the system type that asks to disclose one's data (e.g., social media platform, web shop, registration of a game, etc.) and/or providing a reward for disclosing one's information. This is interesting insofar as one could assume that self-

disclosure tendencies are mostly rooted in personal attributes such as privacy concerns, introversion, overall trust, or even demographic variables like age, gender, or education, but our meta-analysis of the extant literature paints a different picture.

This result that system-based aspects are at least as relevant for influencing user self-disclosure as person-based ones suggests that it is worthwhile for organizations availing themselves of user self-disclosure to invest in system design attributes such as usability or granting rewards and benefits for users.

Organizations that build their business model entirely on users' personal information (e.g., online social networks) could use this finding to encourage users to disclose (more) personal information; in turn, this would lead to better user profiles that the organizations could exploit for their benefit, for instance, as the enriched profiles allow for better targeted advertising or result in higher prices when selling the profiles to third parties. On the other hand, systems could also be designed in a self-disclosure-encouraging way that benefits users; for instance, by establishing an atmosphere where users exchange more information about themselves or on a deeper level. One example where such an approach could be particularly beneficial are online mental health consultations and counseling. However, fully exploiting the effects of system-based criteria could also raise political debate concerning how to regulate the field such that user rights are protected with the goal to minimize self-disclosure (e.g., by establishing design regulations for platforms).

Overall, based on this paper's findings, efforts that aim at generating more precise and systematic insight into the effect of various system attributes on user self-disclosure as well as on their potential interaction with other predictors (whether system-based or not) and developing and assessing pertinent design patterns and guidelines therefore seems to be a promising endeavor from both a research and practical perspective.

6. References

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Acknowledgments

Appendix 1: Sample and categories

publication	n	categories
Andrade, Kaltcheva and Weitz [22]	114	e, s
Bane, Cornish, Erspamer and Kampman [58]	307	e
Barak and Gluck-Ofri [39]	480	d, s
Berendt, Günther and Spiekermann [59]	206	p, s
Cho [24]	260	d, p
Cho [60]	881	e
Christofides, Muise and Desmarais [31]	343	p
Couper, Singer, Conrad and Groves [28]	3671	s
Couper, Singer, Conrad and Groves [61], study 1	1831	p, s
Couper, Singer, Conrad and Groves [61], study 2	6400	p, s
De Souza and Dick [62]	263	d, e, p, s
Frye and Dornisch [33]	214	p, s
Gupta, Iyer and Weisskirch [16]	809	d, s
Hui, Tan and Goh [63]	331	s
Jia, Zhao and Lin [64]	105	p, s
Joinson [65]	49	d, s
Joinson, Paine, Buchanan and Reips	515	s

[37], study 1			study 1		
Joinson, Paine, Buchanan and Reips [37], study 2	1189	s	Norberg, Horne and Horne [54], study 2	68	p
Joinson, Reips, Buchanan and Schofield [6], study 1	181	s	Nosko, Wood and Molema [25]	400	s
Joinson, Reips, Buchanan and Schofield [6], study 2	759	d, p, s	Peter, Valkenburg and Schouten [73]	600	p, s
Joinson, Woodley and Reips [66], study 1	1144	s	Posey, Lowry, Roberts and Ellis [29]	529	d, e, p, s
Joinson, Woodley and Reips [66], study 2	3544	s	Premazzi, Castaldo, Grosso, Raman, Brudvig and Hofacker [23]	178	e, s
Krasnova, Spiekermann, Koroleva and Hildebrand [67]	259	s	Qian and Scott [30]	242	e, s
Lee, Im and Taylor [14]	259	e, p, s	Rifon, Larose and Choi [35]	210	s
Leung [68]	576	p, s	Savicki and Kelley [74]	2692	d
Li, Sarathy and Xu [69]	182	p, s	Schoenbachler and Gordon [75]	1338	e
Lu, Tan and Hui [70]	95	p, s	Schouten, Valkenburg and Peter [10]	1203	d, p, s
Ma and Leung [27]	591	d, p, s	Singer and Couper [76]	7210	d, p, s
Meinert, Peterson, Criswell and Crossland [34]	261	p, s	Stefanone, Lackaff and Rosen [77]	452	d, s
Mesch and Beker [71]	790	p	Tow, Dell and Venable [78]	51	s
Metzger [3]	213	d, e, p, s	Valkenburg and Peter [79]	812	s
Metzger [4]	189	e, p, s	Yee and Bailenson [80]	32	s
Mital, Israel and Agarwal [72]	131	s	Youn [81]	326	d, p, s
Moon [20]	60	s	Zimmer, Arsal, Al-Marzouq and Grover [32]	264	p, s
Nickel and Schaumburg [40]	39	p			
Norberg, Horne and Horne [54],	23	p			

d… demographics; e… environmental; p… person-based;
s… system-based.