Consumer Disclosures On Social Media Platforms:

A Global Investigation

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Consumer Disclosures on Social Media Platforms: A Global Investigation

Wat delen consumenten over zichzelf op sociale mediaplatforms?

Een wereldwijd onderzoek

Thesis

to obtain the degree of Doctor from the
Erasmus University Rotterdam
by command of the
rector magnificus
prof.dr. F.A. van der Duijn Schouten
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by
Daryna Kolesnyk
born in Kyiv, Ukraine

Erasmus University Rotterdam

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Chapter 1

Introduction

Through user generated content (UGC)[1] on social media platforms (SMPs) consumers disclose highly detailed data about their preferences and needs. UGC can be used to help marketers serve consumers' needs, thus improving consumers' well-being (Tirunillai & Tellis, 2014). However, there have been cases of data misuse as well (Martin, Abhishek & Palmatier, 2017). UGC also informs consumers about the personal lives, professional achievements and consumption of their peers. Such information might be helpful for consumers. For instance, it can help them make better consumption choices (Gummerus et al., 2017). At the same time, such information can be discouraging, demotivating and even depressing if consumers engage in negative social comparison with others on social media (Fardouly & Vartanian, 2015).

The goal of this dissertation is to help marketers and consumers use UGC on SMPs in a way that enhances consumers' well-being. In order to achieve this goal, two issues need to be taken into account. First, if marketers and consumers want to draw correct inferences from UGC, they should know to what extent the information disclosed on SMPs is accurate and truthful (Anderson & Simester, 2014). Second, it should be clearly defined what information consumers want to share, and do not want to share with marketers (Martin, Abhishek & Palmatier, 2017). These two issues – truthfulness of social media disclosures and consumers' attitudes to the use of their data from SMPs for marketing purposes – are the focus of this dissertation.

[1] Note that we only include information that users explicitly share on SMPs, rather than clickstream data or web browsing data outside the SMP.

The first issue – reliability of online consumer disclosures – has been gaining momentum in the marketing literature in the last decade (Anderson & Simester, 2014; De Langhe et al., 2015; Schweidel & Moe, 2014). Deceptive disclosures not only misinform marketers, but also provide an unrealistically positive baseline for consumers about their peers' success, establishing a fake reference point and potentially even threatening consumers' health (Smith et al., 2013). Thus, knowing the extent to which user generated content on social media is deceptive is of paramount importance for consumers' well-being. However, to our best knowledge, there are no systematic attempts to estimate the truthfulness of user generated content on SMPs globally.

Absence of such attempts could be explained in part by the lack of methodologies to assess truthfulness on a global scale, and also by cost of data collection that such an attempt would require. Until now, large-scale assessments of the truthfulness of consumers' disclosures on social media have been infeasible. One approach, often taken in scholarship and practice, is to accept that the data from social media contain some degree of error. This approach has been taken by many scholars. As long as the biases are relatively small, or not systematically related to consumer traits or behaviors, valuable insights can then still be obtained (e.g., Culotta & Cutler, 2016; Liu, Singh, & Srinivasan, 2016; Ma et al., 2015; Nam & Kannan, 2014). However, if the size of the bias is not quantified, studies may not find effects or find counter-intuitive effects (Muchnik et al., 2013; Schweidel & Moe, 2014). We propose a method to quantify the prevalence of deceptive disclosures on SMPs.

The second issue – which disclosures on SMPs by consumers can be used by firms, and which cannot – has been a subject of intense discussion. In fact, this discussion led to many countries establishing policies aimed specifically at protecting consumers' online data and meeting consumers' expectations regarding their online privacy (e.g., General

Data Protection Regulations (GDPR) implemented all over the European Union in 2018). The role of data privacy in marketing is certainly complex and multidimensional (Martin & Murphy, 2017, for a recent review). It is the complexity of the privacy discussion that has made it difficult to derive simple guidelines about consumers' preferences.

Researchers have studied the public opinion on specific ways of data monetization, such as targeted advertisement (for instance, Turow et al., 2015), and solutions have been proposed to mitigate consumers' reluctance to share their data on SMPs (for instance, Tucker, 2014). However, it is still unclear what consumers prefer on SMPs. Some consumers are in favor of keeping SMPs free for all users, allowing SMPs to use consumers' data in exchange for their services. Others might find a "paying with data" business model unfair, and would prefer to pay with monetary fee instead (Anderl, März, & Schumann, 2016; Schumann, von Wangenheim, & Groene, 2014; Schwartz, 2004). Until now, it has been difficult to articulate which types of SMP disclosures consumers would rather not share with the marketers and which segments of consumers would be willing to pay for not having their social media data shared with firms. This dissertation aims to answer this question in a generalizable manner.

Since this dissertation aims to provide generalizable insights into consumers' disclosures on SMPs, it mandates a large-scale international study (Brown et al., 2005). For this reason, primary data for this dissertation were collected across 25 countries and more than 14,000 respondents. The insights in this dissertation do not implicitly assume cross-cultural generalizability, as many studies based on a single country do. Instead, this dissertation explicitly considers potential contingency factors in consumers' disclosure preferences (Steenkamp, 2005). Below I further elaborate on the contribution of each chapter.

Chapter 2 proposes a method to assess deceptive self-presentation on social media on a large scale, which does not depend on the availability of an external objective criterion, the availability of linguistic cues of deception, does not require access to private SMP accounts and is easily applicable across varying contexts, languages and platforms. The method relies on a self-report measure that incorporates a truth-telling mechanism – randomized response technique (Warner, 1965). In this chapter the proposed method is used to assess gender differences in two domains of deceptive self-presentation: physical appearance and personal achievement. The results reveal a substantial prevalence of deceptive self-presentation on SMPs, predicted gender differences in such behavior, with lower incidence of deception associated with higher level of gender equality in countries. This research expands the stream of literature that looks at truthfulness of online disclosures (Anderson & Simester, 2014; De Langhe, Fernbach & Lichtenstein, 2015). The estimates of deception on social media can also be used to inform consumers and encourage them to discount overly positive information on social media.

Chapter 3 analyses information disclosure on SMPs from a different angle, namely, focusing on consumers' perspective on data monetization practices. This chapter reports that consumers find it most unfair when the use of their data from social media violates the norms of information flow (Nissenbaum, 2004). Furthermore, it reveals to what extent those consumers would be willing to switch to an alternative social media business model, where consumers could pay a fee in order not to have their data used. The results indicate that universally women, older people and people with higher social economic status are more likely to opt for paying a fee.

Chapter 4 complements Chapter 2 by addressing a methodological issue associated with assessing sensitive consumer behavior across cultures. All previously developed econometric multilevel models for large-scale international survey data on sensitive topics have to assume at least partial measurement invariance – that is, that at least part of the items function equally across cultures. Such an assumption rarely holds if the dataset spans a large number of countries. Thus, Chapter 4 proposes a multilevel model that both relaxes the measurement invariance assumption and incorporates a privacy-protecting mechanism. The proposed model can, thus, be used by marketers and other social scientists to assess sensitive behavior across cultures (De Jong, Pieters, & Fox, 2010; De Jong, Pieters, & Stremersch, 2012; Fox & Glas, 2003). The practical application of the model uses the method to assess deceptive consumption disclosures on social media.

Taken together, the results of research presented in this dissertation aim to help marketers and consumers to use UGC in ways that are most beneficial for consumers' well-being.

Chapter 2

Posting Lies about Yourself: A Multi-National Investigation of Gender Gaps in Deceptive Self-Presentation on Social Media

Social media platforms (SMPs) such as Facebook, Twitter, Youtube, and Instagram are prominent communication channels for people worldwide. Although people generally seem to present a realistic image of themselves on SMPs, Back and colleagues (2010, p. 374) have called for further study of specific forms of impression management and individual differences in such behavior. Responding to this early call, we investigate gender differences in deceptive self-presentation on SMPs. We define deceptive self-presentation on SMPs as behavior aimed at enhancing the impression of oneself in the eyes of others by means of deliberate incorrect disclosures about oneself in any form, including text, images, videos, and location tags. We focus specifically on gender differences for two main reasons. First, gender is one of the most studied predictors of deceptive self-presentation strategies offline. Second, this demographic factor is easy to infer from most profiles (unlike, for instance, socio-economic status or age), so it has much practical value as a predictor.

The prevalence and determinants of such deceptive self-presentation are still largely unknown, because the issue is socially sensitive and hard to study. Prior studies had to rely on comparatively small (Hancock, Toma & Ellison, 2007; Toma & Hancock, 2010) or specific samples (e.g., Wilson, Gosling & Graham, 2012), and did not study the social context in which genders interact. Social context and, in particular, gender inequality, is known to affect well-being and behavior of men and women (Batz-Barbarich et al., 2018; Elson & Seth, 2019). How those changes in the relative well-being of genders affect social media disclosures is mostly unknown.

The present research aims to help in closing this knowledge gap. It uses truth-telling techniques (De Jong, Pieters & Stremersch, 2012; John, Lowenestein & Prelec, 2012) to elicit responses from over 12,000 participants in 25 countries in order to address two questions. First, this research examines to what extent men and women differ in deceptive self-presentation on SMPs in the domains of *physical attractiveness* and *personal achievement*. Mating theories suggest that these domains are differentially important for men and women (Buss, 2016; Gangestad, 1993). Deception in these domains can be used with the goal to attract the opposite gender, or with the goal to signal superiority to same-sex competitors (Tooke & Camire, 1991). Both goals could be pursued via SMPs. Second, this study examines whether and how gender differences in deceptive self-presentation depend on the gender equality in society (that is, equal access to resources and opportunities irrespective of gender).

Gender differences in deceptive self-presentation

According to evolutionary theories, in primal environments men most valued women's physical attractiveness (a signal of health and fertility). Conversely, women most valued men's ability to acquire resources (a guarantee of offspring's survival) (Buss & Schmitt, 1993; Symons, 1979). According to sexual selection theory, mate preferences define domains where intrasexual competition is most fierce (Buss, 1988). Therefore, deception in these domains could be productive in attracting better mates and in providing an advantage in intrasexual competition. Thus, men should be more prone to self-enhancement in the domain of personal achievement, while women – in the domain of physical attractiveness. If such tendencies persist and reflect themselves in social media behavior, men as compared to women are more likely to mispresent themselves as successful in personal achievement on SMPs, while women as compared to men are more likely to mispresent themselves as physically attractive on SMPs (*H1*).

The societal contexts in which behavior takes place can moderate the expression of gender predispositions (Eagly & Wood, 1999). Gender equality in a society is a natural candidate to moderate mating-associated behavior. Gender equality refers to “equal rights, responsibilities and opportunities of women and men” (UN Women, 2018). Societies high in gender equality pose fewer restrictions for men and women to fit into specific roles in order to be valued, and thus to attract potential mates. Women in such societies have more opportunities for financial self-sustainability and experience less pressure to take the traditional role of homemaker. Men can dedicate more time to family and relationships in other ways than earning money. Countries differ widely in gender equality, with many still favoring male opportunities more (UN Women, 2018).

This analysis raises the question whether and how gender equality at the societal level influences, respectively, deceptive self-presentation and gender differences in deceptive self-presentation. In societies with higher gender equality, having more equal opportunities and more flexibility in choice of a potential partner reduces the overall mating pressure (Gangestad, 1993; Schmitt, 2005). It is reasonable to hypothesize (*H2*) that this leads to lower levels of deceptive self-presentation on SMPs for both domains in countries with high as compared to low gender equality. We have no reason to predict that gender equality affects the two domains differently. The first two hypotheses specify main effects, respectively, for differences between genders (*H1*) and between societies that differ in gender equality (*H2*). How will gender and society interact, if at all, in their effects on deceptive self-presentation? There are two competing predictions.

On the one hand, research has found *smaller* gender differences in mating behavior and preferences in societies with more equal gender opportunities (Schmitt, 2005; Zentner

& Mitura, 2012). For instance, in such societies partner's ability to earn money is valued by men and women more equally than it is in societies with low gender equality (Zentner & Mitura, 2012). Such attenuation of gender differences, if it arises, would be consistent with both constructionist and evolutionary perspectives. Since social roles of men and women are more similar in countries high in gender equality, in these societies the differences between men and women in mating preferences should be smaller as well (Eagly & Wood, 1999). Likewise, according to strategic pluralism theory gender-typical qualities are less crucial for the survival of offspring in the non-demanding environment of gender equality. Thus, people might be willing to trade a mate's gender-typical qualities for other traits valued by both genders (like creativity or kindness), and this should reduce the contrast between mating preferences of men and women (Gangestad & Simpson, 2000).

On the other hand, and less intuitively, research has found *larger* gender differences in mating preferences in societies with more equal gender opportunities. For instance, gender differences in the importance of partner's physical attractiveness are larger in more gender equal countries (Schmitt, 2015). Evolutionary mismatch theories could offer an explanation for such amplification of gender differences (Crawford, 1998). Evolutionary mismatch refers to situations where the evolutionary mechanisms that developed in ancestral environments mismatch the conditions of the current environment, because the environment changed faster than those mechanisms adapt (Li et al., 2018). Some authors suggest that modern developed societies are closer to the primal environments in terms of gender equality and equal access to resources compared to modern societies where genders have less equal opportunities (Korotayev & Kazankov, 2003; Schmitt et al., 2008). In light of this reasoning, gender differences shaped in the primal environments would actually be more, not less, pronounced in societies that are relatively high on gender equality.

Taken together, in countries with higher levels of gender equality, gender differences in deceptive self-presentation on SMPs about their physical attractiveness and personal achievement could be larger or smaller, or possibly smaller for one domain, and larger for the other. The available evidence does not favor one mechanism and hypothesis over the other for deceptive self-presentation on SMPs. Moreover, both mechanisms may be at play and partly cancel each other out. Therefore, we refrain from formulating a specific hypothesis. Instead, we acess what general public would predict in the lay belief study, and then explore the actual gender gaps in the main study. By running the lay belief study, we test whether the findings of the main study are intuitive or counter-intuitive from the perspective of general public. This allows us to choose the optimal strategy for communication of our findings.

Lay beliefs about gender differences

A sample of US residents participated in an online study on lay beliefs about gender differences in deceptive self-presentation (N = 790[2]; Amazon Mechanical Turk; 60% male, median age = 30, SD = 11). Participants read a description of deceptive self-presentation with examples of such behavior in the two domains, and were then randomly assigned to, respectively, a low or high gender equality condition. Participants read a brief definition of either low or high gender equality at the country level, and answered two questions, namely which gender they believed would lie more on SMPs, in each of the domains. Response options were, respectively, men, women, no difference between men and women ("same"). Exact instructions and questions are in the Appendix.

[2] The sample size for the lay belief study was determined a priori based on a sample necessary to reveal small to medium effect size at 0.05 significance level with power 0.8.

The majority of participants (52%; $n = 408$) believed that men engage more in deceptive self-presentation on SMPs about their personal achievement than women do, whereas only 20% ($n = 157$) believed that women engage more in such behavior than men do. The remaining 28% ($n = 225$) expected no gender differences. The proportion of these three responses are significantly different from each other (Likelihood-Ratio of testing the proportions to be different versus at least two of the proportions being the same = 238.23, $p < .001$, df = 1). Lay beliefs for physical appearance were less univocal. Equal proportions of participants believed that women lie more 38% ($n = 303$), and that both genders deceive equally about physical appearance 39% ($n = 310$). However, only 22% ($n = 177$) believed that men lie more in this domain. The two proportions ("women lie more" and "both genders lie equally") are not statistically different from each other – a multinomial distribution with three different probabilities does not fit significantly better than a distribution with an equality constraint on two of the parameters (Likelihood-Ratio test = 0.08, $p = .777$, df = 1). Thus, lay beliefs do not offer a clear prediction with respect to physical attractiveness. That is, lay beliefs are not fully in line with *H1* for lying about physical attractiveness, but they are consistent with *H1* for lying about professional achievement. Interestingly, lay beliefs about gender differences for personal achievement were much larger than for physical attractiveness 251 (32%) versus 126 (16%). The main study tests the veracity of these lay beliefs of gender differences between domains.[3]

Lay beliefs were consistent with the idea that higher gender equality leads to smaller gender differences. Table 1 shows the results of the multinomial regressions. The results show that for physical attractiveness ($\chi(2) = 5.84$, p = 0.054), participants in the high (compared to low) gender equality condition are less likely to believe that either men

[3] Multinomial regressions with gender as independent variable and beliefs as dependent variable did not reveal statistically significant gender effects neither in the domain of physical attractiveness ($\chi(2) = 5.62$, $p = 0.060$), nor in the domain of professional achievement ($\chi(2) = 4.11$, $p = 0.128$).

(although marginally significant) or women deceive more and favor the “both genders deceive equally” option. The same holds for the domain of personal achievement ($\chi(2)$ = 8.06, p = 0.018). Thus, lay beliefs favor the “attenuation” hypothesis that the gender gap in posting lies on SMPs is smaller in societies that favor equality for both genders.

Table 1. Results of the multinomial regression with participants' beliefs as dependent variable and gender equality condition (low vs high) as independent variable.

		Physical attractiveness					Personal achievement				
		B	*SE*	*Wald*	*df*	*p*	*B*	*SE*	*Wald*	*df*	*p*
Men lie more	Intercept	-.30	.16	3.35	1	.067	.55	.14	15.81	1	.000
	High GE	-.42	.23	3.45	1	.063	-.45	.19	5.58	1	.018
Women lie more	Intercept	.154	.14	4.08	1	.283	-.71	.19	13.33	1	.000
	High GE	-.44	.20	4.75	1	.029	-.67	.29	5.50	1	.019

**The reference category of the dependent variable is: “No difference between men and women”.*

MAIN STUDY

Cross-national sample

The data of the main study are part of a larger project on cross-cultural differences and similarities designed by researchers from several European universities. Kantar Media group collected the data in 2016 through an online survey accessing participants from national panels in 25 countries (sample sizes per country are in Table 3). The full questionnaire, originally designed in English, was translated and back translated into 19 languages/dialects (items with translations are in the Appendix). In Australia, India, Singapore, South Africa, the UK and the USA the questionnaire was in English. The total sample size comprised 12,257 participants (51% female). Age ranged from 18 to 90 years with mean age of 40.5 years old. Participants completed the questionnaire online, on their own device (computer, laptop, tablet, or smartphone).

Measures

Eight items were developed to measure deceptive self-presentation on social media. In order to develop an efficient self-report measure of deceptive self-presentation we engaged in the following steps. First, we generated an initial pool of 29 items based on the literature and examples found on the Internet in discussions and media. In addition, we asked a culturally-diverse group of 51 students with social media accounts and who participated in a survey methodology course to generate items based on the definitions of the domains of deceptive self-presentation. Second, the resulting items were tested for clarity, comprehensiveness, sensitivity, and incidence by the same group of 51 students, in a later class of the course. Third, the four items providing the most complete coverage of the deceptive self-presentation domains were selected for both physical attractiveness and personal achievement. Fourth, in two separate pretests (one student sample at another university with n = 510, and one non-student sample from Amazon Mturk with n = 1005), the target items were tested for sensitivity, by comparing the results of the standard direct questioning technique (asking the question directly without privacy protection) with those of the randomized response methodology (De Jong, Pieters, & Fox, 2010). The first study implemented the randomized response mechanism by directing respondents to a website in which they could toss an electronic coin to answer the questions. The second study used an electronic coin shown on the same screen as the sensitive question, which they were asked to respond to as directed by the flip of the electronic coin. We found that the items were indeed sensitive, as indicated by significant differences in item scores across direct questioning and randomized response methods. Fifth and finally, the items were slightly reformulated based on the results of the pretests.

The items have a binary response scale (yes/no) to facilitate comprehension and implementation across countries. Binary response scales prevent the common extremity and midpoint biases in cross-cultural research, and minimize interpretational differences between countries (Smith & Schwartz, 1997). Table 2 lists the items. Because of the sensitivity of querying participants about their deceptive behaviors, we use a truth-telling mechanism (randomized response) to elicit truthful answers.

Table 2. Items used to measure deceptive self-presentation on social media.

Item	On [name of preferred social network], I have…
Physical attractiveness	
1	lied about my physical features, such as my height, weight, size of clothes, skin color, to appear more attractive.
2	posted an outdated picture of myself on my social media profile to appear more attractive than I actually am.
3	lied about my age to appear more attractive.
4	used computer software to appear more attractive in a picture than I actually am.
Personal achievement	
5	lied about my educational achievements, such as my grades, degrees or diplomas.
6	made it appear as if I made more money than I actually did.
7	made it appear as if I worked for a particular firm or organization, while it was not completely true.
8	made it appear as if I had a job that I did not have.

Truth-telling mechanism

Answering questions about one's deceptive behavior is sensitive, which might promote lying on the questions themselves. Therefore, we administered the questionnaire using the Randomized Response Technique (RRT) (Fox & Tracy, 1986; Lensvelt-Mulders et al., 2005; Warner, 1965) to encourage truthful responses. The RRT protects people's privacy by introducing an element of randomness in the response process, which masks the participant's true answer to a sensitive question. Because the randomness is known, the prevalence of affirming the sensitive question can be identified at the level of the sample and the population from which it is drawn. RRT has been used successfully across social sciences and countries (e.g., De Jong et al., 2012; Himmelfarb & Lickteig, 1982).

The RRT in our study used an electronic randomization device (an electronic spinner). Participants provided their answer to a question depending on the outcome of the randomization device, which could have one of the two possible outcomes: it could either instruct participants to give a truthful response to a question, or give a forced answer “yes” regardless of what the participant’s truthful response would be. The researcher does not know the outcomes of the randomization device but only the probability that the participant has to give a truthful response. Thus, the proportion of observed “yes” scores is equal to $p_1\mu + (1-p_1)$, where μ is the true proportion of “yes” answers, p_1 is the known probability that the participant has to answer the question honestly (e.g., 50%) , and $(1- p_1)$ is the known probability of a forced “yes” response (e.g., 50%). To prevent nonadherence to the reponse procedure, the software automatically selected the answer “yes” for the participant if the electronic spinner indicated a forced “yes” answer.

Items administered with randomized response constituted a block in the questionnaire, which contained item blocks for unrelated, other research. At the beginning of the block, participants read a definition of social media platforms and indicated which ones they used (if any). When indicating multiple social media, participants indicated their preferred platform (on which they posted most often). Target questions were for the preferred social media platform. Participants without a social media account or who never shared content on their social media profile were excluded. Instructions of the randomized response technique were as follows:

> *“The next questions are about behaviors that may be sensitive. Therefore, we will provide a privacy protection mechanism, called “randomized response”. Your answers to each of the following questions will depend on the outcome of a spinning device. Before you answer each question, you click on the “Rotate the disk” button. The answer you give to the question depends on the outcome of the spinner as follows:*
>
> *If the spinner indicates “Give your truthful answer” (grey), then please provide your truthful answer to the question.*

If the spinner indicates “Answer ”Yes”" (pink), then fill out a "Yes" answer (regardless of your true answer).

The idea behind this procedure is that only you know the outcome of the spinning device. The software has been programmed in such a way that this outcome is not available to the researchers and so your privacy is fully protected. Because this procedure fully protects your privacy you can, with all your heart, provide your true answer to a question if the spinning device tells you to do so.”

Items for the physical attractiveness and personal achievement domains appeared consecutively on the screen in the order of Table 2. Instruction was “Please indicate which of the behaviors below you have done at least once on your preferred social network.” Participants used the electronic spinner before answering each item on the screen. Items started: “On [*name*] I have... “, where the software replaced [*name*] by the name of the preferred social media platform that the participant had indicated earlier in the questionnaire.

Gender equality

We obtained a nation-level measure of gender equality from Schwartz and Rubel-Lifschitz (2009). The measure is a standardized index of three indicators of gender equality: one indicator based on averages of women’s health, education, employment and social equality, a second indicator based on differences between men and women in income, education, and representation in government, and a third indicator based on the average number of children in families. We imputed the score for United Arab Emirates, as it was unavailable in the original publication, by taking the average (-2.25) of two available scores for countries in the region (Egypt = – 1.74, and Yemen = – 2.75). Average score of the gender equality measure in our sample of 25 countries was M = 0.02 (SD = 1.06, minimum = -2.25, maximum = 2.02), with negative score indicating larger differences in opportunities between men and women, positive score indicating more equal opportunities between men and women.

Control variables

We included the following control measures for participants: age, employment status ("1" if the respondent was employed more than 8 hours a week, "0" otherwise), relationship status ("1" if the respondent was in a committed relationship, "0" otherwise), education level ("1" if the respondent completed higher education, "0" otherwise), preferred social media platform ("1" if the preferred platform was Facebook, "0" otherwise), and number of years using the preferred social media platform. For each of the 25 countries, we included a dummy variable indicating per capita gross domestic product (GDP per capita) in the top 33% or not. Data are for 2015 in current USD, obtained from The World Bank Data Catalog[4]. Statistically controlling for this variable ensures that potential gender equality effects are not due to GDP differences.

Statistical analyses

We estimated a regression model that accounts for the specific characteristics of our data. That is, the data have a multilevel structure, because individual participants to the survey (level-1: N = 12257) are nested in countries (level-2: N = 25). Also, the response data are binary, because participants answer each of eight questions with yes or no. Finally, the data have a random component imposed by the randomized response technique.

First, we use equation (1) to assess the true proportion of deceptive self-presentation behaviors in each of the 25 countries:

$$\lambda_{kj} = p_1\mu_{kj} + (1 - p_1) \tag{1}$$

[4] Gender Statistics, The World Bank, https://datacatalog.worldbank.org/dataset/gender-statistics, last retrieved in February 2020

where λ_{kj} is the observed "yes" score and μ_{kj} the true proportion of "yes" answers for item k in country j.

Second, we compute gender differences in each country, averaged across the four items within each of the two domains:

$$\lambda_{d,j,male} = p_1\mu_{d,j,male} + (1 - p_1) \quad (2)$$

$$\lambda_{d,j,female} = p_1\mu_{d,j,female} + (1 - p_1) \quad (3)$$

where $\lambda_{d,j,male}$ represents the average observed proportion of deceptive self-presentation for men in country j across the items in the domain d (physical attractiveness or personal achievement), whereas $\lambda_{d,j,female}$ represents this value for women.

Third, we estimate a multilevel logistic RRT model to obtain gender effects and the variation in these across countries as a function of gender equality. The probability of an observed 'yes' response by individual i in country j to item k is:

$$Pr\ (Y_{ijk} = 1)\ = p_{1ij}Pr\ (\tilde{Y}_{ijk} = 1)\ + (1 - p_{1ij}) \quad (4)$$

where $Pr\ (\tilde{Y}_{ijk} = 1)$ is the true probability of the 'yes' response, and p_{1ij} is the probability that individual i in country j has to answer the question honestly. Next, we specify the effects of gender on deceptive self-presentation in each of the two domains. The multilevel model for $\Pr(\tilde{Y}_{ijk} = 1)$ then is:

Level-1 model (Participants):

$$\Pr\ (\tilde{Y}_{ijk} = 1) = \ \alpha_{j,d(k)} + \ \beta_{j,d(k)}Gender_{ij} + \gamma_{j,d(k)}Z_{ij} \quad (5)$$

Level-2 model (Countries):

$$\alpha_{jd} = \ \bar{\alpha}_{0d} + \bar{\alpha}_{1d}GE_j + \bar{\alpha}_{2d}GDP_j + u_{0j} \quad (6)$$

$$\beta_{jd} = \ \bar{\beta}_{0d} + \bar{\beta}_{1d}GE_j + u_{0j} \quad (7)$$

$$\gamma_{j,d} = \bar{\gamma}_{0d} \quad (8)$$

The model assumes the effects of the predictors to be equivalent across the four items for deceptive self-presentation in each domain d, and use the notation $d(k)$ to indicate the domain that item k belongs to. That is, $d(k)=1$ for items 1 to 4, and $d(k)=2$ for items 5 to 8. The level-1 model includes an intercept, individual-level variable gender and the vector $\boldsymbol{Z}_{ij}$ with the individual-level control variables, described before.

The level-2 model specifies that the intercept and the gender coefficient vary across countries, while the coefficients for the control variables do not vary across countries. The variable GE_j captures the level of gender equality in country j. The variable GDP_j captures whether country j is above the sample 33rd quantile on GDP per capita 2015. Equation (6) specifies the intercept as a function of Gender Equality and per capita GDP. Equation (7) specifies that the gender effect can vary as a function of Gender Equality. Finally, equation (8) specifies the fixed effects of the control variables. We estimate the multilevel model simultaneously for all items within each domain.

RESULTS

Descriptive results

Table 3 presents the prevalence of each of the deceptive self-presentation behaviors per country. These prevalence estimates were obtained by back transforming the observed proportions (which contain added noise) for the randomized response mechanism (equation (1)). The estimated proportion of people engaging in such behaviors ranges from a low 5% (misrepresenting education – item 5, or employment place – item 7 in the Netherlands) to a high 58% (using an outdated picture – item 2 – in China).

From the behaviors that we capture, the lowest level of deception occurs for the item pertaining to the workplace (item 7): around 12% people across all 25 countries have lied about the employer they work for at least once. The highest level of deception globally – 29% – concerns the use of an outdated picture in order to look better. Across the 25 countries, about 17% of individuals in the sample (every 6ths social media user) performed each of the behaviors at least once.

Table 3. Deceptive self-presentation on social media in 25 countries

			Physical Attractiveness				Personal Achievement			
			Item							
Country		*n*	1	2	3	4	5	6	7	8
			Looks	Photo	Age	Soft-ware	Study	Money	Work place	Job
Australia	AUS	333	0.12	0.15	0.11	0.10	0.15	0.13	0.13	0.20
Brazil	BRA	671	0.18	0.36	0.13	0.23	0.12	0.18	0.09	0.12
Bulgaria	BGR	475	0.13	0.32	0.16	0.16	0.10	0.13	0.13	0.09
China	CHN	680	0.25	0.58	0.14	0.42	0.10	0.25	0.15	0.11
France	FRA	377	0.17	0.20	0.09	0.18	0.11	0.10	0.09	0.09
Germany	DEU	329	0.13	0.21	0.16	0.16	0.12	0.08	0.16	0.12
India	IND	669	0.24	0.43	0.28	0.35	0.21	0.25	0.22	0.21
Indonesia	IDN	684	0.13	0.34	0.11	0.24	0.09	0.15	0.11	0.10
Italy	ITA	517	0.22	0.33	0.15	0.16	0.14	0.11	0.13	0.10
Japan	JPN	229	0.12	0.13	0.17	0.19	0.08	0.18	0.15	0.14
Mexico	MEX	557	0.14	0.31	0.08	0.20	0.17	0.20	0.10	0.09
Netherlands	NLD	337	0.06	0.08	0.06	0.07	0.05	0.06	0.05	0.12
Philippines	PHL	585	0.19	0.37	0.14	0.37	0.15	0.15	0.13	0.17
Poland	POL	488	0.16	0.19	0.19	0.19	0.14	0.24	0.10	0.14
Portugal	PRT	461	0.07	0.28	0.06	0.19	0.11	0.12	0.11	0.13
Russia	RUS	525	0.20	0.38	0.17	0.16	0.12	0.24	0.10	0.10
Singapore	SGP	445	0.16	0.32	0.21	0.24	0.11	0.21	0.16	0.16
South Africa	ZAF	564	0.16	0.35	0.17	0.17	0.08	0.17	0.08	0.05
Spain	ESP	511	0.14	0.15	0.11	0.16	0.13	0.13	0.07	0.08
Sweden	SWE	374	0.19	0.27	0.08	0.13	0.15	0.12	0.09	0.07
Thailand	THA	586	0.24	0.57	0.30	0.51	0.27	0.23	0.16	0.26
Turkey	TUR	571	0.11	0.30	0.09	0.10	0.05	0.17	0.09	0.15
UAE	ARE	485	0.24	0.25	0.15	0.33	0.19	0.12	0.13	0.17
UK	GBR	386	0.17	0.17	0.11	0.07	0.13	0.19	0.12	0.13
US	USA	418	0.18	0.23	0.12	0.05	0.11	0.11	0.08	0.12
Item average proportion			0.16	0.29	0.14	0.20	0.13	0.16	0.12	0.13

Note – "Looks" stands for deception about physical characteristics (such as weight, height, size of clothes, skin color, etc); the country abbreviations are as follows: UAE – United Arab Emirates, UK – United Kingdom of Great Britain and Northern Ireland, US – The United States of America.

To facilitate interpretation of the similarities and differences between countries, Figure 1 plots average prevalence across the behaviors in the two domains. In countries below the diagonal line, people engage in more deceptive self-presentation on social media about physical attractiveness, while in countries above the diagonal deception about personal achievement prevails. The further a country is located from the diagonal, the higher its ratio of deception about physical attractiveness over deception about personal achievement. Most countries lie below the diagonal. The only two countries above the diagonal, where people deceive about personal achievement more than about physical attractiveness are Australia and the United Kingdom. In the Netherlands (at the diagonal) the prevalence of deceptive self-presentation in both domains is approximately even (around 7%).

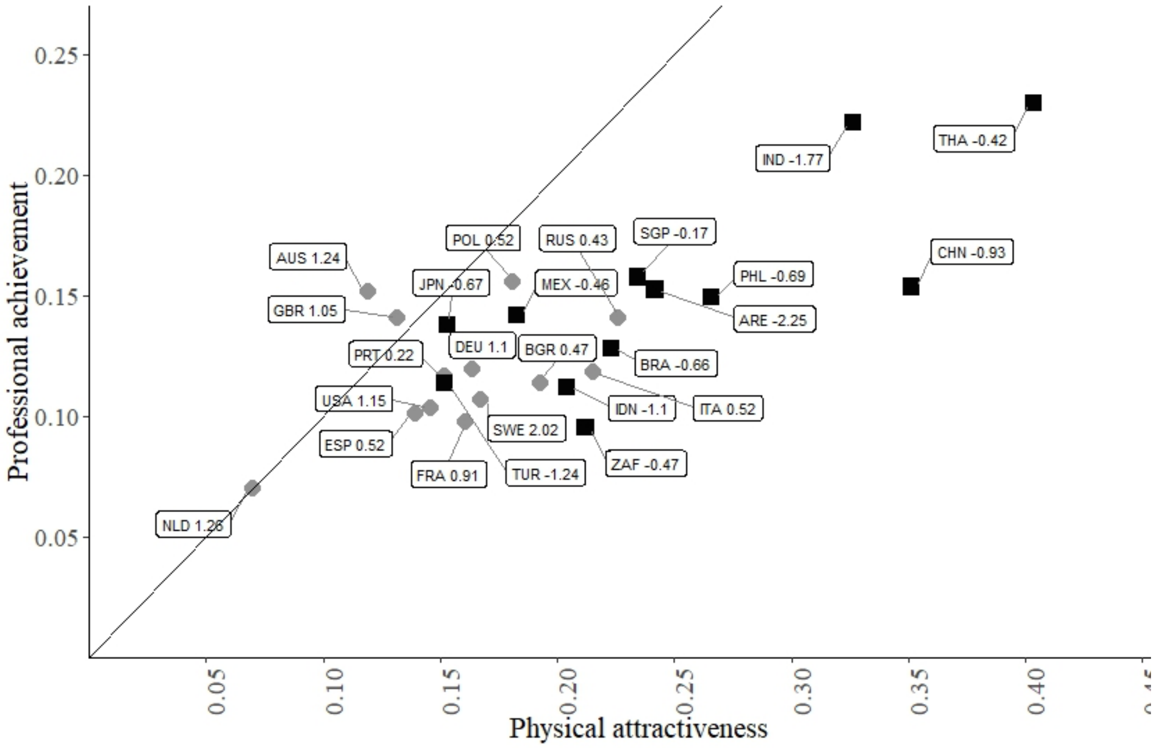


Figure 1. The prevalence of deceptive self-presentation in the two domains across 25 countries (domain score is an average across prevalence rate of the 4 behaviors in the domain). Countries with gender equality above the mean are marked in lighter tone and round shape. The diagonal line represents equality of the prevalence of deceptive self-presentation in the two domains.

The prevalence estimates for each gender in each of the two domains (averaged across the four items per domain) are displayed in Table 4. On average, the prevalence of deceptive self-presentation on social media about physical attractiveness is higher among women (18% prevalence among men vs 20% among women), while deceptive self-presentation about personal achievement on average is higher among men (14% among men vs 10% among women). However, the gender gap varies substantially across countries and ranges from 0% to 12%.

If lay beliefs would be supported, the gender differences should be larger for personal achievement than for physical attractiveness. In absolute values this is indeed so – averaged across the countries, the gender gap in deception about physical attractiveness on average is two percent, while it is four percent for deception about achievement ($Z = 15.81$, $p < 0.001$).

Multilevel logistic RRT model

We then formally test our hypotheses using the model from equations (5) to (8). Because the model likelihood is complex to evaluate in the presence of the randomized response mechanism, we rely on Bayesian estimation routines. We used Winbugs software (Lunn et al., 2000) to estimate the posterior means of the model parameters, with 15,000 iterations and 5,000 burn-in. The annotated code used in the data analysis is in the Appendix. Table 5 summarizes the results.

In support of hypothesis 1, men across the 25 countries in the sample engage more in deceptive self-presentation of their personal achievement than women do, while women engage in more deceptive self-presentation of their physical attractiveness than men do.

Hypothesis 2 is supported for the physical attractiveness but, surprisingly, not for the personal achievement domain. Deceptive self-presentation for physical attractiveness is lower in countries with more gender equality, as indicated by the negative sign of the effect (-0.18). The main effect of gender equality on deceptive self-presentation about personal achievement is not significant.

The main effects of the control variables indicate that younger and employed participants deceive more in both domains. Having a social media account for a longer period of time was associated with higher deception rates in the domain of physical attractiveness, but not in the domain of personal achievement. Participants with a higher level of education deceived less about personal achievement, but deceived as much as participants without higher education did about physical attractiveness. Participants who use Facebook as their main SMPs deceived as much as participants did who use other platforms as preferred SMPs. Finally, participants who are in a committed relationship deceived as much as participants who are single did.

Table 4. Prevalence estimates of deceptive self-presentation (averaged across the four items within each domain).

Country	GE score	Physical attractiveness Men	Physical attractiveness Women	Physical attractiveness Diff.[a]		Personal achievement Men	Personal achievement Women	Personal achievement Diff.[a]	
Australia	1.24	0.12	0.10	0.03		0.18	0.11	0.07	
Brazil	-0.66	0.20	0.24	-0.05		0.13	0.13	0.00	
Bulgaria	0.47	0.18	0.20	-0.03		0.12	0.07	0.06	
China	-0.93	0.33	0.38	-0.05		0.14	0.16	-0.02	
France	0.91	0.15	0.16	-0.01		0.04	0.12	-0.09	*
Germany	1.10	0.14	0.16	-0.02		0.10	0.11	-0.01	
India	-1.77	0.37	0.28	0.09	*	0.25	0.20	0.05	
Indonesia	-1.10	0.21	0.20	0.02		0.12	0.09	0.03	
Italy	0.52	0.22	0.21	0.01		0.18	0.04	0.14	*
Japan	-0.67	0.14	0.15	-0.01		0.13	0.09	0.04	
Mexico	-0.46	0.20	0.17	0.03		0.15	0.13	0.01	
Netherlands	1.26	0.02	0.07	-0.04		0.07	0.02	0.05	
Philippines	-0.69	0.25	0.28	-0.02		0.17	0.13	0.04	
Poland	0.52	0.16	0.20	-0.05		0.21	0.10	0.11	*
Portugal	0.22	0.10	0.17	-0.06		0.14	0.06	0.09	*
Russia	0.43	0.21	0.24	-0.03		0.20	0.08	0.11	*
Singapore	-0.17	0.22	0.25	-0.03		0.16	0.15	0.01	
South Africa	-0.47	0.21	0.22	-0.01		0.09	0.07	0.02	
Spain	0.52	0.15	0.12	0.04		0.11	0.06	0.05	
Sweden	2.02	0.08	0.20	-0.12	*	0.10	0.08	0.02	
Thailand	-0.42	0.39	0.42	-0.03		0.23	0.23	0.00	
Turkey	-1.24	0.12	0.17	-0.05		0.12	0.08	0.04	
UAE	-2.25	0.25	0.22	0.02		0.16	0.10	0.06	
UK	1.05	0.12	0.12	-0.01		0.14	0.13	0.01	
USA	1.15	0.08	0.17	-0.09	*	0.10	0.08	0.02	
Average		0.18	0.20	-0.02		0.14	0.10	0.04	

Note - [a] The difference score is obtained by subtracting the prevalence estimate for women from the prevalence estimate for men. Thus, negative value means that the prevalence of deception is higher among women, while a positive value means higher prevalence among men. Asterisks indicates that the difference in a country is statistically significant at p < .05, using a Bayesian Z-test.

The significant positive cross-level interaction between gender and gender equality indicates that the gender gap (female-male) is larger in countries with higher gender equality. . Zooming in on the cross-level interaction between gender and gender equality in the domain of personal achievement, indicates that while women's deceptive self-presentation drops with higher levels of gender equality, men's levels of deceptive self-presentation about personal achievement actually remains unchanged.

Table 5. Results of the multilevel logistic randomized response theory regression model for physical attractiveness and personal achievement domains.

	Physical attractiveness		Personal achievement	
	Mean	95% CI	Mean	95% CI
Level-1:				
Intercept	-1.26	[-1.57; -0.95]	-1.84	[-2.26; -1.41]
Gender (0 = male, 1 = female)	0.13	[0.001; 0.26]	-0.52	[-0.72; -0.33]
Level-2:				
Gender equality (GE)	-0.18	[-0.36; -0.01]	-0.01	[-0.18; 0.17]
Cross-level interaction				
Gender x GE	0.14	[0.02; 0.27]	-0.24	[-0.43; -0.06]
Control variables				
Level-1:				
Age	-0.02	[-0.02; -0.02]	-0.02	[-0.03; -0.02]
Years on social media platform	0.04	[0.02; 0.06]	0.02	[-0.01; 0.05]
Employed (1 = yes, 0 = no)	0.18	[0.06; 0.29]	0.32	[0.11; 0.53]
Higher education (1 = yes, 0 = no)	-0.08	[-0.22; 0.05]	-0.23	[-0.42; -0.04]
Relationship (1 = yes, 0 = no)	0.00	[-0.11; 0.11]	0.10	[-0.06; 0.26]
Facebook (1 = yes, 0 = no)	-0.06	[-0.19; 0.07]	-0.09	[-0.26; 0.10]
Level-2				
GDP (1 = 33% top, 0 = no)	-0.48	[-0.82; -0.15]	-0.07	[-0.47; 0.28]

Note – "Relationship" is engaged in long-term relationship. 95% CI is the 95% Credible Interval, which indicates a significant effect at 5% if the CI does not contain 0.

Figure 2 presents the model-based estimates of gender differences in prevalence of deceptive self-presentation in the two domains. To facilitate interpretation, we plotted the predicted values of the model for gender equality level one standard deviation above and below the sample mean. The figure shows that for higher gender equality level with respect to physical attractiveness there is a larger drop for men than women, while for personal achievement there is a drop for women, but not for men.

Taken everything together, these results provide support for hypothesis 1 that women tend to deceive more about physical attractiveness, while men tend to deceive more about personal achievement. The results partially support hypothesis 2 that gender equality would be associated with lower levels of deceptive self-presentation on social media overall, namely this is the case for both genders in the domain of physical attractiveness, and only for women (but not for men) in the domain of personal achievement. In addition, the results partially support evolutionary mismatch perspective that in societal contexts with higher gender equality primal gender dispositions become amplified (that is, gender gap becomes larger).

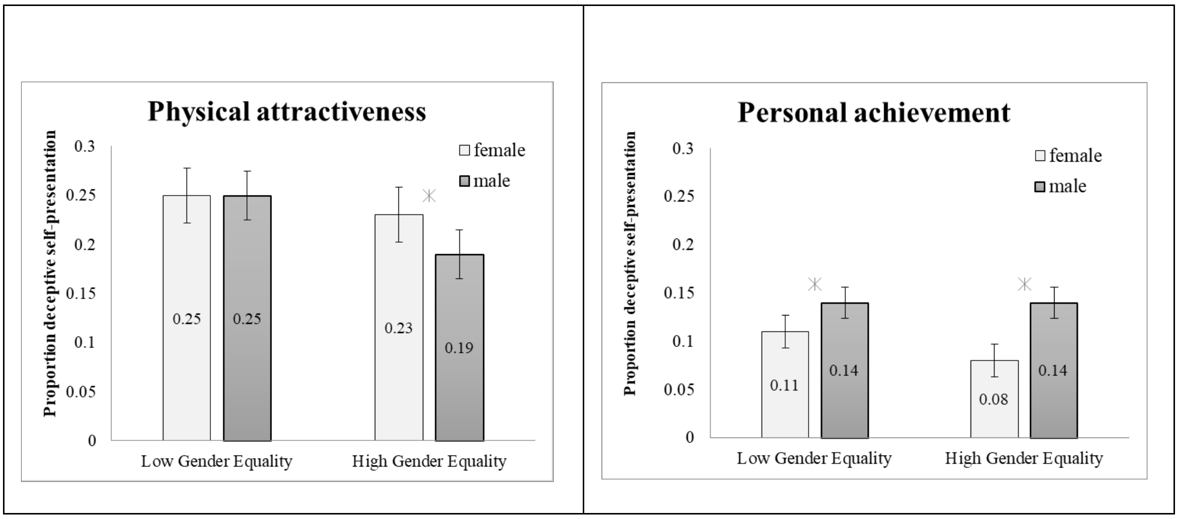


Figure 2. Estimated gender differences in deceptive self-presentation on social media for countries low (minus one standard deviation) and high (plus one standard deviation) on gender equality. Note: all other variables were set to zero. An asterisk denotes a statistically significant difference at p < .05 between two adjacent bars.

DISCUSSION

This study is the first to assess the universality of gender differences in deceptive self-presentation on SMPs across countries, with a truth-telling mechanism to add to their veracity. Data across 25 countries (N = 12,257) revealed that men and women engaged in deceptive self-presentation primarily about qualities that are traditionally important for evaluations by the opposite sex. Specifically, women were more likely to deceive on SMPs about their physical appearance than men were: average prevalence rates were 18% for men and 20% for women. Yet, men were more likely to deceive about personal achievement on SMPs than women were: average prevalence rates were 14% for men and

10% for women. These gender differences were partially consistent with lay beliefs, and previous research on the deceptive self-presentation strategies used by genders in mating contexts (Tooke & Camire, 1991; Toma & Hancock, 2010; Toma, Hancock & Ellison, 2008), but went beyond these as well.

Across countries, we expected higher level of country gender equality to be associated with lower deceptive self-presentation in both domains (Hypothesis 2). Mating perspectives agree that gender differences in mating preferences and, thus, mating strategies are contingent on the social contexts (Eagly, 2013; Buss & Schmitt, 2019). Our expectation was based on the idea that because gender equality is associated with more freedom in mating choices (Schmitt, 2005), the overall motivation to engage in deceptive self-presentation is reduced. Higher gender equality indeed led to lower deceptive self-presentation in the domain of physical appearance, but gender equality did not affect deception in the domain of personal achievement. This is consistent with the notion that women's preference for a partner with equal or higher access to resources remains even when women's socio-economic status increases (Townsend, 1989).

Further, we found that the magnitude of gender differences varied with the level of gender equality in countries. Previous studies reported that higher levels of gender equality and the general development of countries could both amplify (Schmitt, 2015) and attenuate gender differences in mating behavior and preferences (Eagly & Wood, 1999; Schmitt, 2005). People's lay beliefs reflected an "attenuation" hypothesis. In contrast, we observed "amplification" of the gender differences. Specifically, our data indicated that with higher gender equality the prevalence of gender "*a*typical" lies dropped more sharply than the prevalence of gender "typical" lies did. That is, the drop in deceptive self-presentation about physical attractiveness associated with gender equality was significantly smaller for women compared to men. The reverse pattern emerged for deception about personal achievement: the drop in countries higher in gender equality was smaller for men compared to women. This is consistent with the notion that gender equality does not make gender differences larger or smaller per se, but that it facilitates the expression of gender predispositions (Schmitt et al., 2008; Schwartz & Rubel-Lifschitz, 2009). That is, whether gender differences are larger or smaller depends on whether low gender equality suppresses or enhances the gender differences for a specific trait or behavior. In case of deception about attractiveness and achievement on SMPs, gender equality was associated with larger rather than smaller gender gaps. Further evidence could come from future research that examines whether the same pattern would hold for gender differences in other areas of deceptive strategies identified by Tooke and Camire (1991), such as deception about one's promiscuity or readiness to committed relationships and from one's achievements in sports or hobbies.

It is important to note that higher gender equality was associated with lower deception on SMPs for men and women worldwide, potentially decreasing the negative effects of social media consumption (Fardouly & Vartanian, 2015). Furthermore, these gender differences in the prevalence of deceptive self-presentation across the globe were statistically significant, but not very large in an absolute sense (2% difference for physical attractiveness and 4% difference for personal achievement). This might be to changes in labor division worldwide. Eagly and Wood (2013) have proposed that because of higher involvement of women in the workforce, men in the recent year have been placing more value to mate's financial prospects, while women have been attributing more value to mate's physical appearance. The aggregated rates of deceptive self-presentation on SMPs are in line with such conjectures.

Taken together, our study addresses the recent call for studying how the Internet and online behavior in general "may change our mating psychology in many ways" (Buss

& Schmitt, 2019, p.104). Future cross-national research could compare our estimates of deception on SMPs to the deception rates of comparable offline behaviors across cultures. Higher deception rates on online SMPs than offline would support the prediction of matching theories that exposure to more attractive peers on SMPs can decrease satisfaction with oneself (Li et al., 2018), and thereby stimulate a need to engage in deceptive self-presentation.

APPENDIX

Instructions and questions for the lay belief study

Some people lie about themselves on social media platforms (Facebook, Instagram, Twitter, and other platforms). Let's consider this behavior in two domains: physical attractiveness and professional achievement.

<u>Physical attractiveness</u>

Some people try to appear more physically attractive than what is true. Examples: posting an outdated picture of themselves where they look younger, posting a graphically manipulated ("photoshopped") picture of themselves, lying about own height, weight, age, and so on.

<u>Professional achievement</u>

Some people try to appear more successful professionally than what is true. Examples: lying about one's education, work, professional connections, and so on.

[at this point respondents were randomly allocated to one of the three conditions: neutral, low gender equality or high gender equality]

Neutral: no additional information about countries.

Low gender equality: Social media platforms are used in different countries. In some countries, women have fewer opportunities than men, such as less access to education, jobs, and they receive less payment for the same work. These are **Countries with High Gender Inequality**. We ask you to share your beliefs about how much men and women lie on social media in countries with <u>High Gender Inequality.</u>

High gender equality: Social media platforms are used in different countries. In some countries, men and women have equal opportunities, such as access to education, jobs, and they receive equal payments for the same work. These are **Countries with High Gender Equality**. We ask you to share your beliefs about how much men and women lie on social media in countries with <u>High Gender Equality</u>.

Who, do you believe, lies more on social media about their **physical attractiveness**: men or women, or are they the same in this respect?

Who, do you believe, lies more on social media about their **professional achievement**: men or women, or are they the same in this respect?

```
model {
#specifying the level-1 model with random intercept and random gender slope, as well as fixed effects for the control variables
for (i in 1:12257) {
#the equation for the physical attractiveness items
      for (k in 1:4) {
        Y[i,k] ~ dbern(p[i,k])
        p[i,k] <- p1[i] * ptrue[i,k] + (1-p1[i])*1
        logit(ptrue[i,k]) <- beta01[country[i],1] + beta01[country[i],2]*gender[i] +
beta1[1]*agec[i] + beta1[2]*yearsSMc[i] + beta1[3]*employ[i] +beta1[4]*education[i]
+beta1[5]*relation[i] + beta1[6]*facebook[i]
                              }
#the equation for the personal achievement items
      for (k in 5:8) {
        Y[i,k] ~ dbern(p[i,k])
        p[i,k] <- p1[i] * ptrue[i,k] + (1-p1[i])*1
          logit(ptrue[i,k]) <- beta11[country[i],1] + beta11[country[i],2]*gender[i] +
beta2[1]*agec[i] + beta2[2]*yearsSMc[i] + beta2[3]*employ[i] +beta2[4]*education[i]
+beta2[5]*relation[i] + beta2[6]*facebook[i]
                              }
                        }

#specifying normal priors for the coefficients of the control variables
for (t in 1:6) {
   beta1[t] ~ dnorm(0,1)
   beta2[t] ~ dnorm(0,1)
                   }
#specifying equation for the  level-2 predictors:
for (j in 1:25) {
#level-2 equation for the physical attractiveness
   beta01[j,1:2] ~ dmnorm(mu1[j,1:2],Omega1[1:2,1:2])
   mu1[j,1] <- mu3[1] + mu3[2]*GE[j] +mu3[5]*GDP33[j]
   mu1[j,2] <- mu3[3] + mu3[4]*GE[j]
#level-2 equation for the personal achievement

   beta11[j,1:2] ~ dmnorm(mu2[j,1:2],Omega2[1:2,1:2])
   mu2[j,1] <- mu4[1] + mu4[2]*GE[j] + mu4[5]*GDP33[j]
   mu2[j,2] <- mu4[3] + mu4[4]*GE[j]
}
#specifying priors for the mean and precision parameters of the random slopes
for (t in 1:5) {
   mu3[t] ~ dnorm(0,1)
   mu4[t] ~ dnorm(0,1)
}
Omega1[1:2,1:2] ~ dwish(Lamda[,],4)
Oinv1[1:2,1:2] <- inverse(Omega1[1:2,1:2])

Omega2[1:2,1:2] ~ dwish(Lamda[,],4)
Oinv2[1:2,1:2] <- inverse(Omega2[1:2,1:2])
}
```

```
#Initial values
list(mu3=c(0,0,0,0,0), mu4=c(0,0,0,0,0),
beta1 = c(0,0,0,0,0,0),
beta2 = c(0,0,0,0,0,0),
Omega1=structure(.Data=c(1,0,0,1),.Dim=c(2,2)),
Omega2=structure(.Data=c(1,0,0,1),.Dim=c(2,2)))
```

ENGLISH

Please indicate which of the behaviors below you have done at least once on your preferred social network.
On [X] I have ...
1: lied about my physical features, such as my height, weight, size of clothes, skin color, to appear more attractive.
2: posted an outdated picture of myself on my social media profile to appear more attractive than I actually am.
3: lied about my age to appear more attractive.
4: used computer software to appear more attractive in a picture than I actually am.

1: lied about my educational achievements, such as my grades, degrees or diplomas.
2: made it appear as if I made more money than I actually did.
3: made it appear as if I worked for a particular firm or organization, while it was not completely true.
4: made it appear as if I had a job that I did not have.

ARABIC

على []، ...

1: ذكرت سماتي الجسمانية غير الحقيقية، مثل الطول والوزن وحجم الملابس ولون البشرة حتى أبدو أكثر جاذبية.
2: قمت بنشر صورة قديمة لنفسي على صفحة شبكة التواصل الاجتماعي الخاصة بي حتى أظهر في شكل أكثر جاذبية من شكلي الحقيقي.
3: كتبت سنًا غير حقيقي لي حتى أبدو أكثر جاذبية.
4: استخدمت أحد برامج الكمبيوتر حتى أبدو أكثر جاذبية في الصورة من شكلي الحقيقي.

1: ذكرت مؤهلاتي التعليمية غير الحقيقية، مثل الصفوف الدراسية، أو الدرجات، أو الدبلومات.
2: جعلت الأمر يبدو وكأنني حصلت على أموال أكثر مما حصلت عليه في الواقع.
3: جعلت الأمر يبدو وكأنني عملت في شركة أو مؤسسة معينة، لكن الأمر ليس حقيقيًا تمامًا.
4: جعلت الأمر يبدو وكأنني عملت في وظيفة لم أعمل بها بالفعل.

BULGARIAN
В [] аз съм…

1: лъгал относно мои физически характеристики, като височина, тегло, размер на дрехите, цвят на кожата, за да изглеждам по-привлекателен.
2: публикувал съм свои по-стари снимки в моя профил в социалните медии, за да изглеждам по-привлекателен, отколкото съм всъщност.
3: лъгал съм относно моята възраст, за да изглеждам по-привлекателен.
4: използвал съм компютърен софтуер, за да изглеждам по-привлекателен на снимки, отколкото съм всъщност.

1: лъгал относно моите постижения в образованието, като оценки, образователни степени или дипломи.

2: правил съм да изглежда, като че ли имам повече пари отколкото имам в действителност.
3: правил съм да изглежда, като че ли работя за дадена фирма или организация, докато това не е било напълно вярно.
4: правил съм да изглежда, като че ли имам работа, която не съм имал.

CHINESE

在 [], 上…

1: 谎报了我的身体特征（例如我的身高、体重、衣服尺码、肤色），以显得更有吸引力。
2: 在我的社交媒体资料里发布了一张以前的照片，以让我显得比实际更有吸引力。
3: 谎报了我的年龄，以显得更有吸引力。
4: 使用电脑软件处理图片，以让我显得比实际更有吸引力

1: 谎报了我的学历，例如我的成绩、学位或学历。
2: 让我看起来比实际更有钱。
3: 让我看起来像任职于某个公司或组织，实际并不完全属实。
4: 让我看起来有工作，实际并没有

DUTCH

Op [] heb ik…

1: gelogen over mijn uiterlijke kenmerken, zoals mijn lengte, gewicht, kledingmaat, huidskleur, om aantrekkelijker te lijken.
2: een oude foto van mezelf op mijn sociale media profiel geplaatst om aantrekkelijker te lijken dan ik in werkelijkheid ben.
3: gelogen over mijn leeftijd om aantrekkelijker te lijken.
4: computersoftware gebruikt om aantrekkelijker te lijken in een foto dan ik in werkelijkheid ben.

1: gelogen over mijn onderwijsprestaties, zoals mijn cijfers, titels of diploma’s.
2: het doen lijken alsof ik meer verdiende dan ik in werkelijkheid deed.
3: het doen lijken alsof ik voor een bepaalde firma of organisatie werkte, terwijl dit niet volledig waar was.
4: het doen lijken alsof ik een baan had die ik niet had.

FILIPINO

1: nagsinungaling tungkol sa aking mga pisikal na katangian, tulad ng aking taas, timbang, sukat ng damit, kulay ng balat, upang lumabas na mas kaakit-akit.
2: nag-post ng isang lumang larawan ng aking sarili sa profile ng aking social media upang lumabas na mas kaakit-akit kaysa sa talagang ako.
3: nagsinungaling tungkol sa aking edad upang lumabas na mas kaakit-akit.

4: gumamit ng computer software upang lumabas na mas kaakit-akit sa isang larawan kaysa sa talagang ako.

1: nagsinungaling tungkol sa aking mga naabot sa pag-aaral, tulad ng aking mga grado, degree o diploma.
2: pinalabas ko na parang kumikita ako ng mas maraming pera kaysa sa talagang kita ko.
3: pinalabas ko na parang nagtatrabaho ako sa isang partikular na kumpanya o organisasyon, na hindi naman talaga lubos na totoo.
4: pinalabas ko na parang mayroon akong trabaho na wala naman.

FRENCH

Sur [] j'ai...

1: menti sur mon apparence physique, comme mon poids, ma taille, la taille de mes vêtements, la couleur de ma peau, pour apparaître plus attirant(e).
2: posté une ancienne photo de moi-même sur mon profil pour apparaitre plus attirant(e) que je ne le suis en réalité.
3: menti sur mon âge pour apparaître plus attirant(e).
4: utilisé un logiciel d'ordinateur pour apparaitre plus attirant(e) sur une photo que je ne le suis en réalité.

1: menti sur mon parcours académique, comme sur mes notes, mon niveau, ou mes diplômes.
2: laissé croire que je gagnais plus d'argent que je n'en gagne en réalité.
3: laissé croire que je travaillais dans une entreprise ou organisation donné, alors que ce n'était pas totalement vrai.
4: laissé croire que j'occupais un poste qu'en réalité je n'occupais pas.

GERMAN

Auf [] habe ich ...

1: gelogen bezüglich meiner körperlichen Eigenschaften, z.B. Größe,s Gewichts, Kleidergröße, oder Hautfarbe, um attraktiver zu erscheinen.
2: ein veraltetes Bild von mir auf einem Profil in einem sozialen Netzwerk gepostet, um attraktiver zu erscheinen, als ich eigentlich bin.
3: bezüglich meines Alters gelogen, um attraktiver zu erscheinen.
4: Computerprogramme genutzt, um auf einem Bild attraktiver zu erscheinen, als ich eigentlich bin.

1: gelogen bezüglich meiner Erfolge in der Bildung, wie z.B. meine Noten, Abschlüsse, oder Zeugnisse.
2: es so erscheinen lassen, als ob ich mehr Geld verdiene, als es in Wirklichkeit der Fall ist .
3: es so erscheinen lassen, als ob ich für eine bestimmte Firma oder Organisation arbeite, obwohl es nicht ganz den Tatsachen entspricht.
4: es so wirken lassen, also ob ich einen Job habe, den ich in Wirklichkeit nicht habe.

INDONESIAN

Di [] saya telah...

1: berbohong mengenai karakteristik fisik saya, seperti tinggi, berat badan, ukuran pakaian, warna kulit saya, agar terlihat lebih cantik/tampan.
2: memposting foto lama saya di profil media sosial saya agar terlihat lebih cantik/tampan dari penampilan saya yang sebenarnya.
3: berbohong mengenai usia saya agar terlihat lebih cantik/tampan.
4: menggunakan software komputer agar terlihat lebih cantik/tampan di foto dari tampilan saya yang sebenarnya.

1: berbohong mengenai prestasi pendidikan saya, seperti nilai, gelar, atau ijazah saya.
2: membuat seolah-olah terlihat bahwa saya telah menghasilkan lebih banyak uang dari penghasilan saya yang sebenarnya.
3: membuat seolah-olah terlihat bahwa saya telah bekerja untuk perusahaan atau organisasi tertentu, sementara hal tersebut tidak sepenuhnya benar.
4: membuat seolah-olah terlihat bahwa saya memiliki pekerjaan yang sebenarnya saya tidak punya.

ITALIAN

Su [] ho...

1: mentito riguardo al mio aspetto fisico, per esempio altezza, peso, taglia, colore della pelle, per sembrare più attraente.
2: pubblicato una immagine non recente di me stesso/a sul mio profilo per sembrare più attraente di quanto effettivamente sono.
3: mentito riguardo alla mia età per sembrare più attraente.
4: usato software per modificare un'immagine in modo da sembrare più attraente di quanto effettivamente sono

1: mentito riguardo ai traguardi educativi che ho raggiunto, quali diplomi, lauree e certificazioni.
2: fatto finta di guadagnare più di quanto effettivamente guadagnavo.
3: fatto finta di lavorare per una particolare azienda o organizzazione mentre ciò non era completamente vero.
4: fatto finta di avere un lavoro che in realtà non avevo.

JAPANESE

で..

1: 魅力的に見えるように、身長、体重、服のサイズ、肌の色など、自分の身体的特徴を偽ったことがある。
2: 実際よりも魅力的に見えるように、ソーシャルメディアのプロフィールに昔の写真を投稿したことがある。
3: 魅力的に見えるように年齢をごまかしたことがある。

4: パソコンのソフトウェアを使って写真を実際よりも魅力的に見えるように加工したことがある

1: 学年や取得した学位など、学歴を偽ったことがある。
2: 実際よりも収入が高いように見せかけたことがある。
3: 特定の企業や組織に勤めているように見せかけたことがある。
4: 実際にはしていない仕事をしているように見せかけたことがある。

POLISH

Korzystając ze [],…

1: skłamałem(-am) odnośnie swoich cech fizycznych (wzrost, waga, rozmiar ubrań, kolor skóry), aby wydawać się bardziej atrakcyjnym(-ą).
2: opublikowałem(-am) nieaktualne zdjęcie na swoim profilu, aby wydawać się bardziej atrakcyjnym(-ą) niż w rzeczywistości jestem.
3: skłamałem(-am) odnośnie swojego wieku, aby wydawać się bardziej atrakcyjnym(-ą).
4: używałem(-am) oprogramowania graficznego, aby wydawać się na zdjęciu atrakcyjniejszym(-ą) niż w rzeczywistości jestem.

1: skłamałem(-am) odnośnie swoich osiągnięć edukacyjnych, np. ocen, stopni zawodowych/naukowych lub innych dyplomów.
2: wywołałem(-am) wrażenie, że zarabiam więcej niż w rzeczywistości.
3: wywołałem(-am) wrażenie, że pracuję w pewnej firmie lub organizacji, choć nie było to w pełni zgodne z prawdą.
4: wywołałem(-am) wrażenie, że mam pewną pracę, choć nie było to zgodne z prawdą.

PORTUGUESE (BRAZILIAN)

Em [], eu ...

1: menti a respeito das minhas características físicas, como altura, peso, tamanho das roupas, cor da pele, para parecer mais atraente.
2: postei uma fotografia antiga de mim mesmo(a) em meu perfil na mídia social para parecer mais atraente do que realmente sou.
3: menti a respeito da minha idade para parecer mais atraente.
4: usei um programa de computador para parecer mais atraente na foto do que realmente sou.

1: menti a respeito das minhas qualificações, como meus graus, títulos ou diplomas.
2: fiz parecer com que eu tivesse ganho mais dinheiro do que realmente ganhei.
3: fiz parecer que eu tivesse trabalhado para uma determinada empresa ou organização, embora isto não fosse totalmente verdade.
4: fiz parecer que eu tinha um trabalho que na verdade não tinha.

PORTUGUESE (PORTUGAL)

Na minha rede social preferida, eu ...

1: …menti a respeito das minhas características físicas, como altura, peso, tamanho das roupas, cor da pele, para parecer mais atraente.
2: …coloquei uma fotografia antiga de mim mesmo(a) no meu perfil da rede social para parecer mais atraente do que realmente sou.
3: …menti a respeito da minha idade para parecer mais atraente.
4: …usei um programa de computador para alterar a minha foto e parecer mais atraente do que realmente sou.

1: …menti a respeito das minhas qualificações, como grau académico, títulos ou diplomas.
2: …fiz parecer que tenho um salário superior ao que realmente tenho.
3: ...fiz parecer que tinha trabalhado para determinada empresa ou organização, embora tal não fosse totalmente verdade.
4: …fiz parecer que tinha um emprego que na verdade não tinha.

RUSSIAN

В сети [] я...

1: врал(а) о моих физических характеристиках, таких как рост, вес, размер одежды, цвет кожи, чтоб казаться более привлекательным(ой).
2: я выложил(а) старую фотографию себя на своей странице в социальной сети, чтоб казаться более привлекательным(ой), чем на самом деле.
3: врал(а) о моем возрасте, чтоб казаться более привлекательным(ой).
4: использовал(а) компьютерные программы, чтоб казаться более привлекательным(ой) на фотографии, чем на самом деле.

1: врал(а) о моих достижениях в образовании, например об оценках, научных званиях или дипломах.
2: создал(а) видимость как будто я зарабатываю больше денег, чем на самом деле.
3: создал(а) видимость как будто я работал(а) в конкретной фирме или организации, хотя это не было полностью правдой.
4: создал(а) видимость как будто у меня была работа, которой у меня на самом деле не было.

SPANISH (CASTELLANO)

En [], he...

1: mentido acerca de mis rasgos físicos, como mi estatura, peso, talla de ropa o color de piel, para parecer más atractivo/a.
2: publicado una foto antigua de mí en mi perfil de redes sociales para parecer más atractivo/a de lo que realmente soy.
3: mentido acerca de mi edad para parecer más atractivo/a.
4: usado software informático para parecer más atractivo/a en una fotografía de lo que realmente soy.

1: mentido acerca de mis logros educativos, como mis calificaciones, títulos o diplomas.
2: aparentado ganar más dinero del que gano realmente.
3: aparentado trabajar en una empresa u organización en particular y no era completamente cierto.
4: aparentado tener un empleo que no tengo.

SPANISH (MEXICAN)

En [], he...

1: mentido acerca de mis rasgos físicos, como mi estatura, peso, talla de ropa, color de piel, para parecer más atractivo/a.
2: publicado una foto antigua de mí en mi perfil de redes sociales para parecer más atractivo/a de lo que realmente soy.
3: mentido acerca de mi edad para parecer más atractivo/a.
4: usado software informático para parecer más atractivo/a un una fotografía de lo que realmente soy.

1: mentido acerca de mis logros educativos, como mis calificaciones, títulos o diplomas.
2: hecho parecer como si ganara más dinero del que gano realmente.
3: hecho parecer como si trabajara en una empresa u organización en particular, mientras no era completamente cierto.
4: hecho parecer como si tuviera un empleo que no tengo.

SWEDISH

På [] har jag någon gång ...

1: ljugit om mina fysiska egenskaper, t.ex. längd, vikt, klädstorlek och hudfärg, för att framstå som mer attraktiv.
2: lagt upp ett gammalt kort på mig själv på min profilsida för att framstå som mer attraktiv än jag egentligen är.
3: ljugit om min ålder för att framstå som mer attraktiv.
4: använt datorprogram för att framstå som mer attraktiv på en bild än jag egentligen är.

1: ljugit om mina utbildnings prestationer, t.ex. betyg, examina eller diplom.
2: fått det att framstå som att jag har tjänat mer pengar än jag egentligen gjorde.
3: fått det att framstå som att jag jobbade för ett visst företag eller en viss organisation, vilket inte var helt sant.
4: fått det att framstå som att jag hade ett jobb som jag inte hade.

THAI

ใน [] ฉันเคย...

1: โกหกเกี่ยวกับรูปร่างหน้าตาของฉัน เช่น ความสูง น้ำหนัก ขนาดเสื้อผ้าที่ใส่ สีผิว เพื่อให้ตนเองดูดีขึ้น
2: ใช้รูปเก่าของตัวเองในโซเชียลมีเดียเพื่อให้เหมือนกับว่าฉันดูดีกว่าที่ฉันเป็นอยู่

3: ระบุอายุไม่ตรงกับความเป็นจริงเพื่อให้ดึงดูดความสนใจได้มากขึ้น
4: ใช้แอปหรือโปรแกรมแต่งรูปถ่ายตัวเองเพื่อให้ตัวฉันในรูปดูดีเกินจริง

1: ระบุความสำเร็จการศึกษาไม่ตรงตามความเป็นจริง เช่น เกรด ปริญญาบัตร ประกาศนียบัตร
2: ทำเป็นว่าฉันหาเงินได้มากกว่าความเป็นจริง
3: ทำเป็นว่าฉันทำงานในบริษัทหรือองค์กรใดองค์กรหนึ่งโดยเฉพาะ ซึ่งไม่ใช่เรื่องจริงทั้งหมด
4: ทำเป็นว่าฉันทำอาชีพที่จริงๆ แล้วฉันไม่ได้ทำ

TURKISH

[] üzerinden, ...

1: boyum, kilom, bedenim, ten rengim gibi fiziksel özelliklerimin daha çekici göründüğü konusunda yalan söyledim.
2: aslında olduğumdan daha çekici görünmek için sosyal medya profilimde eski resimlerimden birini paylaştım.
3: daha çekici görünmek için yaşım konusunda yalan söyledim.
4: bir resimde aslında olduğumdan daha çekici görünmek için bilgisayar yazılımı kullandım.

1: notlarım, derecelerim veya diplomalarım gibi eğitim başarılarım hakkında yalan söyledim.
2: kendimi sanki aslında kazandığımdan daha fazla para kazanmış gibi gösterdim.
3: tamamen doğru olmamasına rağmen, kendimi sanki belirli bir şirket veya kurumda çalışıyormuş gibi gösterdim
4: kendimi sanki aslında sahip olmadığım bir işim varmış gibi gösterdim.

Chapter 3
A Global View of Fairness Perceptions and Payment Preferences on Social Media Platforms

The tension between online services' data monetization practices – using consumer data for profit – and consumers' request for fair use of their personal data has been intensified in recent years.[1] Researchers have called for further investigation on the issues concerning consumer data monetization (Beke, Eggers, & Verhoef, 2018; Lamberton & Stephen, 2016). Investigation on those issues is particularly relevant for social media platforms (SMPs) because they are important channels for various marketing activities (Kaplan & Haenlein, 2010; Rapp et al., 2013) and their business models are typically built around extensive monetization of consumer data.[2] On the one hand, SMPs need to make a profit from consumer data to cover the cost of providing free services to consumers. On the other hand, consumers demand fair practices in handling their personal data, which then limits SMPs' profitability from data monetization. To reconcile this conflict, we need to understand how consumers evaluate the fairness of SMPs' data monetization practices and what could be an alternative profit model for SMPs when consumers perceive the data monetization practices associated with the current profit model as unfair.

The main profit for SMPs currently comes from allowing third parties to display targeted advertisements to the SMP users.[3] Those highly targeted ads use the immense volume of personal information revealed by consumers on SMPs. Consumers must allow SMPs to monetize these personal data in exchange for accessing the platforms. Hence, it can be said that consumers are paying for social media services with their personal data (Anderl, März, & Schumann, 2016; Schumann, von Wangenheim, & Groene, 2014; Schwartz, 2004). Some consumers may perceive paying with personal data as unfair, and as consumers become more aware of the implicit payment with data, SMPs face the challenge of ensuring fair use of data while maintaining profitability.

Establishing fair use of data is an important task for businesses such as SMPs that monetize consumer data. In many countries, ensuring fairness of personal data monetization is a regulatory requirement, which could lead to legal and financial consequences.[4] For instance, Google's failure to make its services, including its SMP YouTube, compliant with the EU's general data protection law has already cost the company 50 million euros as of May 2018.[5] Besides regulatory requirements, businesses also need to consider which data monetization practices consumers perceive as unfair. When consumers perceive firm's behavior as unfair, they are willing to punish the unfair behavior (Kahneman, Knetsch, & Thaler, 1986). One recent example is the 2018 Facebook–Cambridge Analytica data scandal. In this incidence, consumers in fact agreed to terms of service that implicitly allowed for political campaign targeting using personal data.[6] Despite having agreed to the terms of services, consumers still considered such monetization of their personal data unfair, which resulted in the #DeleteFacebook movement and 18% loss in Facebook's market value.[7] This is in line with previous research findings that fairness plays a central role in consumers' react to the way firms handle their personal data (Kennedy, Elgesem, & Miguel, 2017; Kim, Barasz, & John, 2019). Therefore, SMPs need to know how consumers assess fairness of the data monetization practices on SMPs in order to prevent damaging consequences.

Furthermore, consumers' fairness perceptions also affect how much information consumers are willing to pass on to firms through social media and how reliable this information is (Culnan & Bies, 2003). The reliability and amount of consumers' information determines how effectively consumers can be targeted with advertisement. Thus, identifying what consumers perceive as unfair data monetization practices by SMPs is also of interest to firms that place targeted advertisement on SMPs.

Based on previous research and theorizing regarding consumers' attitudes to the use of their personal data, it is reasonable to expect that consumers consider social norms of information flow when they assess the fairness of data monetization practices on social media (Kim, Barasz, & John, 2019; Nissenbaum, 2004). Hence, we study the relation of consumers' fairness perceptions to norms of information flow and the consequences of perceptions of unfairness.

A practical question arises once the drivers of fairness perceptions are established: what can be done to ensure fair data processing without compromising SMPs' functionality and profitability? Some social media platforms already offer fee-payment as an alternative access mode for consumers.[8] However, so far, no research has examined paying a fee as a feasible alternative to paying with data for the use of SMPs. In this study, we explore the appeal of a fee-payment choice and identify the consumer segments that prefer this choice.

Our study relies on an extensive survey data from 25 countries from different parts of the world. The survey focuses on Facebook, currently the largest global social media platform that owns the personal data of more than a quarter of the world's population.[9] We used insights from these data to answer our two major research questions: (i) How do consumers around the world assess the fairness of social media data monetization practices and what are their responses to unfair practices, and (ii) How would a fee-payment choice appeal to different cultures and consumer segments, if social media offer such a choice to avoid unfair data practices?

The first main contribution of the present study is the introduction of consumers' fairness perceptions related to information flow norms as an additional dimension for research on data privacy. Knowing how consumers' fairness perceptions emerge from norms of information flow, SMP managers can set up data monetization practices that are more acceptable to consumers. Specifically, platforms that strive to be perceived as engaging in fair data monetization practices should avoid using data obtained from private communication (vs public) and from third parties (vs the focal platform), corresponding to the norms of keeping information within intended audience and intended context. Our study shows that knowing consumers' fairness perceptions is particularly important in individualist cultures, where consumers perceive SMPs' data monetization practices as generally unfair, compared to collectivist cultures. It is also important for advertisers to be aware that when consumers perceive the data monetization practices on SMPs as unfair, the data from those consumers could be inaccurate for advertisement targeting due to privacy-protecting behaviors.

Our study's second main contribution is introducing the choice between paying a fee and paying with the data as a practical solution to the issue that some consumers perceive data monetization practices on SMPs as unfair. SMP managers can expect the fee-payment choice to be preferred by specific consumer segments, such as older age, female, higher socioeconomic status, and consumers from countries that are less tolerant towards ambiguities and uncertainties. In sum, our study empirically demonstrates that consumers' perceptions of the fairness of data practices vary systematically and that introducing the fee-payment choice for consumers could provide a balance between SMPs' profit goal and consumers' desire for fair use of their personal data.

In the next section, we develop our theoretical model that links our key constructs. Next, we describe our methodology, analytical models, and results. We conclude with a discussion of the managerial and theoretical implications of our results.

THEORETICAL BACKGROUND

Research on social media data processing is multidimensional: it includes security, risk management, and legal regulations (for a review, see Martin & Murphy, 2017). In this paper we focus specifically on consumers' perceptions of fairness, particularly on how they are formed and their consequences. Figure 1 shows our conceptual model.

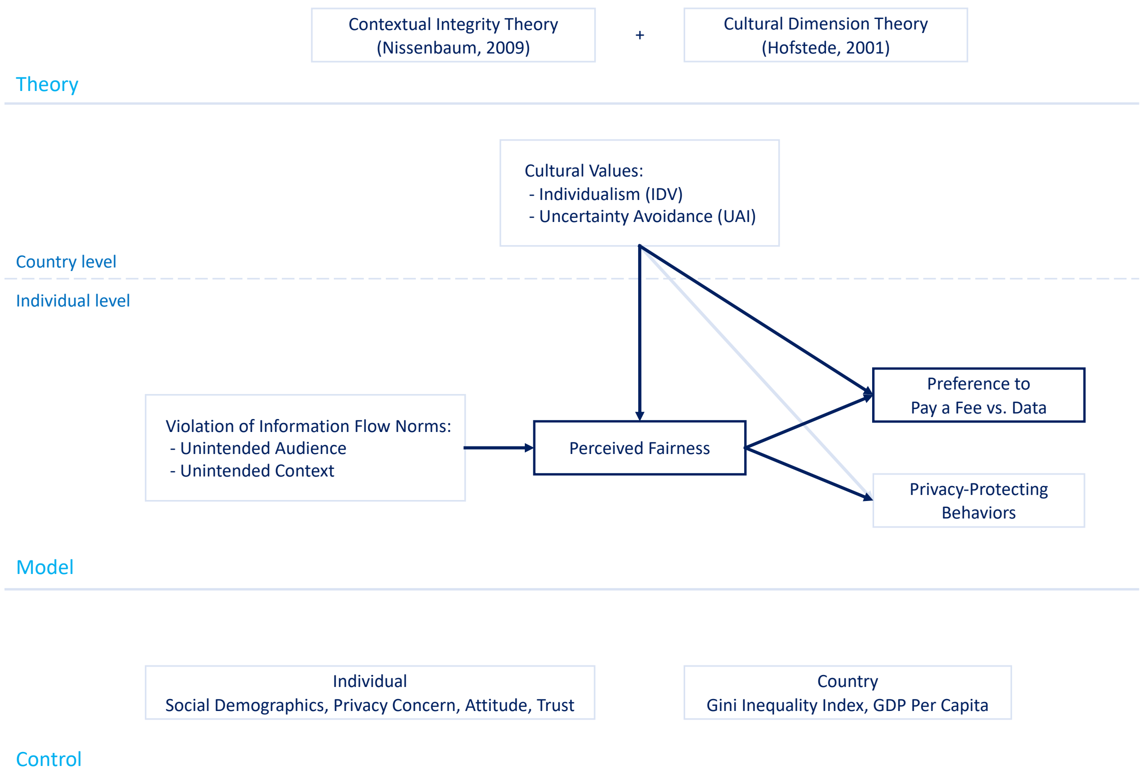


Figure 1. Conceptual Model.

Perceived Fairness

People respond highly negatively to unfairness and punish unfairness even when it is costly for them (Ensminger & Henrich, 2014). For instance, individuals might refrain from disclosing personal information on SMPs or even delete their accounts in response to unfair practices, thus forgoing the benefits as opportunity costs (Krasnova, Veltri, & Günther, 2012). In contrast, when justice is ensured, individuals are equally willing to disclose personal information regardless of their privacy concerns (Culnan & Armstrong, 1999). Under such a condition, consumers are also more willing to accept targeted ads that use personal information (Schumann, von Wangenheim, & Groene, 2014). Fairness is central for establishing trust between companies and their customers (Bleier & Eisenbeiss, 2015; Culnan & Armstrong, 1999; Kim, Barasz, & John, 2019). By extension, fairness is an essential requirement for profitable long-term relationships (Flavián, Guinalíu, & Gurrea, 2006; Gefen, 2002; Qureshi et al., 2009). Therefore, understanding the drivers of consumers' fairness perceptions is in the best interest of SMPs.

There are several ways of defining fairness. In this study, we focus on perceptions of unfairness of data monetization practices arising from violation of norms regarding the flow of personal information (Nissenbaum 2009; Petronio, 2013 as cited in Margulis, 2011). The contextual integrity theory proposes that there are commonly accepted norms defining how information should be used and transferred between parties (Nissenbaum, 2009). These information norms regulate the flow of information between two or more entities across both offline and online situations (Kim, Barasz, & John, 2019; Nissenbaum, 2004). In particular, consumers might expect SMPs to respect two information norms: to keep the disclosed information within the intended audience (public versus only privately accessible to selected individuals) and within the intended context (whether information used by the SMP was disclosed through the same SMP in the first place or through other online platforms). The first norm arises from the fact that self-disclosure is audience-specific (Altman & Taylor, 1973; Tufekci, 2008) and individuals prefer to choose what kind of information to disclose to which audience (Leary & Kowalski, 1990). The second norm originates from the expectation that individuals are entitled to share their personal information themselves and to not have other people pass on their personal information in another context where undesired inference could be made (Kim, Barasz, & John, 2019). The analogy in offline communication is the dislike of individuals to being gossiped about behind their back.

When the data monetization practice of an SMP violates at least one of the two above-mentioned norms of information flow (information flowing to intended audience and within intended context), we expect consumers to perceive that data monetization practice as unfair. Mapping these norms on existing data monetization practices on SMPs, we expect heterogeneity in fairness perceptions across data types, such that the monetizing of data disclosed privately is less fair than data intended for wide audience; and that monetization of data disclosed on other websites is less fair than monetization of data intended for the SMP itself. Thus, we propose:

H1: Consumers perceive the monetization of data by social media platform as less fair when the monetized data is intended for private audience compared to data intended for public audience.

H2: Consumers perceive the monetization of data by social media platform as less fair when the monetized data is intended for other context (other websites) compared to data intended for the studied social media platform.

Fairness assessments are not universally constant. Thus, perceived fairness of data monetization practices should vary across cultures (Ensminger & Henrich, 2014). In order to study how culture affects fairness perceptions, we use the cultural model from Hofstede (2001). Table W1 in the Appendix contains a selection of past studies that examined the effects of Hofstede's cultural dimensions on constructs related to data privacy. To the best of our knowledge, there has not been any research on the cross-cultural variations in perceived fairness of data monetization by SMPs. In this paper, we focus primarily on two dimensions of culture — individualism–collectivism and uncertainty avoidance — that we consider most relevant to perceptions of fairness and privacy-related behaviors. We focus only on these two dimensions for the following reasons. Firstly, Hofstede cultural dimensions are not orthogonal, therefore, including all of them simultaneously into a model is problematic from statistical perspectives, therefore it is more efficient to focus on some of them only. Secondly, theoretical reasoning suggests that those two dimensions are most relevant for privacy-related perceptions. We discuss this reasoning below.

Individualism represents the degree to which members of society prefer maintaining little integration into social groups and loose social ties with members of society outside the immediate family (Hofstede, 2001). Due to loose social ties, personal boundaries are more emphasized in individualist societies compared to collectivist ones (Markus & Kitayama, 1991; Triandis, 1989). Since the right for strict personal boundaries is a social norm in individualist cultures, consumers from such cultures should experience monetization of their personal information by SMPs as a norm violation, which should lead to perceiving data monetization by SMPs as less fair compared to consumers from collectivist cultures.

H3: Consumers from individualist cultures perceive the monetization of data by social media platforms as less fair compared to consumers from collectivist cultures.

The other cultural dimension that likely affects consumers' privacy-related perceptions is uncertainty avoidance (Krafft, Arden, & Verhoef, 2017). Uncertainty avoidance measures society members' discomfort towards ambiguous situations and their efforts to reduce the uncertainty (Hofstede, 2001). Since the risk associated with SMPs' monetization of personal data is unpredictable by nature (it is unknown how and for what purposes third-parties may process data obtained from SMPs), we expect consumers from highly uncertainty-avoiding cultures to perceive SMPs' data monetization practices as less fair compared to consumers from uncertainty-tolerating culture.

H4: Consumers from uncertainty-avoiding cultures perceive the monetization of data by social media platform as less fair in general compared to consumers from uncertainty-tolerating cultures.

Consumers' Responses to Unfair Practices and Privacy-Protecting Behaviors

When consumers perceive that their data have been used unfairly, they might counteract this in ways that would reduce the quality of consumer data obtained from SMPs (Berendt, Günther, & Spiekermann, 2005). Lower quality of data is likely to have negative consequences not only for SMPs, but also for businesses using the consumer data from those platforms.

Not using SMPs is one of the extreme ways to counteract unfair data monetization and some consumers indeed forego the benefits of Facebook to keep their privacy. This limits the reach of companies' social media campaigns. However, there are clearly other methods to protect one's privacy besides quitting the platform altogether. Some examples include abstaining from disclosing some personal information or providing fake information. Research shows that in the face of threats to their privacy, consumers are less willing to make purchases or to share personal information and they might engage in privacy-protecting behaviors (Culnan, 2000; John, Acquisti, & Loewenstein, 2011; Phelps, Nowak, & Ferrell, 2000; Singer, Hippler, & Schwarz, 1992; Tsai et al., 2011; Mosteller & Poddar, 2017). Such consequences are undesirable for companies cooperating with SMPs because they would then have to rely on incomplete or unreliable consumer data for market research and targeting.

Empirical evidence of privacy-protecting behavior on SMPs could be used to motivate the collaboration of SMPs and private companies in establishing fair data monetization practices. In this study, we empirically explore potential defensive behaviors that consumers might engage in as a result of what they perceive as unfair data monetization.

H5: Consumers who perceive the social media platform's data monetization practices as unfair are more likely to engage in privacy-protecting behaviors.

We examine whether the cultural dimensions of individualism–collectivism and uncertainty avoidance index have an effect on privacy-protecting behaviors.

Fee-payment Choice

If stakeholders are interested in preventing the backlash from consumers perceiving the data monetization practices as unfair, they should explore alternative business models that do not involve such practices. One possibility is to allow consumers to directly pay a fee for the services of SMPs, as already well adopted in other digital services such as online news platforms (Pattabhiramaiah, Sriram, & Manchanda, 2019). Introducing a fee-payment choice allows SMPs to make profit without having to monetize consumer data. Consumers who find SMP data monetization practices unfair should then prefer the fee-payment choice over having their data monetized.

H6: The lower the perceived fairness of the social media platform's data monetization practices the more likely consumers prefer paying a fee over paying with data.

It is unlikely that all consumers accept the fee-payment choice. Therefore, a solution that addresses needs of different consumer segments would be giving consumers a choice between paying a fee and paying with data (i.e., allowing their personal data to be used for profit). In general, offering such a choice to consumers makes them more in control of their personal data (Tucker, 2014) and benefits different segments of consumers and the SMPs. For consumers who prefer paying a fee, having such a choice allows them to decrease the risks associated with data vulnerability, and therefore, also prevents potential damaging behaviors, such as negative word-of-mouth, from these customers towards the SMP they use (Martin, Borah, & Palmatier, 2017). Furthermore, SMPs could benefit from additional profit, as the salience of privacy should also make consumers more willing to pay for their privacy (Egelman, Felt, & Wagner, 2013; Tsai et al., 2011). For consumers who prefer paying with data, having a choice raises awareness of data monetization and allows them to make a better-informed choice. The SMPs also benefit from offering a choice to this consumer segment because providing consumers control of personal data facilitates disclosure for consumers who prefer to share data (Mothersbaugh et al., 2012; Tucker, 2014). The salience of the payment choice should remind consumers of values that the SMP provides and the social norm of reciprocity encourages consumers to reciprocate to the SMP (Whatley et al., 2002), even those who choose to pay with data. Such reminders have been shown to increase acceptance of personal data monetization (Schumann, von Wangenheim, & Groene, 2014). Taken together, offering consumers a choice could be beneficial for all parties involved.

Under certain conditions, consumers are willing to pay for their privacy, then introducing the fee-payment choice can actually be profitable (Casadesus-Masanell & Hervas-Drane, 2015; Rust, Kannan, & Peng, 2002). However, whether consumers across the globe would all welcome such a choice is currently unknown, which limits SMPs' ability to forecast changes in profits associated with introducing the fee-payment choice. Therefore, identifying the cultural values associated with preference for paying a fee over paying with data is a task of this paper. We expect the fee-payment choice to be more favored in uncertainty-avoiding cultures than in uncertainty-tolerant cultures because this choice provides a clearly defined cost instead of unpredictable outcomes associated with paying with data.

H7: Consumers from uncertainty-avoiding cultures are more likely to prefer paying a fee over paying with data compared to consumers from uncertainty-tolerating culture.

METHOD

Data Collection

We collected the data through a survey distributed in twenty-five countries across the globe in 2016. The countries were sampled from six continents: eleven in Europe (Bulgaria, France, Germany, Italy, Netherlands, Poland, Portugal, Russia, Spain, Sweden, United Kingdom), nine in Asia (China, India, Indonesia, Japan, Philippines, Singapore, Thailand, Turkey, United Arab Emirates), two in North America (Mexico, United States), one in South America (Brazil), one in Africa (South Africa), and one in Oceania (Australia). We categorized the countries into three groups based on population size and applied three quotas of sample sizes to these groups. The market research agency Kantar Public administered the survey in 2016. The original survey was in English and translated by professional translators to the local languages. In order to verify the quality of translations, native speakers back-translated the survey to English, inconsistencies were discussed and eliminated. We received in total 14,825 completed responses, with 500 to 700 respondents per country. We filtered out the responses who failed the attention check and obtained a remaining sample size of 14,686. Table W2 in the Appendix shows the details of the sample per country. The respondents are between the age of 18 and 96 years old, with an average age of 42.7 years old. Forty-nine percent of them are male. In terms of occupation, 58% have a full-time job, 12% have a part-time job, 12% are retired, 5% are homemakers, 5% are students, 5% are unemployed, and 2% are sick or disabled. Ninety-one percent of respondents answered the income question. The median income lies in the category between USD 22,000 and USD 43,999 per year. The national-level data included the December 2015 version of Hofstede's (2001) cultural values, and the 2015 Gini Inequality Index and 2016 gross domestic product (GDP) per capita from the World Bank.

Measures

We first showed the participants a description explaining Facebook’s profit model, then the participants answered questions measuring the constructs presented below in this subsection. All descriptions and measurement scales of the survey are available in the Appendix. We chose the context of Facebook because it is the largest SMP with 2.23 billion monthly active users, and it accounts for one fifth of the global online advertising revenue.[12] The online advertisements on Facebook heavily rely on consumers’ personal data, and several controversies arose from how Facebook treat consumers’ data privacy.[13]

Fairness. We measured the perceived fairness of Facebook's data monetization practices using seven items measured on a 5-point scale, on which responses ranged from 1 (*not fair at all*) to 5 (*completely fair*). We gave the participants the following instruction:

“Please indicate to what extent you consider it fair that Facebook tracks and uses the following information about you for commercial purposes.” Each of the seven items correspond to one type of data, where the data types were categorized according to activities on SMPs (Beye et al., 2012). The seven items corresponded to demographic information, wall posts, photos, private messages, group memberships, friends' activities, and browsing activities on other websites.

Payment preference. Payment preference is a choice preference between paying a fee and paying with data for using the services of Facebook. The respondents responded to the question “To ensure that I can continue to use Facebook I would…” using a 6-point scale, on which responses ranged from 1 (*definitely prefer to pay with data*) to 6 (*definitely prefer to pay with money*).

Privacy-protecting behaviors. We asked respondents who prefer paying with data about the extent to which they would engage in data-protecting behaviors to prevent Facebook from analyzing their personal data. The measure consisted of eight items corresponding to eight data-protecting behaviors: hiding specific demographic information, posting fewer wall posts, avoiding some topics in wall posts, share fewer photos, communicate less through private messages, avoid specific topics in private messages, actively modify group memberships, and restricting friends list. The respondents chose from a 5-point scale, on which responses ranged from 1 (*would not do that at all*) to 5 (*definitely would do that*).

Social demographics. We collected standard demographic information about the respondents: age, gender, employment status, income, socioeconomic status (Griskevicius et al., 2011), and education.

Privacy concern. We measured privacy concern using three items on a 5-point Likert scale, on which responses ranged from 1 (strongly disagree, i.e., low concern) to 5 (strongly agree, i.e., high concern). We asked the questions in the context of secondary use of personal data. We focused on secondary data monetization because Milberg et al. (1995) found that among the dimensions of data privacy, this was of the highest concern to the consumers.

Attitude towards current data use practices. We asked the respondents to express their attitude towards the current data use practices of organizations and measured their responses using two items on a 5-point scale, on which responses ranged from 1 (strongly disagree, i.e., negative attitude) to 5 (strongly agree, i.e., positive attitude).

Trust. We used one item on a 5-point scale to measure consumers' trust towards Facebook, on which responses ranged from 1 (strongly disagree, i.e., low trust) to 5 (strongly agree, i.e., high trust) (Dinev & Hart, 2004).

National cultural values. We used the national cultural values of individualism and uncertainty avoidance from Hofstede (2001) in our analyses. We used data from Hofstede's published table of cultural dimensions with the latest correction from December 2015.

Gini inequality index. We used the latest available Gini Inequality Indices of 2015 from the World Bank as a measure of inequality in each country. A higher value means more inequality. We use the index to control for country-wise inequalities in modeling fairness.

GPD per capita. We used 2016 GDP per capita at nominal values obtained from the World Bank to control for each country's economic development stage in modeling payment preferences. We converted all values to US dollars using the 2016 Big Mac Index. A higher value indicates more advanced in economic development stage.

Measurement Model

To model fairness, we used a doubly explanatory item response model (De Boeck & Wilson, 2004). The response variables were the participants' fairness ratings of each data type. On the person side, in order to represent each person's overall fairness perception on SMP data monetization practices, we assumed that a latent fairness factor underlies the responses. On the item side, we included two predictors for the norms of information flow. The structural model section below presents the details.

The measurement model had a multilevel structure because individuals were nested within countries. Differential item functioning across countries was incorporated through a random effects structure (De Jong, Steenkamp, & Fox, 2007). Specifically,

$$P\left(Y_{ijk} = c \middle| a^{f}_{jk}, \Theta_{ij}, \tau^{f}_{jk,c}, \tau^{f}_{jk,c-1}\right) = \Phi\left(a^{f}_{jk}\Theta_{ij} - \tau^{f}_{jk,c-1}\right) - \Phi\left(a^{f}_{jk}\Theta_{ij} - \tau^{f}_{jk,c}\right), \quad (1)$$

where

$$a^{f}_{jk} \sim N\left(a^{f}_{k}, \sigma^{2}_{a^{f}_{k}}\right), \quad (2)$$

$$\Theta_{ij} \sim N\left(\Theta_{j}, \sigma^{2}_{\theta_j}\right), \quad (3)$$

$$\tau^{f}_{jk,1} \sim N\left(\tau^{f}_{k,1}, \sigma^{2}_{\tau^{f}_{1}}\right), \quad (4)$$

$$\log\left(\tau^{f}_{jk,c} - \tau^{f}_{jk,c-1}\right) \sim N\left(\eta^{f}_{k}, \sigma^{2}_{\tau^{f}_{2}}\right), \quad (5)$$

and $\Phi(\cdot)$ is the cumulative distribution function of a standard normal distribution. Individuals are indexed by $i \in \{1, 2, \ldots, N\}$, data types are indexed by $k \in \{1, 2, \ldots, K\}$, categories are indexed by $c \in \{1, 2, \ldots, C\}$, and countries are indexed by $j \in \{1, 2, \ldots, J\}$.

The response variable Y_{ijk} was the fairness rating of individual i from country j on data type k. The parameter a^{f}_{jk} was the discrimination parameter of item k in country j, and it measured the strength of association between the particular item and the underlying latent variable. The variable Θ_{ij} was the latent fairness variable of individual i from country j, and it represented the individual's unobserved true fairness perception about Facebook's data monetization practices. The parameter $\tau^{f}_{jk,c}$ was the threshold between categories c and c+1 of item k in country j, and it indicated the difficulty for individuals from country j to choose a category above c for item k. A higher first threshold $\tau^{f}_{jk,1}$ indicated that more people found the use of data type k by Facebook completely unfair.

The measurement model for privacy-protecting behaviors was similar to that of fairness perceptions, with its own set of parameters a^{d}_{jk} and $\tau^{d}_{jk,c}$. The latent variable for an individual's overall protecting behavior was denoted by ζ_{ij}.

Structural Model

In the structural part of the model, we allowed the latent fairness on the person side to vary across countries with value explained by the cultural values uncertainty avoidance and individualism. Specifically,

$$\Theta_{ij} = \beta^{\theta}_{0j} + \beta^{\theta}_{1} Z_{ij} + \epsilon^{\theta}_{ij}, \tag{6}$$

where

$$\epsilon^{\theta}_{ij} \sim N\left(0, \sigma^2_{\epsilon^{\theta}}\right), \tag{7}$$

$$\beta^{\theta}_{0j} \sim N\left(\psi^{\theta} L_j, \sigma^2_{\beta^{\theta}}\right). \tag{8}$$

Z_{ij} = {Fairness$_{ij}$, Age$_{ij}$, Gender$_{ij}$, Socioeconomic Status$_{ij}$, Education$_{ij}$, Concern$_{ij}$, Trust$_{ij}$, Attitudes Towards Current Data Use Practices$_{ij}$} captured the individual-level control variables. The variable L_j contained country j's cultural variables individualism and uncertainty avoidance as well as the control covariate Gini Inequality Index, and the parameters in ψ^{θ} captured the effect of these country-level variables on consumers' latent fairness perceptions.

On the item side of fairness, we had two item indicators: unintended audience indicated whether the data were intended for private (1) or public (0) audience, and unintended context indicated whether the accessed data were directly disclosed on Facebook (0) or obtained from other websites (1). The model was as follows:

(9) $$\tau^{f}_{jk,1} = \beta^{\tau}_{j}\, X_k + \epsilon^{\tau}_{ij},$$

where

(10) $$\epsilon^{\tau}_{ij} \sim N\left(0, \sigma^2_{\epsilon^{\tau}}\right),$$

(11) $$\beta^{\tau}_{j} \sim N\left(\gamma^{\tau}\, U_j, \sigma^2_{\epsilon^{\beta^{\tau}}}\right).$$

$\tau^{f}_{jk,1}$ was the first threshold of fairness perceptions. It was an indication of complete unfairness. X_k captured the item indicators, and the coefficients in β^{τ}_{j} captured the effects of the item indicators for country j. U_j captured country indicators, and γ^{τ} contained the effect weights.

We specified the model for the preference between paying a fee and paying with data as follows:

(12) $$W_{ij} = \beta^{W}_{0j} + \beta^{W}_{1j}\Theta_{ij} + \beta^{W}_{2}\, Z_{ij} + \epsilon^{W}_{ij},$$

where

(13) $$\boldsymbol{\epsilon^{W}_{ij} \sim N\left(0, \sigma^2_{\epsilon^{W}}\right)},$$

(14) $$\beta^{W}_{0j} \sim N\left(\psi^{W}\, V_j, \sigma^2_{\beta^{W}_{0}}\right),$$

(15) $$\beta^{W}_{1j} \sim N\left(\gamma^{W}\, S_j, \sigma^2_{\beta^{W}_{1}}\right)$$

for random effects models,

(16) $$\beta^{W}_{1j} = \beta^{W}_{1}$$

for fixed effects models.

The response variable W_{ij} was the preference between paying with data and paying a fee for individual i from country j. The variable V_j contained country j's cultural variables individualism and uncertainty avoidance and the country-level control covariate GDP per capita, and the parameters in ψ^{W} captured the effect of these country-level variables on payment preference. S_j indicated the country indicator, and γ^W contained the effect weights.

Lastly, we specified the model for the latent privacy-protecting behavior as follows:

$$\zeta_{ij} = \beta_{0j}^{\zeta} + \beta_1^{\zeta}\Theta_{ij} + \beta_2^{\zeta} Z_{ij} + \epsilon_{ij}^{\zeta}, \tag{17}$$

where

$$\epsilon_{ij}^{\zeta} \sim N\left(0, \sigma_{\epsilon^{\zeta}}^2\right), \tag{18}$$

$$\beta_{0j}^{\zeta} \sim N\left(\psi^{\zeta} V_j, \sigma_{\beta_0^{\zeta}}^2\right). \tag{19}$$

We used the notations in the same manner as in the previous models.

RESULTS

For the individual-level variables, we computed Cronbach's alpha for constructs with multiple items and examined the correlations between each pair of individual variables. Table W3 in the Appendix contains the results. All Cronbach's alphas are above the recommended level of .7, which suggests evidence of scale reliability. Except for the somewhat high correlations among perceived fairness of data monetization and the two attitude measures (.52, .49, .65), the remaining variables do not have such a high correlation that should be of concern. We used the two attitude measures only as control covariates in the robustness check.

We also checked for common method variance using Harman's single factor test (Podsakoff et al., 2003). We loaded all items contributing to the seven constructs mentioned above (i.e., perceived fairness of data monetization by Facebook, payment preference, privacy-protecting behaviors, socioeconomic status, privacy concern, trust towards Facebook, and attitude towards organizations' current privacy practices) on one factor. We did this for all respondents and also separately for respondents who answered privacy-protecting behaviors. The proportions of explained variance are 31.8% and 22.6%, respectively; both are below the 50% threshold. Therefore, we conclude that common method variance is an unlikely concern in our study.

Fairness Perceptions about Social Media Data Monetization Practices

The hierarchical item response theory model is estimated through a two-step procedure (Anderson & Gerbing, 1988). First we estimated the measurement model following the procedure in Fox and Glas (2001), De Jong et al. (2008), and De Jong, Steenkamp, and Fox (2007) and then we analyzed the structural model. We first focused on the threshold parameters on the item side of the model. We visually represent the distribution of threshold 1 with histograms (Figure W1 in the Appendix) and the variation across countries in the means with a radar plot (Figure 2). As seen in Figure W1 in the Appendix, the threshold value for private messages is higher than for the other data types, and the distribution has little overlap with the others. This suggests that consumers considered the use of private messages by Facebook more unfair than the use of other data types. This is in line with our expectation in H1 that using data intended for private audience by SMPs is considered less fair than using data intended for the public.

Focusing on cultural effects on the item side, Figure 2 suggests that compared to people from other continents, people from Asian countries are less likely to consider as unfair all SMPs' data monetization practices. This is especially true for Japan where the threshold values of all data types appear lower than for the other countries. In the next model, we examine whether violations of information flow norms influence fairness evaluations and whether the effects are weaker in Japan than in other countries.

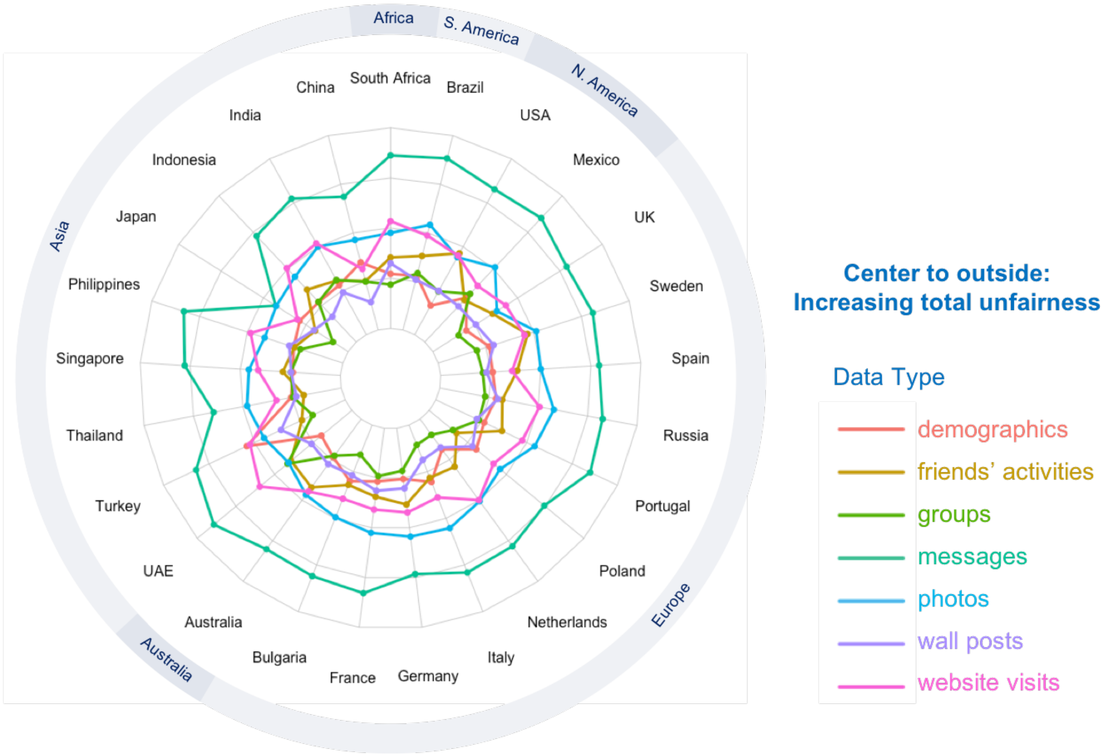


Figure 2. Mean Value of Fairness Threshold 1 (Unfairness).

Table 1 shows the model results of regressing threshold 1 (unfairness) from the measurement model on the two indicators of information flow norm violations (unintended audience and unintended context). The results confirm H1 about intended audience: using data intended only for private audience is considered more unfair than using data intended for the public (γ = 1.463; 95% credibility interval (CI) = [1.323, 1.598]). Moreover, using data intended for other context is considered more unfair than using data initially intended for Facebook (γ = .409; 95% CI = [.266, .554]), which confirms H2 about the effect of intended context. While these effects are nearly universal, an exception arises in Japan. The access of data by unintended audience is considered less extremely unfair in Japan than in other countries (γ = -1.091; 95% CI = [-1.744, -.435]), while the effect of using data in an unintended context is about the same in Japan as in other countries (γ = -.424; 95% CI = [-1.073, .228]). Through further examination of per-country effects, we found consumers from the United Arab Emirates (UAE) to evaluate fairness in a different manner than consumers in other countries (see Figure W2 in the Appendix). Because this might also lead to different consequences in terms of payment preferences, we included a dummy indicator for the UAE in the random effect models for payment preferences.

Table 1. Measurement Model: FairnessThreshold 1 (Unfairness) on Item

	Effect		**95% CI**	
Intercept	-1.070	***	-1.125	-1.012
Item predictors				
Unintended audience	1.463	***	1.323	1.598
Unintended context	.409	***	.266	.554
Effects in Japan				
Unintended audience x Japan	-1.091	***	-1.744	-.435
Unintended context x Japan	-.424	(n.s.)	-1.073	.228

After we have analyzed the item functioning, we dug deeper into the person side of the item response model. A visual check suggests a negative association between consumers' fairness perceptions about SMP data monetization and individualism cultures, and we do not see any clear pattern between those fairness perceptions and uncertainty avoidance cultures (see Figure W3 in the Appendix). Table 2 presents the model results of cultural effects on latent perceived fairness values. We began with two baseline models without any explanatory variables: one pooling individuals from all countries (Model 1), and one with a random intercept in a multilevel model (Model 2). The results of Model 1 show a total variance of 3.089, and the results of Model 2 show a within-country variance of 2.597 and a between-country variance of .564. Between-country variation accounts for 18% of the total variance, and the model fit improves with the two-level structure (DIC_1 = 58,240.793; DIC_2 = 55,716.650), thus supporting the use of a multilevel model. In Model 3, we add the cultural values uncertainty avoidance and individualism into the model. Despite little change in the model fit indicator (DIC_2 = 55,716.650; DIC_3 = 55,715.437), the cultural variables explain 49.7% of the between-country variance in consumer's fairness perceptions. Consumers' fairness perceptions about SMP data monetization are negatively related to the individualist culture of a country (ψ = -.021; 95% CI = [-.030, -.012]). Thus, in more individualist countries, such as United States and Australia, consumers perceive the use of personal data by SMPs as less fair. While this result confirms H3, we do not have any evidence to support H4. We cannot conclude any effect of uncertainty avoidance on consumer's fairness perceptions (ψ = -.006; 95% CI = [-.016, .002]). We add individual demographics and attitudes (Model 4) and a country inequality index (Model 5) as control variables into the model. The effect of individualism remains negative and significant, and the effect of uncertainty avoidance remain insignificant, after adding the control variables, which provide evidence of robustness of our findings.

Table 2. Structural Model: Perceived Fairness of SMPs' Data Monetization

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	- ***	-.188	1.26 **	- ***	-1.251 **
Individual Level					
Residual variance	3.089 ***	2.597 **	2.59 **	1.910 ***	1.964 **
Country Level					
Individualism			-.021 **	-.008 **	-.009 **
Uncertainty			-.006	-.001	-.003
Residual variance		.564 **	.280 **	.144 ***	.147 **
Controls (Individual)					
Age				-.013 ***	-.014 **
Male				.297 ***	.300 **
Socioeconomic status				.095 ***	.093 **
Education				.012	.011
Privacy concern				-.149 ***	-.151 **
Trust towards				.451 ***	.453 **
Attitude towards				.382 ***	.398
Controls (Country)					
Gini inequality index					.000
Model Information					
DIC	58,240.793	55,716.650	55,715.43	51,204.246	48,140.028
Variance explained at individual level				31.3%	31.4%
Variance explained at country level			49.7%	21.7%	29.4%
Sample size at individual level	14,686	14,686	14,686	14,686	13,695
Sample size at country level		25	25	25	23[1]

***99% CI does not contain zero. **95% CI does not contain zero. *90% CI does not contain zero.

[1]*Data for the Gini inequality index is not available for Singapore and UAE.*

Privacy-Protecting Behaviors

The majority of respondents in our study, over 95%, indicated that they would engage in some privacy-protecting behavior. Forty-five percent of the respondents indicated that they would definitely change at least one type of behavior on social media platform, and the remaining 51% percent indicated that they would change their behavior with some degree of certainty. Figure W5 the Appendix shows the responses to the eight types of privacy-protecting behaviors. The most typical of these behaviors are sending fewer private messages and avoiding certain topics in private messages, which correspond to unfair use of personal data due to violating the norm of intended audience.

We tested if the privacy-protecting behavior may be affected by consumers' unfair perceptions. Table 3 shows the results of modeling privacy-protecting behavior with consumer's fairness perceptions and the cultural values uncertainty avoidance and individualism. Table W5 in the Appendix shows the baseline models for privacy-protecting behaviors. Models 0 and 00 respectively model fixed and random intercepts without any predictor variable. Privacy-protecting behavior has a total variance of 2.476, of which approximately 6.8% is between-country variance. The model fit is improved with the random intercept (DIC_0 = 33,712.022; DIC_{00} = 33,234.968), thus supporting the use of a hierarchical model.

In Model 1, we added the fairness latent variable to the model to examine its effect on the privacy-protecting behavior. We found a significant negative effect (β = -.263; 95% CI = [-.285, -.242]), confirming H5. The more unfairness consumers feel, the more privacy-protecting behaviors they engage in, which results in lower quality and less reliable data for businesses advertising through social media. The model fit improved when we included fairness as a predictor (DIC_{00} = 33,234.968; DIC_1 = 32,656.745). In the next two models, we examined the cultural effects on the privacy-protecting behavior alone (Model 2) and together with fairness (Model 3). When we included only the two cultural values (uncertainty avoidance and individualism) in Model 2, individualism has a significant positive effect on the privacy-protecting behavior (ψ = .010; 95% CI = [.004, .015]). However, the effect became only marginally significant (ψ = .008; 95% CI = [-.001, .016]) when fairness was also included in the model (Model 3). We do not find any effect of uncertainty avoidance on privacy-protecting behavior (ψ = -.003; 95% CI = [-.009, .003]). At this point, we added control covariates at the individual and country levels (Model 4 and Model 5), and the effect of fairness remained negative and significant after controlling for individual social demographics and attitudes and country equality and economic factors.

Table 3. Structural Model: Privacy-Protecting Behavior.

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	1.75 **	1.37 **	1.52 **	- **	- *
Individual Level					
Perceived fairness of SMPs' data	-.263 ***		-.263 ***	-.210 ***	-.205 ***
Residual variance	2.19 **	2.34 **	2.19 **	1.90 **	1.96 **
Country Level					
Perceived fairness of SMPs' data	-.056		.151	.099	.295 *
Individualism		.010 **	.008 *	.008 *	.005
Uncertainty		-	-	-.002	.002
Residual variance	.136 **	.109 **	.114 **	.102 **	.065 **
Controls (Individual)					
Age				.001	.001
Male				-.094 **	-.100 **
Socioeconomic				.116 **	.121 **
Education				-.005	-.009
Privacy concern				.635 **	.651 **
Trust towards				-.125 **	-.130 **
Attitude towards				.037 *	.042 **
Controls (Country)					
GDP per capita					.011
Gini inequality index					-.009
Model Information					
DIC	32,656.74	33,233.73	32,656.35	31,380.44	29,347.45
Variance explained at individual level	7.2%		7.2%	19.6%	19.5%
Variance explained at country level	2.2%	38.0%	26.1%	28.7%	52.2%
Sample size at individual level	9,003	9,003	9,003	9,003	8,354
Sample size at country level	25	25	25	25	23

***99% CI does not contain zero. **95% CI does not contain zero. *90% CI does not contain zero.

Preference Between Paying a Fee or Paying with Data to Access Facebook

We continue to use the latent fairness scores in understanding individuals' preferences for paying a fee versus paying with data for social media services. We plot the preferences in Figure 3. While there are more consumers who prefer to continue paying with data rather than a fee, there are also a sizable number of consumers who would like to have the alternative choice (i.e., paying a fee). In Germany and Poland, over half of the sample prefer the fee-payment choice. The proportion of consumers preferring each choice varies across countries. In the two extremes, 58% of consumers in Germany prefer the fee-payment choice, while only 22% do in Thailand.

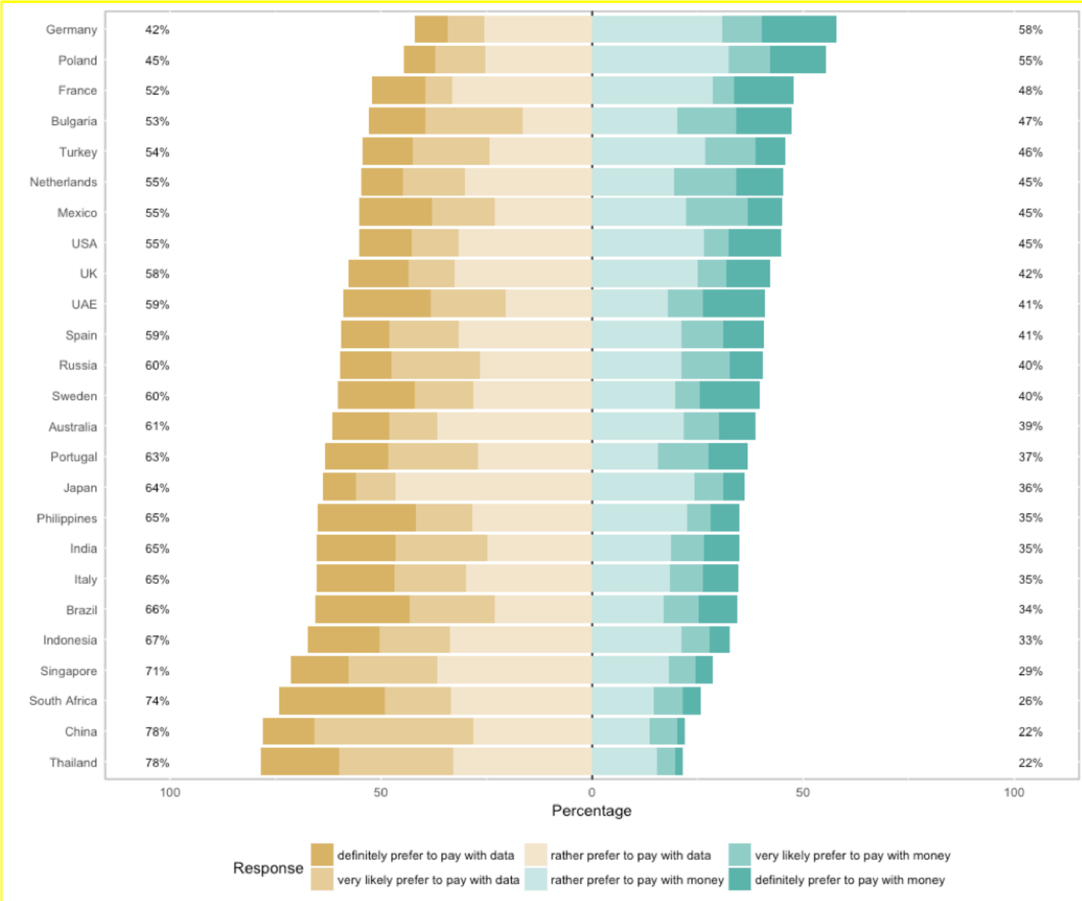


Figure 3. Likert Plot of Preference to Pay a Fee versus Pay with Data to Access Facebook.

Table 4 shows the results of modeling payment preference with consumer's fairness perceptions and the cultural values uncertainty avoidance and individualism. The baseline models without any explanatory variables are available in the Appendix Table W4. The baseline model results show a total variance of 2.087, and around 4% of the total variance is between-country variance. The model fit improves with the two-level structure (DIC_0 = 52,482.635; DIC_{00} = 51,979.233), thus supporting the use of a multilevel model. We then add the latent fairness scores and the cultural values uncertainty avoidance and individualism into the model, respectively (Model 1 and Model 2) and then jointly (Model 3). The model fit shows substantial improvements when fairness is added to the model (DIC_{00} = 51,979.233; DIC_1 = 50.835.780; DIC_3 = 50,835.494), suggesting that it is adequate to keep consumers' fairness perceptions in the model. The cultural variables contribute to a higher percent of explained between-country variance: 43.1% when added directly to the empty model (Model 00 to Model 2), and an increase from 2.2% to 22.9% when added to model with only fairness perceptions (Model 1 to Model 3).

Confirming H6, perceived fairness has a negative effect on preference for the fee-payment choice (β = -.241; 95% CI = [-.255, -.227]). This is in line with our prediction that for those who find SMPs' data monetization practices unfair, they should be more interested in alternative ways to access SMPs such as switching to fee-payment. The preference between paying a fee and paying with data also relates to the uncertainty avoidance value in a country (ψ = .004; 95% CI = [.000, .008]). In societies that are less tolerant towards uncertainties, people prefer the fee-payment choice, confirming H7. This is likely because the fee-payment choice imposes a fixed cost and eliminates the uncertainties that could arise from allowing personal data to be monetized. By contrast, consumers from cultures that are more comfortable with ambiguities and unstructured situations would be less prone to prefer such an offer (paying a fee). In the next models, we added various control variables at individual and country levels, including individual demographics and attitudes (Model 4) and country's economic development (Model 5). The findings remained the same as in Model 3 after adding these control variables into the model, thus attesting to the robustness of our findings.

Table 4. Structural Model: Payment Preference with Fixed Fairness Effect.

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
Intercept	3.13	***	2.54	**	2.79	**	2.67	***	2.55	**
Individual Level										
Perceived fairness of SMPs' data monetization practices	-.241	***			-.241	***	-.195	***	-.195	***
Residual variance	1.86	***	2.01	**	1.86	**	1.83	***	1.83	**
Country Level										
Perceived fairness of SMPs' data monetization practices (country mean)	-.024				.049		.070		.118	
Individualism			.006	**	.002		.001		.001	
Uncertainty avoidance			.005	**	.004	*	.004	*	.005	**
Residual variance	.047	***	.049	**	.041	**	.037	***	.036	**
Controls (Individual)										
Age							.004	***	.004	**
Male							-	***	-	**
Socioeconomic status							.088	***	.089	**
Education							-		.000	
Privacy concern							.070	***	.072	**
Trust towards Facebook							-	***	-	**
Attitude towards							-	***	-	**
Controls (Country)										
GDP per capita									.003	
Model Information										
DIC	50,835.780		51,977.85		50,835.49		50,631.640		50,630.72	
Variance explained at individual level	8.8%				8.8%		10.8%		10.8%	
Variance explained at country level	2.2%		43.1%		22.9%		25.6%		30.5%	
Sample size at individual level	14,686		14,686		14,686		14,686		14,686	
Sample size at country level	25		25		25		25		25	

***99% CI does not contain zero. **95% CI does not contain zero. *90% CI does not contain zero.

We further checked whether specifying a random slope for fairness would improve Model 5. Table 5 shows the model results. The model fit improved when the effect of fairness is specified as random (Model 6; DIC_5 = 50,630.725; DIC_6 = 50,563.284). The approximate effect size and effect direction remain the same as in the fixed effects model (ψ = -.200; 95% CI = [-.236, -.163] for fairness and ψ = .005; 95% CI = [.001, .009] for uncertainty avoidance). In Model 7, we included a dummy variable to indicate the UAE because we questioned whether the effect of fairness remains the same in the UAE as in the other countries. The result shows that while fairness has a negative effect in other countries (γ = -.208; 95% CI = [-.241, -.177]), it does not have any effect in the UAE (γ = .075; 95% CI = [-.089, .246]; see Figure W4 in the Appendix for marginal effects). It is likely that for individuals from the UAE, considerations other than fairness drive the decision to pay either with data or a fee.

A closer look at the socio-demographic covariates reveals the segment of consumers who prefer the fee-payment choice. Compared to younger consumers, older consumers more often prefer paying a fee instead of data (γ = .004; 95% CI = [.002, .005]). This is consistent with the finding that with age, consumers are more sensitive to potential risks (Hallahan, Faff, & McKenzie, 2004). Our results indicate that this increased risk sensitivity may also apply in the context of privacy on social media platforms. Consumers who self-indicated a higher value for socioeconomic status are more likely to prefer the fee-payment choice than those indicating a lower socioeconomic status (γ = .086; 95% CI = [.060, .111]). It is possible that consumers with a higher socioeconomic status have a larger amount of disposable income to accommodate an additional expense, as compared to consumers with a lower socioeconomic status. Another explanation for the increased preference for the fee-payment choice among high-status consumers is related to possibly more serious consequences for such consumers when their personal data is misused. Interestingly, women are more willing to pay a fee than men (γ = -.136; 95% CI = [-.181, -.091]), which could be related to men's higher tolerance for risk (Croson & Gneezy, 2009). Finally, payment preference is also associated with less trust towards the SMP platform (γ = -.072; 95% CI = [-.100, -.044]), less favorable attitude towards organizations' data use practices (γ = -.072; 95% CI = [-.101, -.044]), and high level of general privacy concerns (γ = .072; 95% CI = [.045, .098]).

Table 5. Structural Model: Payment Preference with Random Fairness Effect.

	Model 6		Model 7	
Intercept	2.52	***	2.52	***
Individual Level				
Residual variance	1.82	***	1.82	***
Country Level				
Perceived fairness of SMPs' data monetization	.136		.130	
Individualism	.001		.001	
Uncertainty avoidance	.005	**	.005	**
Fairness random effect				
Mean effect	-.200	***		
Effect in the UAE			.075	
Effect in other countries			-.208	***
Residual variance	.006	***	.004	***
UAE			.010	
Residual variance	.034	***	.036	***
Controls (Individual)				
Age	.003	***	.004	***
Male	-.137	***	-.136	***
Socioeconomic status	.086	***	.086	***
Education	-.001		.000	
Privacy concern	.070	***	.072	***
Trust towards Facebook	-.072	***	-.072	***
Attitude towards privacy practices	-.073	***	-.072	***
Controls (Country)				
GDP per capita (thousand USD)	.003		.003	
Model Information				
DIC	50,563.284		50,561.824	
Sample size at individual level	14,686		14,686	
Sample size at country level	25		25	

***99% CI does not contain zero. **95% CI does not contain zero. *90% CI does not contain zero.

GENERAL DISCUSSION

Responding to consumers' requests, public policies are increasingly demanding SMPs to ensure fair data monetization practices.[16] To the best of our knowledge, there has been no large-scale research identifying exactly what consumers perceive as fair when it comes to data monetization practices by social media platforms. The present study relies on a large-scale survey data collected across 25 countries to accomplish two main tasks: to identify what drives consumers' fairness perceptions of an SMP's data monetization practices, and to examine the appeal of the fee-payment choice as an alternative way to access SMPs in order to avoid what is perceived as unfair data monetization practices. We focus on Facebook in the present study because it is currently the most functionally diverse SMP with the highest number of consumers from all over the world.

We show that perceived fairness of data monetization on SMPs almost universally co-varies with violation of the norms of information flow. We also illustrate that people from individualist cultures tend to find SMPs' data monetization practices more unfair compared to people from collectivist cultures. Importantly, the empirical results of our study show that lack of fairness in data monetization practices stimulates consumers to engage in privacy-protecting behaviors, such as hiding or falsifying personal information. These findings imply that ensuring fair data monetization is not only demanded by legal regulations, but it is also in the best interest of SMPs and all businesses placing advertisements on SMPs.

We examined introducing a fee-payment choice as a potential solution to unfair data monetization practices, and we identified segments of consumers who would prefer paying a fee instead of paying with their data, which is the current practice on major SMPs. We show that the fee-payment choice is indeed more welcomed by consumers who find current data monetization practices unfair. Furthermore, we find that such choice is more likely preferred by older consumers, females, consumers with high self-reported socioeconomic status, those with stronger privacy concerns, have less trust towards the SMP platform and less favorable attitudes towards organizations' data monetization practices in general. Moreover, we show that this alternative is most welcome in cultures that are high on uncertainly avoidance. SMPs can estimate potential boundaries of profitability of introducing a fee and design promotional campaigns based on our findings.

Theoretical Contribution

Our study takes a new aspect of focus to tackle privacy issues on social media and initiates considerations towards a balanced approach in ensuring fair data use. We show the central role fairness in consumers' reaction to social media data monetization practices: consumers evaluate data monetization practices in terms of how fair they are, and these fairness perceptions are important predictors of consumers' future actions on social media. Therefore, we propose a fairness-centered perspective to study data privacy on social media. Fairness by definition aims to maintain a balance, and we further move towards the goal to balance between two currently conflicting interests with a question about preference between paying a fee versus data. The preference provides a realistic assessment of consumers desire to avoid current data monetization practices even at the cost of money. More importantly, it moves away from only imposing restrictions on social media's data monetization and subsequently limiting their profitability in order to ensure fairness. Instead, the preference implies that consumers also have to contribute towards social media's profit goal, if they want social media to fulfill their desire for fair use of personal data. This requirement, that both sides have to contribute towards the counterpart's need, initiates considerations towards a balanced approach to ensure fair data use on social media platforms.

We expand current knowledge about perceived fairness of SMP data monetization practices by illustrating the culturally almost universal link between norms of information flow (Nissenbaum, 2004) and consumers' fairness perceptions. Confirming earlier findings, our data suggest that offline norms of information flow (keeping information within the intended audience and the intended context), can be transferred to the online environment (Kim, Barasz, & John, 2019). Importantly, perceptions of fairness based on normative expectations are universal: consumers find it more unfair when SMPs monetize personal data that were not originally meant for public audience (e.g., private data from personal messages) or data that were not intended for the context of SMPs in the first place (e.g., data obtained from websites other than the focal SMP). Our study shows that this connection between fairness and information flow norms holds consistently for the majority of the countries surveyed, with the exception of Japan, where people find SMPs' use of private data less unfair compared to people from other countries.

Furthermore, we illustrate how unfair data practices can relate to quality reduction in data obtained through social media. Our data reveal that consumers who find data monetization practices unfair are more likely to engage in privacy-protecting behaviors, which compromise the trustworthiness of data from SMPs. These findings imply that researchers should control for consumers' fairness perceptions of data monetization practices on specific SMPs when using SMP data to generate customer or brand insights.

Finally, the cross-cultural nature of our study allows us to contribute to the understanding of the role of cultural values in consumers' evaluation and response to SMPs' data monetization practices. Consumers are more sensitive about their personal data in individualist cultures, and this results in lower perceived fairness about SMPs' data monetization practices. Moreover, cultures characterized as high on uncertainty avoidance are more likely to prefer the fee-payment choice than allowing SMPs to monetize personal data. These findings emphasize that cultural values are still influential even in global "boundary-free" environments as SMPs.

Managerial Implications

The patterns we found in consumers' perceptions can be useful for SMP managers. They can adapt the data policies and business models to involve data monetization practices only in forms that consumers would consider fair. SMP managers can also leverage this knowledge in their communication strategy to the consumers in order to provide transparency about data practices in a favorable manner. For instance, SMPs can communicate to consumers that neither their personal messages nor their behaviors in other websites are used for commercial purposes. Due to the emphasis on not violating norms, this communication strategy can increase consumers' perceived fairness of SMPs' data monetization practices and contribute to building sustainable relationships with consumers in the long term. Given that consumers can switch among SMPs, providing fair data monetization practices can be a competitive advantage especially for more niche SMPs or newly emerging ones.

Importantly, our findings have implications not only for SMPs themselves but for policy makers and all businesses using SMP data. Our findings provide policy makers with guidelines to regulate how organizations should use consumer data and inform consumers about the data practices. For instance, policy makers can ask organizations to report to consumers about how their data practices deviate from typical information flow norms. Compared to a fully-detailed data policy, this report requires much less cognitive effort for an average consumer to process and still covers the essential information that interests consumers. As for businesses that advertise through SMPs, they can benefit from emphasizing that their ads are only based on information that consumers provide publicly on the SMP. In this way, firms build a reputation associated with fair data use, which in turn, facilitates trust in the firm and willingness to share additional data with the firm itself (data that consumers might not want to share with SMPs directly).

Furthermore, managers of businesses working with SMP data should be aware that the current business model of SMPs results in some degree of bias in the data. After all, some consumers might avoid sharing specific information through SMPs or misrepresent information to protect their privacy. Such privacy-protecting behaviors might lead to incorrect inferences based on SMP data or less effective marketing interventions (for instance, targeted ads). This issue is likely to become increasingly prominent as more and more consumers become aware of the nature of the business model behind SMPs. Therefore, in the long run, both SMPs and firms relying on SMP data should aim to reduce such behavior by implementing fair data use practices.

Finally, apart from illustrating that the current SMP data monetization business model has externalities for all parties, we also examine a potential solution for the conflicting needs between fair data use practices and corporate profit pursuit: offering consumers the choice of paying a fee instead of paying with personal data for accessing SMPs. This choice allows SMPs to make a profit while protecting consumer data privacy. Our results indicate that a sizable segment of consumers prefer the fee-payment choice, especially consumers who find the current data monetization practices of SMPs unfair. This result supports the idea of introducing the fee-payment choice as a mean of avoiding unfair data monetization practices. However, not all consumers and not all cultures would be equally receptive to the fee-payment choice. Our study provides guidelines that firms can use to estimate the size of potentially profitable consumer segment. As shown by our findings, the target consumer segment for a fee-payment choice are those older in age, female, of higher socioeconomic status (self-reported), with less trust towards the SMP platform, with less favorable attitudes towards organizations' data monetization practices, and with generally stronger privacy concerns. Our findings also suggest that introducing the fee-payment choice would be particularly rewarding in countries high in uncertainty avoidance due to the stronger preference for this choice.

Limitations and Future Research

Our results open up several possibilities for future research. Our study assumed that individuals trust that their personal data are protected when they choose the fee-payment choice. In reality, consumers may have some doubts about whether their data will be fully protected when they choose this choice. The degree of trust from consumers likely depends on the source of privacy protection guarantee, e.g., whether it is the privacy statement of the firm providing the service, a government regulation, or an independent party's certification. One direction of future research is to establish how such sources affect trust.

Likewise, when individuals choose the fee-payment choice there may also be concerns about disclosure of additional information, such as credit card number, in the payment process. One solution is to use a blockchain payment system. Future research can examine whether the adoption of fee-payment choice and consumers' privacy concerns change when blockchain payment is available.

In addition, the fee-payment choice may have a "reminder effect" that triggers privacy concerns among those who prefer to continue paying with data. Therefore, we recommend to choose where and to whom to introduce the fee-payment choice with care. Future research can examine simultaneously the positive and negative effects of a pay-payment choice.

Furthermore, besides preserving fairness, there are also other motivations for people to choose to pay a fee for otherwise "free" services. For example, mobile applications with interstitial ads require consumers to pay with their attention. In this case, the fee-payment choice removes unwanted ads and thus one avoids distractions. Future research can examine and compare the different motivations for consumers to switch to a fee-payment model.

Lastly, in the current study we restricted our attention to the largest SMP, Facebook, because it accounts for one fifth of the global online advertising revenue and is already involved in multiple privacy controversies.[17,18] Nevertheless, the need for fair data monetization practice is not limited only to Facebook nor only to SMPs. It is relevant to all businesses involving consumer data. Online shopping platforms and search engines are two more examples of such business where consumers may evaluate and respond differently to the data monetization practices than on SMPs. Therefore, future research is required to validate our findings in other contexts and explore the boundaries of these findings.

To conclude, the current study expanded our understanding of how consumers evaluate the fairness of data monetization practices on social media platforms, and it examined the appeal of the choice to pay a fee instead of data to use the services of SMPs. Martin, Borah, and Palmatier (2017) identified transparency and control to be the two key factors for proper management of customer data, and our study extends on these two factors. Our findings suggest how to leverage the knowledge about consumers' fairness perceptions and information flow norms to increase transparency in a favorable direction. In the meantime, providing additionally a fee-payment choice gives consumers more control of their personal data, and our results identify the target group for such a choice. With this extended knowledge, we expect to contribute to the progress towards a reconciliation of the current conflict on SMPs between consumers' request for fair data use practices and the corporate profit pursuit.

APPENDIX

Table W1. Papers Examining Cultural Effects on Data Privacy.

Response Variable	Paper	PDI	IDV	MAS	UAI
Privacy concern	Lowry et al. (2011)	-	-	n.s.	+
Privacy concern	Milberg et al. (2000)	+	+	+	-
Privacy concern	Bellman et al. (2004)	n.s.	-	n.s.	n.s.
Privacy concern	Bellman et al. (2004)	-	n.s.	-	n.s.
Privacy concern	Bellman et al. (2004)	n.s.	n.s.	-	n.s.
Privacy concern	Milberg et al. (1995)	n.s.	n.s.		n.s.
Privacy concern	Dinev et al. (2006a)		+		
Privacy concern	Dinev et al. (2006b)		+		
Institutional trust	Dinev et al. (2006b)		+		
Perceived risk	Dinev et al. (2006b)				+
Privacy regulation	Milberg et al. (1995)	+	-		+
Privacy regulation	Cockcroft and	+			-
Desire for more	Bellman et al. (2004)	-	n.s.	n.s.	n.s.
Self-disclosure	Miltgen et al. (2014)		-		
Self-disclosure	Posey et al. (2010) [b]		-		

A selection of relevant literature findings on the effect of cultural values on various data privacy-related response variables. a Used Globe variable; b collectivism increases disclosure, while individualism has no effect; Long-term orientation and indulgence are not studied.
PDI = power distance index; IDV = individualism; MAS = masculinity; UAI = uncertainty avoidance index.

Table W2. Sample Size per Country.

Country	**Number of Responses**		
	Requested	**Completed Survey (sample collected)**	**Passed Attention**
Australia	500	500	498
Brazil	700	700	698
Bulgaria	500	500	498
China	700	700	697
France	600	600	594
Germany	600	600	594
India	700	699	682
Indonesia	700	700	686
Italy	600	601	600
Japan	600	600	598
Mexico	600	601	593
Netherlands	500	514	509
Philippines	600	600	590
Poland	600	601	595
Portugal	500	500	498
Russia	600	600	597
Singapore	500	500	489
South Africa	600	600	599
Spain	600	599	595
Sweden	500	500	496
Thailand	600	600	587
Turkey	600	600	598
UAE	500	510	502
UK	600	600	597
United States	700	700	696
Total	**14,800**	**14,825**	**14,686**

Table W3. Reliability and Pooled Correlations of Individual Difference Variables.

	CA	**a**	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**
Perceived fairness of SMPs' data monetization practices (a)	-									
Payment preference (b)	-	-.30								
Privacy-protecting behavior (c)	-	-.27	.07							
Age (d)	-	-.24	.11	.12						
Male (e)	-	.09	-.06	-.06	.04					
Socioeconomic status (f)	.84	.13	.01	.03	.01	.05				
Education (g)	-	.12	-.04	-.04	-.21	.03	.13			
Privacy concern (h)	.92	-.11	.07	.33	.05	-.06	-.05	.05		
Trust towards Facebook (i)	-	.52	-.22	-.20	-.20	.00	.11	.10	-.07	
Attitude towards privacy practices (j)	.88	.49	-.21	-.12	-.17	.00	.18	.07	-.07	.65

CA = Cronbach's alpha, calculated for reflective constructs only.

Table W4. Structural Model: Payment Preference Baseline Models

	Model 0		Model 00	
Intercept	3.179	***	3.186	***
Individual Level				
Residual variance	2.087	***	2.013	***
Country Level				
Residual variance			.084	***
Model Information				
Deviance information criterion	52,482.635		51,979.233	
Sample size at individual level	14,686		14,686	
Sample size at country level			25	

Table W5. Structural Model: Privacy-Protecting Behavior Baseline Models

	Model 0		Model 00	
Intercept	1.684	***	1.698	***
Individual Level				
Residual variance	2.476	***	2.342	***
Country Level				
Residual variance			.169	***
Model Information				
Deviance information criterion	33,712.022		33,234.968	
Sample size at individual level	9,003		9,003	
Sample size at country level			25	

Table W6. Structural Model: Payment Preference with Random Fairness Effects.

	Model 1		**Model 2**		**Model 3**	
Intercept	3.121	***	2.730	***	2.594	***
Individual Level						
Residual variance	1.851	***	1.850	***	1.825	***
Country Level						
Perceived fairness of SMPs' data monetization practices (country mean)	-.022		.071		.089	
Individualism			.003		.002	
Uncertainty avoidance			.004	*	.004	**
Fairness random effect						
Mean effect	-.245	***	-.245	***	-.200	***
Variance	.007	***	.007	***	.006	***
Residual variance	.046	***	.039	***	.034	***
Controls at Individual Level						
Age					.004	***
Male					-.136	***
Socioeconomic status					.087	***
Education					.001	
Privacy concern					.071	***
Trust towards Facebook					-.072	***
Attitude towards privacy practices					-.072	***
Model Information						
Deviance information criterion	50,760.757		50,759.126		50,564.486	
Sample size at individual level	14,686		14,686		14,686	
Sample size at country level	25		25		25	

(continuation of Table W6)

	Model 4		Model 5		Model 6	
Intercept	3.117	***	2.729	***	2.620	***
Individual Level						
Residual variance	1.850	***	1.850	***	1.825	***
Country Level						
Perceived fairness of SMPs' data monetization practices (country mean)	-.025		.068		.084	
Individualism			.003		.002	
Uncertainty avoidance			.004	*	.004	*
Fairness random effect						
Effect in the UAE	.021		.021		.076	
Effect in other countries	-.254	***	-.254	***	-.208	***
Variance	.005	***	.005	***	.004	***
UAE	.069		.004		.098	
Residual variance	.048	***	.041	***	.035	***
Controls at Individual Level						
Age					.004	***
Male					-.137	***
Socioeconomic status					.086	***
Education					-.001	
Privacy concern					.071	***
Trust towards Facebook					-.073	***
Attitude towards privacy practices					-.073	***
Model Information						
Deviance information criterion	50,757.135		50,758.284		50,561.733	
Sample size at individual level	14,686		14,686		14,686	
Sample size at country level	25		25		25	

Figure W1. Smoothed Histogram of Fairness Threshold 1 (Unfairness)

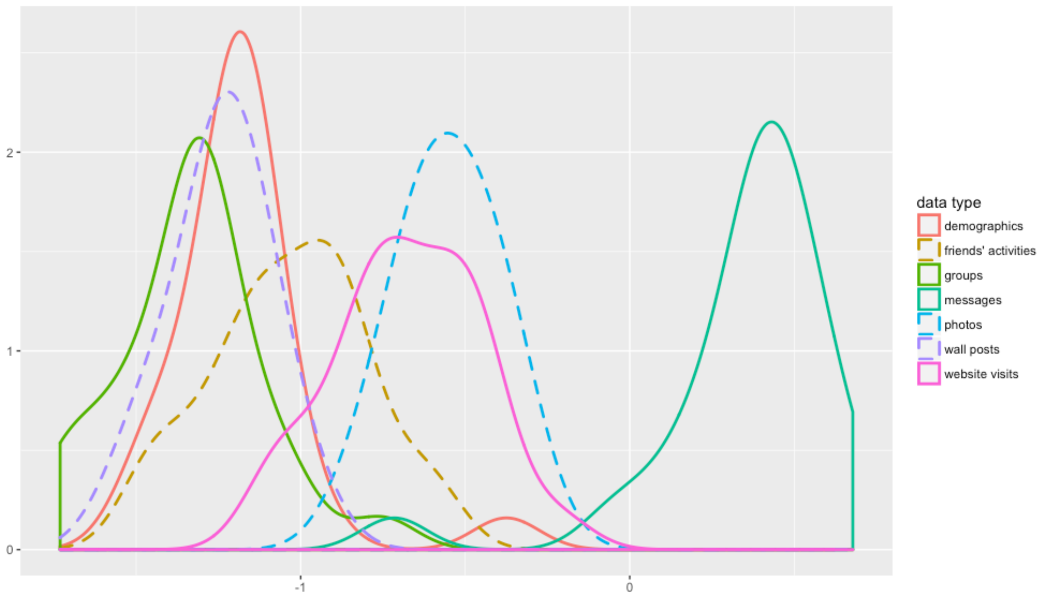
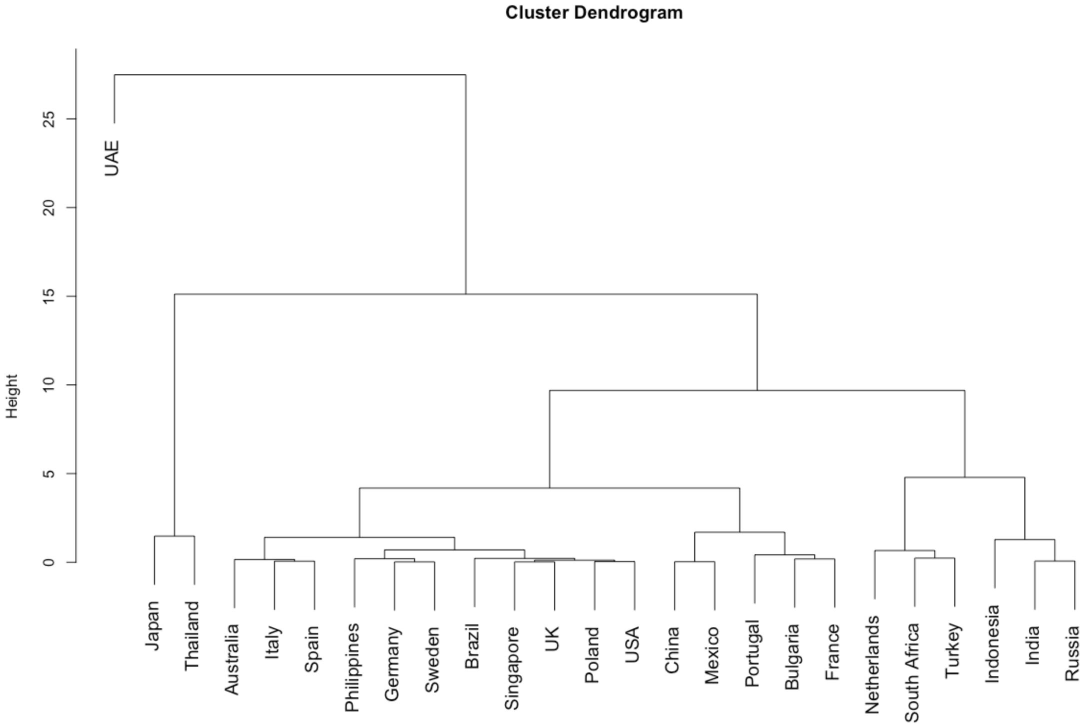


Figure W2. Hierarchical Clustering of Per-country Effects of Information Flow Norms on Fairness Threshold 1 (Unfairness)



We ran per country a model where we regressed fairness threshold 1 on the item predictors and clustered the resulting regression coefficient estimates using Wald's method. The result shows the United Arab Emirates (UAE) as a separate cluster from the rest of the countries.

Figure W3. Mean Latent Fairness Score Per Country versus Cultural Values (Individualism and Uncertainty Avoidance)

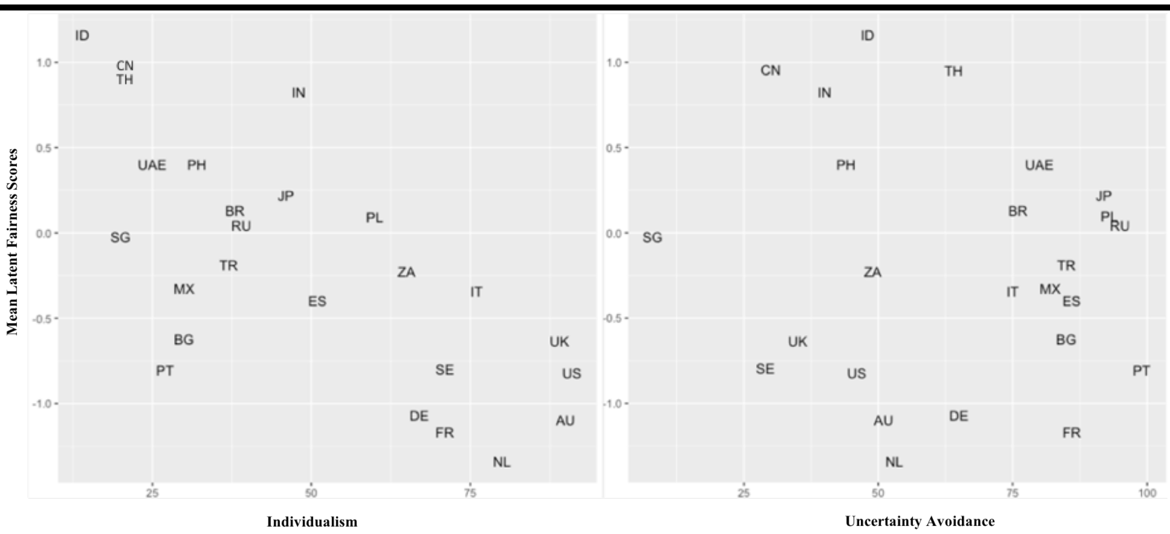


Figure W4. Marginal Plot of the Effect of Fairness on Payment Preference

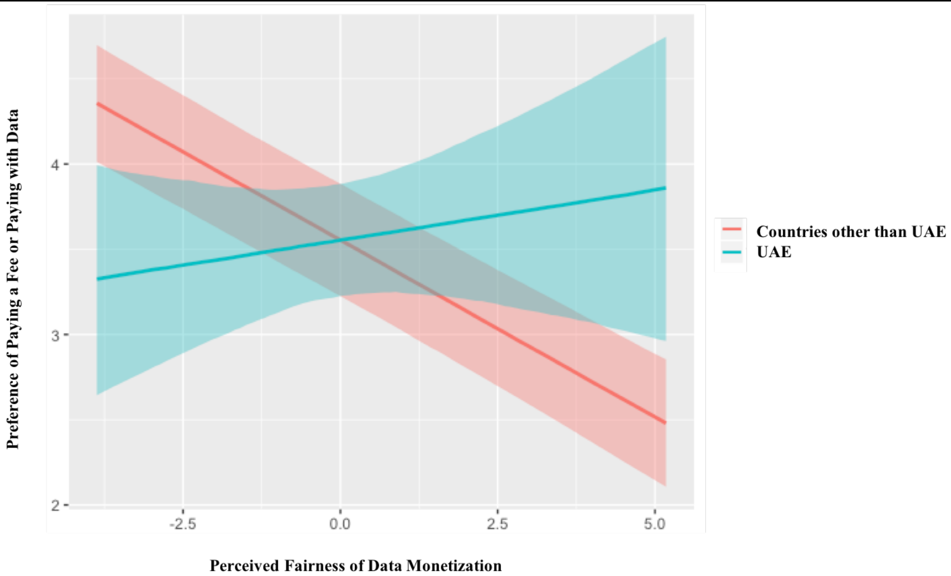
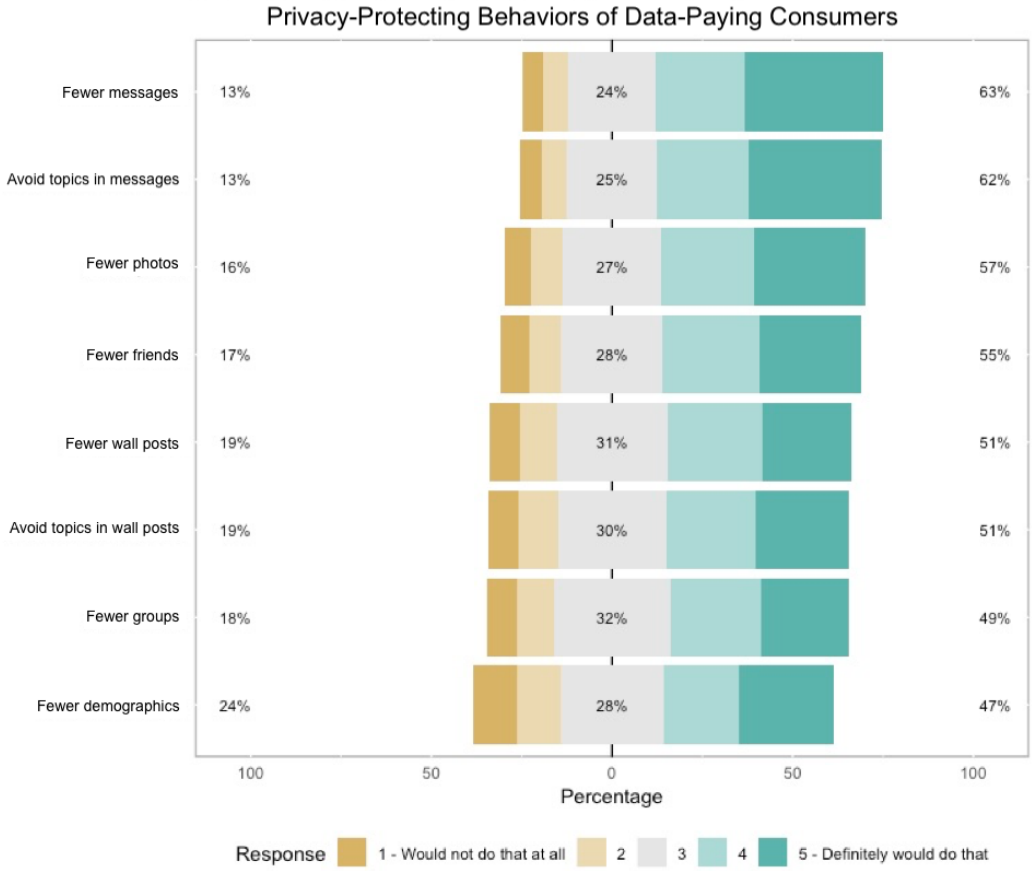


Figure W5. Likert Plot of Privacy-Protecting Behaviors.



The survey measures

Facebook offers you the possibility to stay in touch with your friends, exchange messages, post status updates, photos and videos. Furthermore, you may join common-interest user groups organized by, for instance, workplace or school.

In order to offer you all of these services for free, Facebook uses your data for commercial purposes (e.g., serving you advertisements tailored to your interests, selling data-based insights to companies). By data, we mean: your status updates, demographic information, activities of your friends, private messages, photos, etc.

Fairness

Facebook can potentially analyze all the data that were collected when using the platform, such as: status updates, demographic information, activities of your friends, other websites you visited while Facebook was open in the browser, your private messages, photos, etc.

Please indicate to what extent you consider it fair that Facebook tracks and uses the following information about you for commercial purposes.

	1 – Not at all fair	2	3	4	5 – Completely fair
Your demographic information (age, gender, education, profession, city, etc.)	☐	☐	☐	☐	☐
Text in your public posts (status updates and posts on your or someone's timeline)	☐	☐	☐	☐	☐
Your photos	☐	☐	☐	☐	☐
Your private messages	☐	☐	☐	☐	☐
Your group memberships	☐	☐	☐	☐	☐
Activities of your friends	☐	☐	☐	☐	☐
Other websites you visited while you are logged into Facebook	☐	☐	☐	☐	☐

Payment preference

To ensure that you can continue to use Facebook, there are two possibilities:

1) Facebook could charge you a monthly fee for use of its services. If you pay a monthly fee, Facebook would not collect and use your data for any commercial purposes.

2) You could pay with your "data", which means that you consent to Facebook collecting, analyzing and using your data for commercial purposes.

We would like to know your preference for the two options (please note, this is a purely hypothetical situation, and we are not collaborating with Facebook in any way). Please indicate it below.

To ensure that I can continue to use Facebook, I would...

- ☐ 1 – definitely prefer to pay with data
- ☐ 2 – very likely prefer to pay with data
- ☐ 3 – rather prefer to pay with data
- ☐ 4 – rather prefer to pay with money
- ☐ 5 – very likely prefer to pay with money
- ☐ 6 – definitely prefer to pay with money

Privacy-protecting behaviors

The next questions are about your future behavior. If you know that Facebook would track and analyze all your data, would anything change in your online behavior? Please, indicate to what extent you think you would change the following behaviors.

	1 - Would not do that at all	2	3	4	5 - Definitely would do that
I would delete specific demographic information from my profile (e.g., workplace, education, relationship status, date of birth, etc.)	☐	☐	☐	☐	☐
I would post fewer status updates and posts on someone's timeline	☐	☐	☐	☐	☐
I would no longer post status updates about some topics	☐	☐	☐	☐	☐
I would post fewer photos	☐	☐	☐	☐	☐
I would reduce the number of private messages	☐	☐	☐	☐	☐
I would stop discussing some topics in my private messages	☐	☐	☐	☐	☐
I would manage my group memberships (e.g., not joining some groups, and leaving some of my current groups)	☐	☐	☐	☐	☐
I would be more selective about friends (e.g., deleting some of my current friends and/or being more careful when adding friends)	☐	☐	☐	☐	☐

Socioeconomic status

Please select the option next to each statement that best indicates the extent to which you agree or disagree with that statement.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I have enough money to buy things I want.	☐	☐	☐	☐	☐
I don't need to worry too much about paying my bills.	☐	☐	☐	☐	☐
I don't think I'll have to worry about money too much in the future.	☐	☐	☐	☐	☐

Privacy concern

Please select the option next to each statement that best indicates the extent to which you agree or disagree with that statement.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
In general, I am concerned about my privacy when using the Internet.	☐	☐	☐	☐	☐
I am concerned that information I submit on the Internet could be misused.	☐	☐	☐	☐	☐
I am concerned about submitting information on the Internet, because they could be used in a way that I cannot foresee.	☐	☐	☐	☐	☐

Attitude

Please select the option next to each statement that best indicates the extent to which you agree or disagree with that statement.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I have confidence in the way businesses and the law handle private information.	☐	☐	☐	☐	☐
Existing laws and organizational practices provide a reasonable level of protection for consumer privacy today.	☐	☐	☐	☐	☐

<u>Trust</u>

Please select the option next to each statement that best indicates the extent to which you agree or disagree with that statement.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I trust Facebook.	☐	☐	☐	☐	☐

Chapter 4

Multilevel Item Randomized Response Models for Large-Scale Cross-Cultural Consumer Research on Sensitive Topics

Marketers and policy makers are increasingly interested in studying consumer behavior across cultures using individual-level data, which requires suitable methods. Various research streams have contributed to the development of such methods (for instance, Baumgartner & Steenkamp, 2001; De Jong et al., 2008; Steenkamp & Geyskens, 2006). Those methods accommodate the hierarchical structure of cross-cultural data, with consumers nested in countries, and enable generalizable inferences on consumer behavior across a large number of countries. Unfortunately, the current methods are limited when researching sensitive consumer behavior, such as fake product failure reports, fake reviews, or deceptive disclosures about consumption (Anderson & Simester, 2014; De Langhe, Fernbach & Lichtenstein, 2015).

Obtaining self-report data about sensitive consumer behavior is not trivial, because consumers might be reluctant to admit sensitive behavior and engage in socially desirable responding (Weinhardt et al., 1998). Moreover, the degree of socially desirable responding can vary systematically across countries (De Jong, Pieters, & Stremersch, 2012). Therefore, methods that rely on direct questioning are not suitable for studying sensitive consumer behavior across cultures, and might produce severely biased results.

Significant effort has been invested into developing techniques that simultaneously account for consumers' heterogeneity and protect consumers' privacy. One approach to dealing with social desirability bias is the randomized response technique (RRT; Warner, 1965). This technique has been further developed into item randomized response theory

(IRRT; Bockenholt & van der Heijden, 2007; de Jong, Pieters, & Fox, 2010; Fox, 2005). Application of the IRRT can reduce both overreporting and underreporting by consumers, which makes it attractive for a range of applications dealing with sensitive behaviors. In order to account for the hierarchical structure of cross-cultural data, the technique was further extended into multigroup item randomized response theory (MIRRT; de Jong et al, 2012). However, within the MIRRT framework, a researcher must assume that both the dependent variable and the predictors exhibit adequate cross-cultural measurement invariance (Steenkamp &Baumgartner, 1998). Measurement invariance refers to "whether or not, under different conditions of observing and studying phenomena, measurement operations yield measures of the same attribute" (Horn & McArdle, 1992, p. 117). In practice, measurement invariance implies that measures of self-reported behaviors such as providing fake product reviews or, the context of the present study, lying on social media platforms, should have the same meaning across countries.

The assumption of measurement invariance is not easy to meet or to test for, especially in studies with a large number of countries (De Jong, Steenkamp, & Fox, 2007). Without measurement invariance, the currently available models break down or need to resort to heuristic approaches to address the issue and proceed (Muthen & Asparouhov, 2018). There is currently no model that allows researchers to relax the assumption of measurement invariance in the self-reported outcomes and predictors when dealing with sensitive questions across cultures. Here, we propose a novel multilevel item randomized response model to overcome this challenge, by allowing random item parameters for the outcome variables and for the (latent) predictors in the measurement models.

We apply the model in an empirical cross-cultural study on deceptive self-presentation on social media (DCSM). The topic is increasingly relevant as the number of social media users has been steadily increasing, currently reaching over 3,800,000,000 users[5]. These users share their consumption experiences on various social media platforms (SMPs) and these data increasingly inform marketing strategy (Chevalier & Mayzlin, 2006; Netzer et al., 2012; Schweidel & Moe, 2014; Tirunillai & Tellis, 2012; 2014). The validity of such shared experiences on SMPs is therefore of paramount importance, and to the extent that these are deceptive marketing strategy may be grossly misguided. We are the first to provide a systematic large-scale empirical analysis of the extent to which deceptive consumption disclosures on social media (DCSM) occur, and of personal and country characteristics that can lead to an increase or decrease in such behaviors.

Our analysis reveals that a substantial number of participants engage in deceptive consumption disclosures, and that the prevalence of such behavior varies predictably across countries. Materialistic values have a strong positive effect on DCSM, and so does the tendency for social comparisons on one's ability. Past perceived resource availability also positively affect DCSM. Finally, the norms of the national, cultural environment account for variance in DCSM over and above the individual characteristics of people in countries. Individuals in more traditional and in survival-oriented societies engage in DCSM more.

The rest of the article is structured as follows. First, we discuss existing models for cross-cultural data and show how our model complements existing methods. Then, we present the cross-cultural application of the model, assessing deceptive consumption disclosures on social media platforms across 24 countries and antecedents of such behavior. We conclude with a general discussion.

[5] https://datareportal.com/social-media-users Last retrieved: May, 2020.

Multilevel models for cross-cultural research

Cross-cultural research often relies on multilevel regression models (De Jong & Steenkamp, 2010; Matsumoto & Yoo, 2006; Steenkamp, Ter Hofstede & Wedel, 1999; Van de Vijver, van Hemert & Poortinga, 2015). These models accommodate the hierarchical structure of cross-cultural data, in which respondents are nested within countries (Snijders & Bosker, 2012). Ignoring the nested structure of the data will lead to biased estimates and to standard errors that are too small (Aitkin, Anderson & Hinde, 1981, Raudenbush & Bryk, 2002). A general multilevel model suitable for cross-cultural research, with individuals and countries indexed by *i* and *j*, respectively, can be specified as:

$$\Theta_{ij} = \beta_{0j} + \beta_{1j}\xi_{ij1} + \cdots + \beta_{sj}\xi_{ijs} + \delta_1 W_{ij1} + \cdots \delta_T W_{ijT} + \varepsilon_{ij} \quad (1)$$

$$(\beta_{0j}, \ldots, \beta_{Sj}) \sim MVN\ (V_j\gamma, T) \quad (2)$$

$$\varepsilon_{ij} \sim N\ (0, \sigma^2) \quad (3)$$

In this model, the dependent variable for *i* in country *j* is Θ_{ij} . The intercept β_{0j} and the slopes β_{sj} of the latent predictors ξ_{ijs} are country-specific and follow a multivariate normal distribution. The vector $V_{j\gamma}$ contains country-level variables, such as cultural variables or country-level economic and demographic indicators. Furthermore, the model assumes that there are several control variables W_{ijt}, t-1,…,T measured without error. The effect δ_t of the control variable W_{ijt} is fixed across countries.

MEASUREMENT MODELS

Equation (1) assumes that the dependent variable Θ_{ij} and the predictors ξ_{ijs} are measured without error. For data collected via surveys, this assumption is not realistic. Various types of measurement error models have been proposed. Early work in marketing relied on approaches based on classical test theory (CTT) which assumes continuous, normally distributed data (Baumgartner & Homburg, 1996; Churchill, 1979; Gerbing & Anderson, 1988; Steenkamp & Van Trijp, 1991). In recent years, item response theory (IRT), which offers a number of theoretical advantages over CTT, has gained ground. A key advantage is that IRT models can more easily handle various data types, such as binary and polytomous data and mixes of those.

In this paper, we assume without loss of generality that the outcome ("dependent") variable theta is the underlying "latent" variable, linked to a set of binary items (1=yes, 0=no) with a probit link function – see equation (4). The predictors are measured with polytomous items such as on a 5-point Likert scale. The latent predictors are assumed to have a normal distribution – see equation (6) (De Jong et al., 2007). For the latent predictors we specify a measurement model generalized for *C* ordered response categories. The subscript *s* specifies that the parameter is of the measurement model for latent predictors and not for the dependent variable. $\Pr(Y_{ijk} = 1)$ is the observed probability of the response being "yes" to item *k* for respondent *i* in country *j*. $Pr(X_{ijsk} = c)$ is the probability of respondent *i* in country *j* choosing response category *c* (c = 1,2,…, C), for item *k.* This probability is equal to the person's probability of responding above c – 1, minus the probability of responding above *c*. Then, the IRT measurement models are specified in equations (4) and (5).

$$P(Y_{ijk} = 1) = \Phi(a_{kj}(\Theta_{ij} - b_{kj})),\ k = 1, \dots, K \quad (4)$$

$$P(X_{ijsk} = c) = \Phi(a_{kjs}(\xi_{ijs} - \gamma_{kjs,c-1})) - \Phi(a_{kjs}(\xi_{ijs} - \gamma_{kjs,c})), k = 1, \dots, K_s \quad (5)$$

$$\xi_{ijs} \sim N\ (\overline{\xi_{js}}, \sigma^2_{\xi s}) \quad (6)$$

The parameter a_{kj} is the discrimination parameter, and is conceptually similar to a factor loading. It indicates how well an item discriminates between respondents high and low on the latent trait Θ_{ij}. The difficulty parameter b_{kj} is measured on the same scale as the latent trait, and indicates how likely it is that item k in country j will elicit an affirmative response on item k for the dependent variable. Items with a low value for b_{kj} (low difficulty) have a higher probability of eliciting an affirmative response than items with a high value for b_{kj}.

The measurement model for the predictors is a bit more involved. The thresholds contained in the vector $\boldsymbol{\gamma}_{kjs}$ are measured on the same scale as ξ_{ijs}, and determine the difficulty of responding above a certain response category c. The threshold γ_{kjsc} is defined as the value on the ξ_{ijs} scale so that the probability of responding above a value c is .5. The difficulty parameters γ_{kjsc} are, thus, subject to restriction $\gamma_{kjs1} \leq \gamma_{kjs2} \leq \ldots \leq \gamma_{kjsc}$. For a more extensive discussion, see De Jong, Steenkamp & Fox (2007).

Data collection methodologies for sensitive consumer behavior

Researchers have developed several methods to measure sensitive consumer behavior. Direct questions about sensitive behavior tend to produce socially desirable responding (SDR), which threaten construct validity. Therefore, most methods dealing with sensitive items aim to protect respondents' privacy and provide a safe environment for honest responses to sensitive items (De Jong et al., 2012). Many of those methods (such as bogus pipeline, or multi-item SDR scales) are hard and costly to implement in cross-cultural settings and with unknown effectiveness[6]. There are, however, two approaches to assessing sensitive behavior, which deserve particular attention, as they elicit relatively unbiased results and can be used across cultures. These two truth-telling mechanisms are the Item

[6] *Bogus pipeline technique uses a fake lie detector, thus, requires bringing all participants to the lab (Roese & Jamieson, 1993). Separate multi-item scales assessing SDR (Paulhus, 2002) significantly increase the length of the survey and might not function in the same way across cultures.*

Count Technique and Randomized Response Technique, both using indirect self-report techniques.

Item Count Technique (ICT), also known as list experiment, is a method which incorporates respondents' privacy protection in its design. It typically uses a control-treatment group design to which respondents are randomly assigned. Respondents in the control group received a list of items and only need to indicate how many of these items are true for them. Respondents in the treatment group receive the same task, but their list of items includes one additional item: the sensitive, target item. The mean difference between the groups represents the prevalence of behavior for the target item. The method was recently developed into Item Count Response Technique (ICRT; De Jong & Pieters, 2019). ICRT relaxes some of the ICT assumptions and allows estimating prevalence of sensitive behavior on the individual level.

Randomized Response Technique (RRT; Warner, 1965) is also a method that incorporates privacy protection in its design, yet in a different way than ICT. In the RRT design the respondent's answer is determined by a randomization device (typically a coin, a dice, or a spinner). Depending on the outcome of the randomization device, the respondent is asked to provide either a truthful answer or a forced answer. The outcome of the randomization device is only known to the participant, and not to the researcher. In this way participant's privacy is protected, but the randomness in answers can be incorporated in the data analysis. This allows inferring individual-level latent score for the sensitive behavior, but not the individual's response to the specific sensitive item. Although RRT methods have known issues due to the complexity of instructions and procedural non-adherence (John et al., 2018), there are ways to mitigate these. Unlike ICT, RRT does not require developing an additional item list. Therefore, it can be easily applied to multi-item scales (Churchill, 1979), and has been applied in cross-cultural context before (De Jong et al., 2012). Thus, this paper focuses on the randomized response mechanism to assess sensitive behavior.

The forced response method is one of the most efficient randomized-response designs and is easily implemented. It involves the parameters p_1 and p_2 that are set by the researcher. The parameter p_1 is the probability of having to provide a truthful response. Thus, with probability p_1, the respondent has to answer truthfully, and with probability 1-p_1 a forced response has to be given. The parameter p_2 is the probability that a forced "yes" has to be chosen, irrespective of the true response. For binary items, researchers often specify that p_2=1. Furthermore, these probabilities can be individual specific. Thus, the randomized response technique is accommodated by modifying equation (4) as follows:

$$Pr\ (Y_{ijk} = 1)\ = p_{1ij}\pi_{ijk}\ + \left(1 - p_{1ij}\right)p_{2ij} \tag{7}$$

$$\pi_{ijk} = \Phi(a_{kj}(\Theta_{ij} -\ b_{kj})) \tag{8}$$

Equations (7) and (8) specify that with probability p_{1ij} respondent i in country j has to give a truthful answer, while with probability 1-$p_{1\mathrm{ij}}$, respondent i in country has to give a forced response (i.e., "yes"). Probability π_{ijk} is then the true probability of answer "yes" for item k.

Measurement invariance

In order to conduct meaningful international and more generally, between-group, comparisons, it is necessary to have a certain degree of measurement invariance (MI; Steenkamp & Baumgartner, 1998). Full measurement invariance holds when all parameters in the measurement model are invariant across all countries. MI implies for equations (4) and (8):

$$a_{kj}=a_k\,,\ b_{kj}=b_k$$

$$a_{kjs}=a_{ks},\ \gamma_{kjs}=\gamma_{ks}$$

Even with a small number of countries (groups), the full MI assumption can be hard to meet. In that case, researchers try to establish partial MI, which holds either when the measure is invariant for a subset of countries, or when a subset of parameters for some items – called anchor items – is invariant across all countries (Vandenberg & Lance, 2000). That is, partial measurement invariance in equations (4) and (8) implies:

$a_{kj}=a_k$, $b_{kj}=b_k$ for anchor item k, $a_{kj}=a_{kj}$, $b_{kj}=b_{kj}$ for non-anchor items, and

$a_{kjs}=a_{ks}$, $\gamma_{kjs}=\gamma_{ks}$ for anchor item k, $a_{kj}=a_{kj}$, $\gamma_{kjs} = \gamma_{kjs}$ for non-anchor items

Testing for partial invariance requires that at least two anchor items are invariant across all countries. When the study spans across large number of countries or has few items, it might not be feasible to find such anchor items (De Jong et al., 2007). Moreover, the large number of required tests capitalizes on chance.

When measurement invariance cannot be assumed, researchers might prefer to model the cross-country variation in item parameters using a random effects structure for the item parameters (De Jong et al., 2007). The idea is to model cross-country effects in the measurement model as a function of an overall mean discrimination and difficulty parameter, and cross-country heterogeneity. That is, for the dependent variable, we :

$$\log(a_{kj}) \sim N(\bar{a}_k, \sigma_a^2) \quad (9)$$

$$b_{kj} \sim N(\bar{b}_k, \sigma_b^2) \quad (10)$$

The log function for a_{kj} ensures that the discrimination parameter distribution includes only positive numbers. For the predictors, the equations are specified as:

$$\log(a_{kj(s)}) \sim N(\bar{a}_{k(s)}, \sigma_{a,(s)}^2) \quad (11)$$

$$\gamma_{kj(s)1} \sim N(\bar{\gamma}_{k(s)1}, \sigma_{\gamma 1(s)}^2) \quad (12)$$

$$\log(\gamma_{kj(s)2} - \gamma_{kj(s)1}) \sim N(\bar{\gamma}_{k(s)2}, \sigma_{\gamma 2(s)}^2) \quad (13)$$

$$\log(\gamma_{kj(s),c} - \gamma_{kj(s),c-1}) \sim N(\bar{\gamma}_{k(s),c}, \sigma_{\gamma 2(s)}^2) \quad (14)$$

Details about model estimation can be found in the Appendix.

In order to gain insight into how often the three approaches (full invariance, partial invariance, non-invariance) have been used to analyze cross-cultural data in top marketing journals after the publication of Steenkamp and Baumgartner (1998)'s seminal paper, we conducted a literature review. While the approach proposed by Steenkamp and Baumgartner relies on SEM-based linear models, it is also possible to test measurement invariance for IRT models (see e.g., Reise, Widaman & Pugh, 1993). Software programs like Mplus (Asparouhov & Muthen, 2016) that can estimate multigroup ordinal IRT models can accomplish this. However, those models also need an anchor item that would be invariant across countries and, thus, suffer from the same limitation.

We reviewed research published between 1998 - 2018 in four top marketing journals – *Marketing Science, Journal of Marketing, Journal of Marketing Research and Journal of Consumer Research*. Our search was conducted in the archive for each journal, using the keyword "survey + cross-cultural" and then we selected papers that analyzed simultaneously data obtained from self-reports from more than two countries. We coded for each paper whether the used model required testing the MI assumption. We further coded whether the authors report testing for MI by searching in the text of each paper for the terms: "invariance", "equivalence", and "differential item functioning". If none of the abovementioned terms appeared, we assumed that the MI assumption was not tested. We further coded whether the model accommodates any privacy protection mechanism, whether it relies on Classical Test Theory (CTT) or Item Response Theory (IRT), and whether the model accommodates hierarchical structure. The results are presented in Table 1.

Table 1 illustrates that methods used in cross-cultural research within the last two decades still often assume measurement invariance and use multigroup confirmatory factor analysis (CFA) for testing this assumption (Steenkamp & Baumgartner, 1998). Several studies apparently did not test for MI, as Table 1 shows.

Moreover, studies that relied on Item Response Theory did not use random effects specifications for both dependent and independent variables in multilevel models. For instance, De Jong et al. (2008) and De Jong, Steenkamp & Fox (2007) only had measurement models for the dependent variable. If the predictors are subject to measurement error, some scholars have used a two-step approach, where the measurement models are calibrated first for each latent construct, after which a multilevel model is specified using the posterior means of the latent construct scores (Steenkamp et al., 2010). In the psychometric literature, Fox (2005) considers the case of measurement error in both dependent variables as well as predictors in multilevel models, but not random effects structures for item parameters.

From Table 1 it becomes apparent that among currently existing IRT models with item parameters varying across countries there are no models that incorporate randomized response privacy protection. Thus, this paper proposes a model for assessing sensitive behavior across multiple countries without assuming measurement invariance, while also allowing for measurement error in both dependent variable and predictors.

Our new model merges the random effects IRT model for dependent variables in a multilevel model proposed by De Jong et al. (2008), with random effects IRT models for the predictors, and a randomized response model. We focus here on a binary response scale ("yes/no") for the dependent variable, but the procedure can be easily extended to polytomous response scales (De Jong et al., 2012).

In sum, our model incorporates privacy protection mechanism and allows for item differential functioning for both dependent variable and predictors, which is novel. This means that researchers can use privacy protecting mechanism in cross-cultural surveys without having to bet on whether they would be able to establish at least partial measurement invariance for the obtained data. In other words, our model allows researchers to make meaningful comparisons across countries, even if items that measure the constructs of interest function differently across all countries.

Table 1. Approaches to measurement invariance in cross-cultural research in marketing top journals, 1998-2018

Authors	Year	Journal	Number of countries	Sample size	Does the model assume MI	Tested for MI[7]	CTT or IRT	Multilevel model for countries
Steenkamp et al.	1999	JM	11	3283	Yes	Yes	CTT	Yes
Song et al.	2000	JM	4	968	Yes	Yes	CTT	No
Wulf et al.	2001	JM	3	1727	Yes	Yes	CTT	No
Baumgartner & Steenkamp	2001	JMR	11	10477	Yes	No	CTT	Yes
Coviello & Brodie	2002	JM	5	308	Yes	No	CTT	No
Erdem et al.	2006	JM	7	882	Yes	Yes	CTT	Yes
Steenkamp & Geyskens	2006	JM	23	8886	Yes	No	CTT	Yes
Ouellet*	2007	JM	3	954	Yes	Yes	CTT	No
Tellis et al.	2009	JM	17	759	Yes	Yes	CTT	No
Lans et al.	2010	MS	10	NA	Yes	Yes	CTT	No
Fischer et al.	2010	JMR	5	5769	Yes	Yes	CTT	No
Torelli et al. (Study 1 pilot)	2012	JM	8	1954	Yes	Yes	CTT	Yes
Steenkamp & Geyskens	2014	MS	23	20987	Yes	No	CTT	Yes
Honenberg & Homburg	2016	JM	38	406	Yes	Yes	CTT	Yes
Batra et al.	2017	JMR	22	64000	Yes	No	CTT	No
Klein et al.	2019	MS	3	NA	Yes	Yes	CTT	No
De Jong et al.	2007	JCR	11	5484	No	-	IRT	Yes
De Jong et al.	2008	JMR	26	12506	No	-	IRT	Yes
De Jong et al.	2009	MS	28	~13000	No	-	IRT	Yes
Steenkamp & de Jong	2010	JM	28	~13000	No	-	IRT	Yes
Steenkamp et al.	2010	JMR	26	12424	No	-	IRT	Yes
De Jong et al.	2012	MS	6	2903	No	-	IRT	Yes
This paper				Yes	No	-	IRT	Yes

**This paper is the only one of this table that asked consumers about sensitive subject (racism), however, the authors did not use a privacy protecting*

CROSS-CULTURAL APPLICATION

We apply the proposed model to access the prevalence and antecedents of deceptive consumption disclosures on social media (DCSM) across 24 countries across the globe.

Deceptive self-presentation on social media (DCSM)

Recent years have seen a surge of using online information posted by consumers for marketing and public policy purposes, but an equivalent soaring worry about the trustworthiness of the these data (e.g., Anderson & Simester, 2014; De Langhe, Fernbach & Lichtenstein, 2015; Mayzlin et al., 2014; Muchnik et al., 2013). As a case in point, Anderson and Simester (2014) demonstrate that a noticeable amount of online product reviews might be from people who never purchased the product. Mayzlin et al. (2014) find similar effects and document how fake reviews on hotel websites vary as a function of specific hotel characteristics. In another domain, Toma and colleagues (2008) showed that people tend to deceive on their online dating profiles. However, to the best of our knowledge, no research to date has examined the accuracy of consumption-related data from social network platforms (SMPs).

This is surprising in view of the world-wide prominence of SMPs as media of peer-to-peer communication, and worries about significant rates of deceptive consumption disclosures on SMPs[8]. We define deceptive consumption disclosures on social media (DCSM) as deliberate misrepresentations of one's consumption or ownership of brands, products or services in order to look better in the eyes of others. Such attempts to self-enhance one's image to others can manifest themselves through text posts, comments, photos, pictures, videos, tags, links or other means of disclosure.

[8] https://brightside.me/wonder-curiosities/18-times-people-lied-on-social-media-so-hard-its-hilarious-425210/ (example 16, 4). Last retrieved: June, 2020.

Previous studies have shown that self-enhancement more generally is linked to socio-demographic, psychographic, and cultural variables (Fiske, 2018; Steenkamp, De Jong & Baumgartner, 2010). Here, we propose a conceptual framework in which DCSM is hypothesized to be affected by individual-level variables, as well as country-level variables. The individual-level variables include the following psychographic factors: materialism (Richins & Dawson, 1992), social comparison on ability (Gibbons & Buunk, 1999), and past and current resource availability (Griskevicius et al., 2011). We also include a number of socio-demographic control variables at the individual level. On the country level, we expect the cultural environment to account for variance in DCSM over and above the individual characteristics of country citizens (Erbring & Young, 1979). As such, our model includes both micro and macro drivers of DCSM. The conceptual framework is displayed in Figure 1.

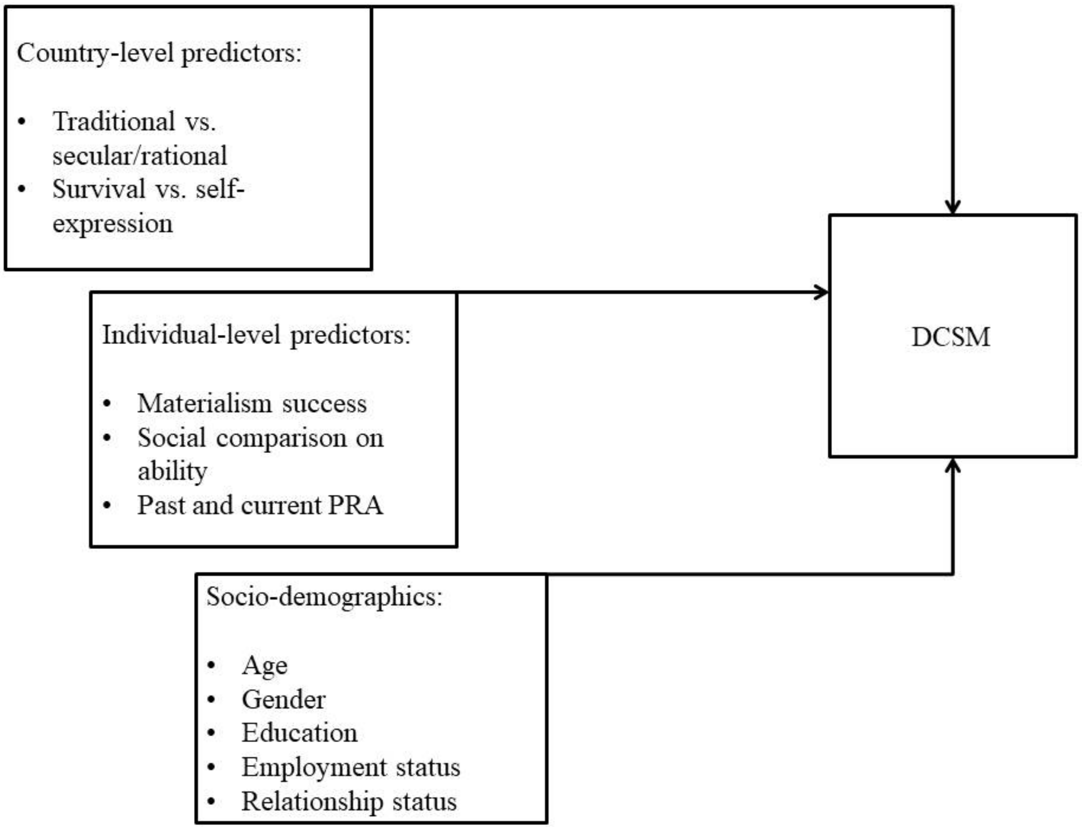


Figure 1. Conceptual Model of Determinants of Deceptive Consumption Disclosures on Social Media.

Individual-level predictors of DCSN: Psychographics

Among the variety of potential consumer states and traits that could be relevant determinants of DCSN, materialism orientation is a salient candidate. Clearly, consumers would only signal their identity through deceptive exposure of wealth, if they believe that wealth and material possessions enhance their identity (Sedikides, Gaertner & Toguchi, 2003). Richins and Dawson (1992) see materialism as a set of beliefs about the value of possessions in one's life. Consumers with higher levels of materialism derive meaning in life more from their possessions than other consumers do. They believe that they need to own things that project an image of perfect life in order to feel successful, and in order to be happy. Therefore, we expect higher scores on materialism to be associated with higher levels of DCSM.

A second prominent candidate trait behind DCSM is social comparison orientation. The need to demonstrate wealth on social media should be particularly relevant for people who are more prone to evaluating themselves against others. In contrast, people who rely more on internal criteria for judging themselves should rely less on demonstrating and lying about their possessions on SMPs. Social comparison is typically conceptualized as consisting of two dimensions: comparison on ability, and comparison on opinions (Gibbons & Buunk, 1999). Comparison on ability is evaluating how well one is doing relative to others in various domains of life, including wealth and possessions. Comparison on opinion is evaluating to what extent one's way of thinking is similar to others. Notably, DCSM contributes to enhancing the dimension of "How much better one is doing" (ability comparison), but is less relevant for "How similarly or differently one thinks" (opinion comparison). Therefore, we hypothesize a positive effect of social comparison orientation on ability on DCSM.

Another factor that we expect to contribute to DCSM is perceived resource availability (PRA; Griskevicius et al., 2013). PRA refers to people's appraisal of their access to resources relative to others. While PRA should be strongly related to income, we believe PRA would be a more relevant construct for predicting DCSM than actual income. We speculate that the need for self-enhancement, such as by DCSM, is likely to be higher when perceiving to have a relatively low position on relevant resources (such as money) as compared to the reference group (Rick & Loewenstein, 2008). Therefore, we expect individuals with lower PRA to engage in more DCSM. We include measures of childhood PRA and current PRA, because childhood PRA ("feelings of being relatively deprived in childhood") predict individual's responses to environmental cues in adulthood (Griskevicius et al., 2013).

Country-level predictors of DCSN: National culture.

The attitudes and behavior of individuals within a given nation are shaped by the dominant culture, including the values, beliefs, and norms in a society (Schwartz, 2007), including the prevalence and acceptability of lying and dishonesty in general. As a case in point, Fisman and Miguel (2007) found significant systematic variation across 149 countries in the status abuse by the diplomats... Cross-cultural variations in honesty were also found for prevalence of cheating in experimental studies (Hugh-Jones, 2016), and in prevalence of socially desirable responding in surveys (Steenkamp, De Jong & Baumgartner, 2010). We speculate that DCSM also varies systematically with variations in cultural values related to honesty.

There four leading conceptual frameworks about national-culture value systems, specifically, Hofstede, Schwartz, Triandis and Inglehart (overview by Vinken, Soeters & Ester, 2004). Choice of a framework depends on the cultural aspects that are most relevant for the research question. In case of DCSM, Inglehart's framework (Inglehart & Baker, 2000; Inglehart & Welzel, 2005) appears most fitting, because of its foundation in economic development and materialism, which are directly relevant to consumer culture and DCSM as part of it.

According to Inglehart's theory the variation in national-culture values can be organized into two bipolar dimensions: traditional versus secular-rational values and survival versus. self-expression values. The values on the traditional/secular-rational dimension range between valuing interests of traditional social institutions (family, government, nation, religion, law, social norms) and valuing individual interests. The survival/self-expression dimension ranges between the materialistic values of security (physical and economical) on the one pole and the post-materialistic values of self-expression on the other pole.

We predict DCSM to be higher for traditional cultures, which emphasize hierarchy. Since social hierarchies are often associated with wealth, possessions and supported by money, wealth is implicitly important in traditional cultures, hence DCSM might be used to signal both wealth and power. Predictions for the survival/self-expression dimension arise from the dimension definition. Survival concerns are tied to security in all forms, including material security. Therefore, possessions and consumption play a more central role in the survival cultures compared to self-expression cultures which are focused on more post-materialist values (Inglehart, 2008). Consequently, DCSM should be higher in survival cultures.

In our empirical application, we control for various socio-demographic variables that might potentially shape DCSM (age, gender, education, urbanization, employment, and marital status), and that if left out might bias the associations between psychographics and DCSM.

METHODOLOGY

We rely on a large-scale consumer survey to detect deceptive consumption disclosure on social media platforms, for several reasons. First, alternative data collection methods based on comparing actually deceptive and non-deceptive disclosure cases (Andersen & Simester, 2014) are not feasible because they require obtaining records of consumers' purchases made through all possible channels. Second, data collection methods that rely on language analysis (Humphreys et al., 2011; Newman et al., 2003) are not easily applicable across varying languages. Third, we aimed to cover deceptive self-disclosure on social media platforms in general rather than focusing on a single one and access to private social media accounts cross-nationally is hard and might be unethical. Therefore, we chose a self-report method with privacy protection to efficiently access DCSM across countries.

Since a multi-item instrument to assess DCSM was unavailable, we developed such an instrument. Details on item generation, item selection are in the Appendix. The data were collected simultaneously with the data used in essay 1 and 2.

DCSM Measure

The final item set is in Table 2. Translations of the items into 19 languages from the 24 national samples are in the Appendix.

Table 2. The final DCSM items.

Item	Item text: On *XYZ* I have made it appear as if I …
1	Paid a higher price for a product or service than I actually did
2	Owned products that I actually did not own
3	Owned more expensive brands than I actually did
4	Paid for a product or service that I actually got for free
5	Had a holiday or (short) trip that I actually did not have
6	Used services (such as sport clubs, dining, hotels, spa, etc.) that I did not use

GLOBAL DATASET

Kantar Media group, a multinational company with online panels in multiple countries, collected the data in 2016 through a Web survey accessing respondents from national panels in 25 countries. The final sample sizes were as follows: Australia (n = 333), Brazil (n = 671), Bulgaria (n = 475), China (n = 680), France (n = 377), Germany (n = 329), India (n = 669), Indonesia (n = 684), Italy (n = 517), Japan (n = 229), Mexico (n = 557), Netherlands (n = 337), Philippines (n = 585), Poland (n = 488), Portugal (n = 461), Russia (n = 525), Singapore (n = 445), South Africa (n = 564), Spain (n = 511), Sweden (n = 374), Thailand (n = 586), Turkey (n = 571), United Kingdom (n = 386), the USA (n = 418). The total sample size was 12,257 respondents (51% female). Age ranged from 18 to 90 years old.

The data were collected as part of a larger project designed by several researchers from different European universities. The survey was originally designed in English and was translated by bilinguals (mostly professional translators) into 19 languages/dialects (namely, Arabic (standard), Bulgarian, Chinese, Dutch, Filipino, French, German, Indonesian, Italian, Japanese, Polish, Portuguese (Brazilian version), Portuguese (Portuguese version) Russian, Spanish (Mexican version), Spanish (Castellano), Swedish, Thai and Turkish. In Australia, India, Singapore, South Africa, the UK and the USA the survey was administered in English. The specific data for the present study have not been analyzed or published in a any form before.

The survey began with questions about demographics and social media use. Only participants, who had a social media account and used it to share information on social media were selected to answer the items about DCSM. Participants were also asked to indicate their preferred social media platform, that is, the one they used the most for posting and sharing information, videos, pictures, and so on. Further, participants read the following instructions for the RR procedure:

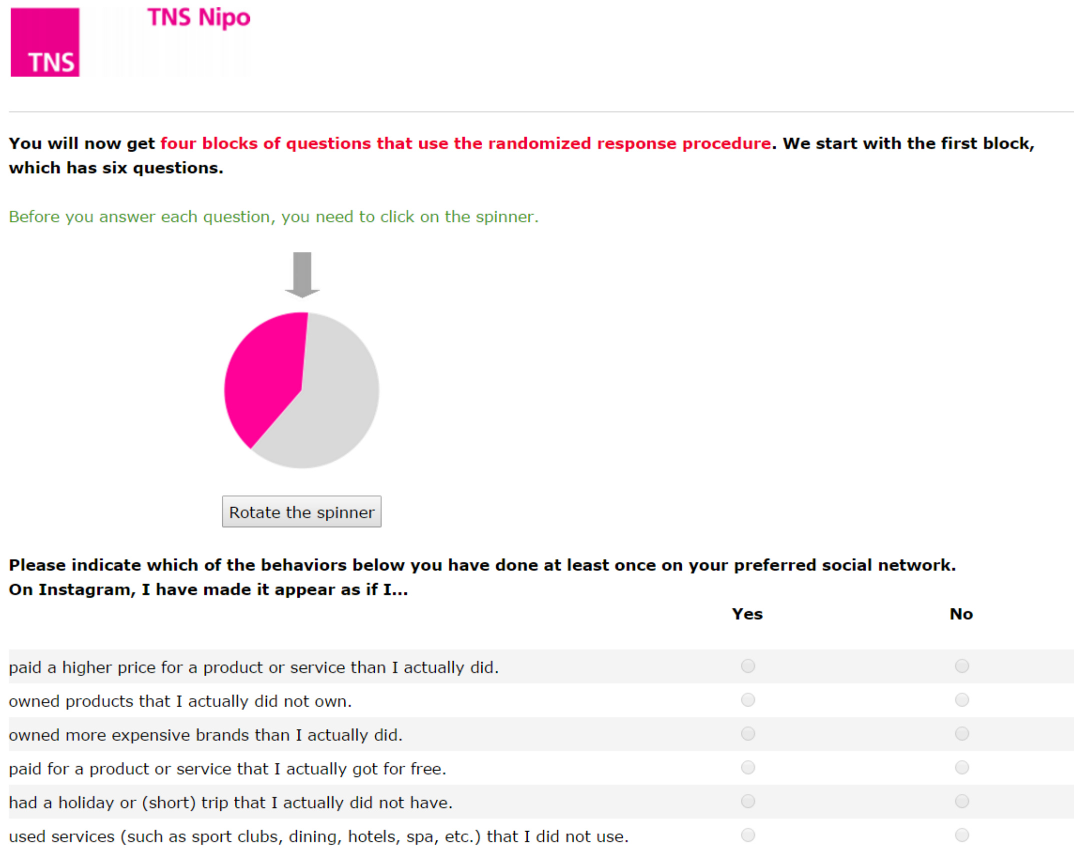
"The next questions are about behaviors that may be sensitive. Therefore, we will provide a privacy protection mechanism, called "randomized response". Your answers to each of the following questions will depend on the outcome of a spinning device. Before you answer each question, you click on the "Rotate the disk" button. The answer you give to the question depends on the outcome of the spinner as follows:

If the spinner indicates "Give your truthful answer" (grey), then please provide your truthful answer to the question.

If the spinner indicates "Answer"Yes"" (pink), then fill out a "Yes" answer (regardless of your true answer).

The idea behind this procedure is that only you know the outcome of the spinning device. The software has been programmed in such a way that this outcome is not available to the researchers and so your privacy is fully protected. Because this procedure fully protects your privacy you can, with all your heart, provide your true answer to a question if the spinning device tells you to do so.

On the next screen the six DCSM items appeared (a screenshot of the survey screen with the items is in Figure 2). The name of the participant's social media platform was automatically inserted in the item. For instance, if participant's preferred social media platform was Instagram, then the items would begin with "On Instagram I have made it appear as if I…". Participants were reminded to rotate the spinner before giving response to each item and the software was programmed so that the answer to every next item could not be given unless the spinner was rotated. Furthermore, the software was programmed so that if a forced response "Yes" was required, the software did not allow to provide any other answer. This eliminated the possibility of procedural non-adherence.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You will now get four blocks of questions that use the randomized response procedure. We start with the first block, which has six questions.

Before you answer each question, you need to click on the spinner.

Rotate the spinner

Please indicate which of the behaviors below you have done at least once on your preferred social network.
On Instagram, I have made it appear as if I...

	Yes	No
paid a higher price for a product or service than I actually did.		
owned products that I actually did not own.		
owned more expensive brands than I actually did.		
paid for a product or service that I actually got for free.		
had a holiday or (short) trip that I actually did not have.		
used services (such as sport clubs, dining, hotels, spa, etc.) that I did not use.		

Figure 2. A screenshot from the global survey with randomized response technique.

Antecedents and control variables measurement

After the DCSM measure, the psychographic data were collected. We used a 9-item short version of the materialism scale (Richins, 2004) to measure materialistic values. The example item is: “I admire people who own expensive homes, cars, and clothes”. Social comparison on ability was measured with items from instrument developed by Gibbons and Buunk (1999). Three items with highest reported factor loadings the comparison on ability factor were chosen for the global study. The example item is: “I often compare how my loved ones (boy or girlfriend, family members, etc.) are doing with how others are doing”. The items to measure PRA – three for perceived childhood resourse availablity and three for perceived current resource availability - were taken from Griskevisius et al. (2011). Example items are: “My family usually had enough money for things when I was growing up” (childhood PRA), “I have enough money to buy things I want” (current PRA).

The country-level scores for the two cultural dimensions – survival vs. self-expression vales and traditional vs. secular-rational values - were retrieved from Inglehart and Welzel (2010, p.554 graph).

STATISTICAL MODEL FOR THE GLOBAL DATASET

The construct DCSM is measured by six items, each administered with a randomized response mechanism. The part of the measurement model for the dependent variable was estimated based on equations (7)-(10), where the single latent variable is estimated based on the responses to the six binary items. In the regression analysis part, there are several latent predictors. In particular, materialism, social comparison on ability, and past and present perceived resource availability, all measured with validated measurement scales (Bearden, Netemeyer, & Haws, 2011). Despite their prior validation, it is important in cross-cultural research to ensure that measurement invariance is satisfied before drawing conclusions. Thus, the part of the measurement model for the latent predictors was estimated using equations (5), (6), (11)-(14). We rely on Markov Chain Monte Carlo methods to estimate and accommodate the complexity of the model (25000 iterations)

RESULTS

The item parameters and latent variable country means for DCSM are in Table 3. The measurement model includes two item parameters (equation (8)). Note that because the scale of the item parameters is not fixed, only the relative not the absolute values of parameter estimates are informative. That is, item 6 ("I have made it appear as if I used services (such as sport clubs, dining, hotels, spa, etc.) that I did not use ") is answered "yes" by a relatively large number of respondents – it has the lowest average difficulty across countries (-0.18). Conversely, the item 4 ("I have made it appear as if I paid for a product or service that I actually got for free") is a behavior that relatively few people report to have engaged in , so the average difficulty parameter across countries for this item is the highest (0.11).

Figure 3 presents variation in DCSM scores across countries, the countries were sorted by country average DCSM score from lowest to highest and the score of the country with the lowest mean (Netherlands) was added to all scores to make zero the starting point and the lowest score for convenience. The polarization emerges: developed countries almost all fall below the mean (which is 1.53 for this sample), featuring lower DCSM averages, while developing countries are above the median. For instance, the mean of DCSM in China is 6 times the mean of DCSM in the USA.[9]

[9] http://www.oecd.org/industry/global-trade-in-fake-goods-worth-nearly-half-a-trillion-dollars-a-year.htm

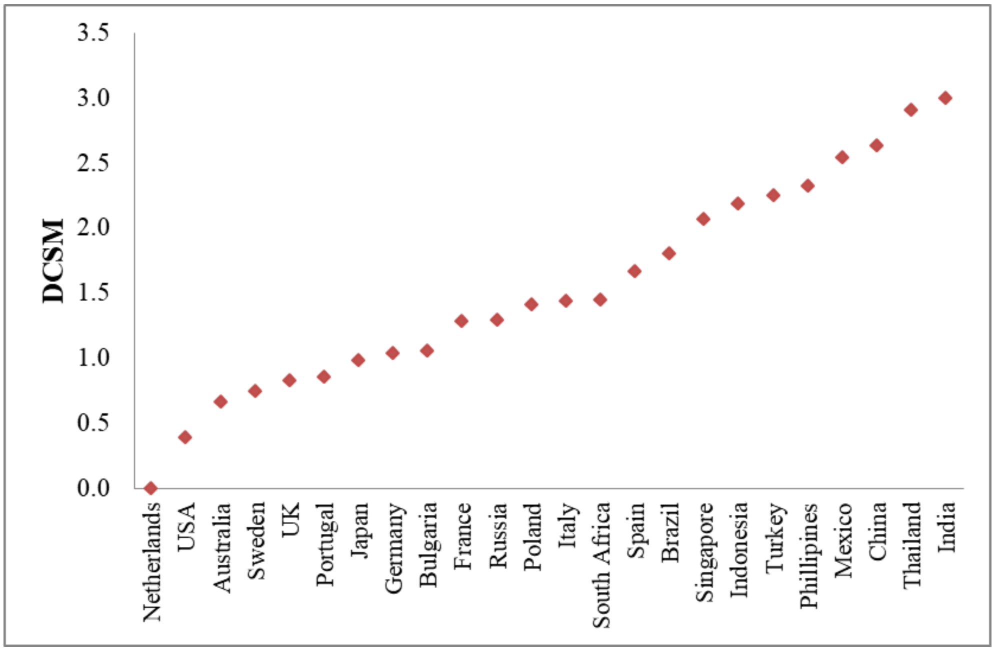

Figure 3. Country means of deceptive consumption disclosures on social media platforms, sorted from lowest (least deception) to highest (most deception) values.

Table 3. Country scores and item parameters for DCSM.

	DCSM	Item 1		Item 2		Item 3		Item 4		Item 5		Item 6	
Country		a_1	b_1	a_2	b_2	a_3	b_3	a_4	b_4	a_5	b_5	a_6	b_6
Australia	-3.34	0.60	0.02	0.58	0.12	0.46	0.07	0.38	-0.15	0.76	0.08	0.82	-0.15
Brazil	-2.20	0.50	-0.13	0.48	0.02	0.44	-0.02	0.50	0.16	0.83	0.09	0.84	-0.12
Bulgaria	-2.95	0.49	-0.11	0.58	0.01	0.43	-0.06	0.49	0.18	0.87	0.15	0.74	-0.17
China	-1.37	0.49	-0.34	0.60	0.07	0.42	0.05	0.46	0.07	0.79	0.22	0.83	-0.06
France	-2.72	0.58	-0.08	0.56	0.05	0.47	0.03	0.45	0.04	0.79	0.11	0.75	-0.16
Germany	-2.96	0.55	-0.11	0.59	0.21	0.41	0.06	0.50	0.12	0.79	-0.05	0.76	-0.23
India	-1.01	0.44	-0.26	0.56	0.10	0.35	0.01	0.43	0.30	0.80	-0.04	1.02	-0.11
Indonesia	-1.81	0.48	-0.06	0.53	0.17	0.46	0.03	0.41	-0.02	0.82	0.04	0.90	-0.16
Italy	-2.56	0.56	-0.16	0.52	0.03	0.51	0.25	0.45	0.08	0.81	-0.06	0.75	-0.14
Japan	-3.02	0.57	-0.05	0.58	0.16	0.47	0.05	0.43	-0.02	0.80	0.07	0.75	-0.21
Mexico	-1.46	0.45	0.12	0.67	0.08	0.40	0.21	0.39	0.18	0.76	-0.33	0.94	-0.26
Netherlands	-4.00	0.56	-0.05	0.55	0.05	0.44	0.05	0.41	0.02	0.80	0.03	0.84	-0.10
Phillipines	-1.68	0.53	-0.20	0.51	0.25	0.44	0.13	0.57	0.19	0.82	-0.21	0.73	-0.16
Poland	-2.59	0.58	-0.03	0.60	0.21	0.43	-0.07	0.48	0.11	0.76	-0.07	0.74	-0.15
Portugal	-3.15	0.54	-0.01	0.62	0.12	0.47	0.03	0.49	0.12	0.74	0.00	0.75	-0.26
Russia	-2.71	0.56	0.02	0.54	0.11	0.48	-0.07	0.44	0.16	0.82	-0.03	0.77	-0.19
Singapore	-1.94	0.54	-0.14	0.55	-0.14	0.44	0.20	0.50	0.18	0.81	0.05	0.77	-0.13
South Africa	-2.56	0.52	-0.14	0.50	0.13	0.49	0.07	0.46	0.17	0.86	0.09	0.77	-0.32
Spain	-2.34	0.64	0.00	0.50	-0.10	0.49	0.14	0.49	0.17	0.71	0.05	0.78	-0.26
Sweden	-3.26	0.55	0.00	0.53	0.04	0.43	0.06	0.45	0.11	0.74	-0.05	0.89	-0.17
Thailand	-1.10	0.42	-0.39	0.44	0.05	0.46	0.11	0.51	0.18	0.97	0.06	0.79	-0.01
Turkey	-1.75	0.44	-0.02	0.58	0.00	0.45	0.08	0.38	0.13	0.87	-0.04	0.88	-0.15
UK	-3.18	0.60	0.01	0.58	0.11	0.47	0.03	0.49	0.12	0.79	0.10	0.67	-0.37
USA	-3.62	0.57	-0.10	0.62	0.27	0.48	0.10	0.45	0.07	0.75	-0.04	0.73	-0.30
Average		0.53	-0.09	0.56	0.09	0.45	0.06	0.46	0.11	0.80	0.01	0.80	-0.18

The regression coefficients of the structural multilevel model are in Table 4. There is a strong positive effect of materialism on DCSM (β_1=0.35, CI_{95}=[0.26, 0.46]). Therefore, in support of our expectations, consumers with more materialistic values engage more in DCSM.

Further, there is a positive effect of social comparison on ability on DCSM (β_2=0.13, CI_{95}=[0.05, 0.20]), suggesting that consumers who are prone to compare their own performance to others, are also more prone to DCSM.

Interestingly, the effect of resource availability on DCSM is actually opposite to our expectations. The effect of childhood PRA is positive and significant, while the effect of present PRA is not significant. Growing up in a seemingly resourceful environment makes one more rather than less predisposed for DCSM (β_3=0.11, CI_{95}=[0.05, 0.17]). However, the perception that one currently has enough resources does not affect DCSM above and beyond the childhood PRA (β_4=0.05, CI_{95}=[-0.01, 0.11]). That is, what consumers experience in childhood regarding resource abundance or scarcity is more strongly associated with their current deceptive consumption disclosure levels than their current perceived access to resources are.

The associations of DCSM with the control variables are also informative. Age has a significant negative effect on DCSM, suggesting that younger people are more likely to engage in DCSM (β_5=-0.01, CI_{95}=[-0.01, -0.002]). Also, men are more likely to engage in DCSM than women (β_6=-0.34, CI_{95}=[-0.48, -0.20]), which is in line with theories on conspicuous consumption (Sundie et al., 2011). There was no effect of relationship status on DCSM (β_9=-0.12, CI_{95}=[-0.29, 0.04]). Additionally, less DCSM occurs among respondents with higher education (β_7=-0.18, CI_{95}=[-0.25, -0.11]). Another interesting finding is that employed respondents reported engaging in DCSM significantly more than unemployed respondents did (β_8=0.42, CI_{95}=[0.22, 0.62]), while controlling for all other variables.

Table 4. Results of the multilevel structural model for the predictors of DCSM

Variable	Coeff.	SD	95% CI	
Intercept (γ_{00})	-2.76	0.19	-3.14	-2.40
Socio-demographics				
Age (β_5)	-0.01	0.003	-0.01	-0.002
Female (β_6)	-0.34	0.07	-0.48	-0.20
Higher education (β_7)	-0.18	0.04	-0.25	-0.11
Employment (β_8)	0.42	0.10	0.22	0.62
Single (β_9)	-0.12	0.08	-0.29	0.04
Psychographics				
Materialism (β_1)	0.35	0.05	0.26	0.46
SOCCOM ability (β_2)	0.13	0.04	0.05	0.20
PRA past (β_3)	0.11	0.03	0.05	0.17
PRA current (β_4)	0.05	0.03	-0.01	0.11
Country culture				
Traditional/Secular Rational (γ_{01})	-0.33	0.14	-0.61	-0.06
Survival/Self-expression (γ_{02})	-0.23	0.14	-0.51	0.04

The country-level effects are mostly consistent with our predictions: the effect of traditional/secular-rational dimension is strong and negative - people are much less prone to engage in DCSM if they come from cultures that are higher on secular-rational values (γ_{01}= - 0.33, CI_{95}=[-0.61, -0.06]). The effect of self-expression values on DCSM is significant and in the predicted direction (γ_{02}= - 0.23, CI_{95}=[-0.51, -0.04]).

GENERAL DISCUSSION

Marketing researchers and policy makers have a stake in accurately documenting, understanding and predicting sensitive consumer behaviors, such a consumer fraud, shoplifting, or, which was the topic of the empirical application here, deceptive reporting of consumption practices on social media platforms. Yet, the task to obtain accurate reports from consumer surveys on such sensitive topics is challenging, because consumers may opt to lie in surveys about their deception online. Privacy protection mechanisms, such as the randomized response technique, in consumer surveys aim to address this vexing issue. However, until now, researchers who would want to apply such models in cross-cultural studies would need to assume measurement invariance in order to make valid cross-country comparisons. This is an important limitation, because such assumption is likely to be met only when the number of countries is limited.

In view of the soaring interest in cross-national comparisons for marketing and public policy purposes a methodology is needed that relaxes the assumptions of measurement invariance in an efficient way. Here, we proposed such a methodology. Our novel multigroup hierarchical IRT model with varying item parameters does not require the MI assumption. Moreover, the model accommodates privacy protection and allows for heterogeneity in item parameters across countries. This enables cross-cultural comparisons for latent constructs that otherwise would be prone to social desirability bias. The model is suitable for a variety of applications and opens possibilities for novel research directions.

In order to illustrate the model's effectiveness, we applied it to examine the prevalence and drivers of deceptive consumption disclosures on social media (DCSM). The data were obtained using self-report methodology with a randomized response mechanism for the dependent variable across 24 countries. We contribute theoretically to several streams in the marketing literature, such as consumers postings on SMPs (Ghose, Goldfarb, & Han, 2012; Shriver et al., 2013; Toubia & Stephen, 2013), detection of fake consumption disclosures online (Anderson & Simester, 2014; De Langhe et al., 2015). Methodologically our proposed model advances marketing research that relies on data from social media (Culotta & Cutler, 2016; Liu et al., 2016; Ma et al., 2015; Nam & Kannan, 2014). Moreover, our model opens up avenues for more cross-national research using larger samples of countries than are typically employed, and while relaxing measurement invariance assumptions that are hard if at all possible to meet. We also provide estimates of the prevalence of DCSM across 25 countries, which could be used to inform managerial strategies. For instance, a detection algorithm could infer an overly strong focus on materialism from the type of posts made by an individual (images, text, videos, and so on), and subsequently assign a specific weight to such an individual in the follow-up analysis based on the parameters in our regression models. Similarly, weights may be determined based on other covariates, or the sum total of covariates.

Our findings relate DCSM to psychographics that fuel consumers' need to signal status through deceptive consumption disclosures. As expected, DCSM is higher for consumers who value material possessions, as reflected in higher material success scores. Also in line with this reasoning, personal inclination toward social comparison on ability translates into higher DCSM. An important finding is that consumers with higher perceived resource availability (PRA) in their childhood are those who engage in DCSM more frequently. This is somewhat counter-intuitive, as previous research shows that identification with low-status groups increases rather than decreases the desire for consuming high-status products and services (Mazzocco et al., 2012). However, we find higher PRA to be associated with higher DCSM. The effect is not significant for the present PRA, once childhood PRA is taken into account. One possible explanation could be that consumers with high PRA, and particularly those with high PRA since young age, need to keep their status. That is because losing social position can be more painful than not holding that position initially and could also provoke dishonest behavior that enhances social position, such as DCSM (Rick & Loewenstein, 2008). Furthermore, the psychological costs of deceiving might be lower for people with high PRA, because higher perceived status is associated with higher sense of entitlement, self-focused social cognitive tendencies and increased unethical behavior (Mazar et al., 2008; Piff, 2014; Schurr & Ritov, 2016; Shalvi et al., 2015). Also, higher social class predicts elevated levels of ethical misconducts, narcissistic behavior and less pro-social behavior across a variety of contexts (Piff et al., 2010 and 2012; Piff, 2014). This finding implies, somewhat counter-intuitively, that deceptive status signaling could be more critical for people who already believe that they have been privileged in life. The fact that the effect of childhood PRA is stronger than the present PRA is in line with previous findings for several psychological phenomena (Griskevicius et al., 2011).

Importantly, the model also allows for inclusion of country-level variables. We utilized the material values framework by Inglehart and Baker (2000) to study variation in DCSM across cultures. Cultures low on the traditional/secular–rational dimension ("traditional cultures") score significantly higher on DCSM. Cultures low on the survival/self-expression dimension ("survival cultures") also seem to be more prone to DCSM, although the effect is only marginally significant. Another important application of the model is revealed here. Namely, our multilevel regression results can be used to infer the likelihood of DCSM in other countries that were not in our sample, using the regression weights and the Inglehart scores of such non-included countries (Kotabe & Helsen, 2015).

Our application is only one of many potential applications of the proposed model. Due to the limited number of observations per country given the randomized response data collection, in this application we did not include cross-level interactions for country-level and individual level variables. However, the model could also be generalized to include cross-level interaction effects.

Furthermore, the model is suitable not only for applications with a large number of countries, but also with fewer groups. Furthermore, it is not bound to cross-cultural studies and can be used also for comparison across heterogeneous groups within one country. The model is particularly suitable for making comparison across different language groups in countries where multiple languages are spoken. Furthermore, although in our application we have used binary response scale for the dependent variable, the model can be used for dependent variables with multiple response categories.

To conclude, the proposed model opens the horizon for research on sensitive consumer behaviors in cross-cultural context. We hope that researchers and practitioners will take this as an inspiration to develop their ideas.

APPENDIX

Item generation

Multiple sources were used to generate *reflective* items to measure our construct. That is, a higher score on the DCSM construct should generate a *higher probability* to observe a specific deceptive consumption disclosure captured by the item, just like in a typical IRT model. We constructed a number of items based on the literature on conspicuous consumption, status signaling, materialism, value of possessions to the self and related topics (Bardhi et al., 2012; Belk, 2013; Richins, 1994; Schau & Gilly, 2003). The literature on deception (Ellison, Hancock, & Toma, 2012; Mazar & Ariely, 2006; Mazar, Amir, &Arieli, 2008;), impression management and self-presentation was also used (Leary & Kowalski, 1990). Furthermore, we browsed the Internet and social media profiles searching for real examples of suspicious behavior focused on possessions, wealth and consumption of goods or services. Additionally, we found a number of online articles, posts and forum discussions about deceptive or overly positive self-presentation on SMPs in several languages[10]. Most frequently encountered and interesting behaviors were converted into items.

A culturally diverse group of 51 students who took a methodology course from a large European university were asked to generate items too, based on a description of the construct we provided. Some of the items suggested by students were reformulated and added to the item pool. All items were formulated as positive statements that could be answered on a binary scale (yes/no). Since the scale is to be used across cultures, we intentionally avoided reverse-worded item formulation as this might introduce systematic error in the cross-cultural context

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[10] Examples in English: http://pulptastic.com/35-people-caught-lying-facebook/; https://twentytwowords.com/people-got-caught-lying-on-internet/; https://www.liveabout.com/facebook-liars-who-are-full-of-you-know-what-1924625. Last retrieved: August, 2019.

(Wong, Rindfleisch, & Burrough, 2003). Some items were repetitive with slightly varying formulations. Overall the initial item pool included 50 items. After ambiguous, double-barreled, loading, leading, hard-to-comprehend and redundant items were deleted, 22 items remained. From those, based on face validity of the items, 10 of them were chosen for further refinement.

Item selection

In the first step of data collection the 10 items were presented to a culturally-diverse group of students, who received extensive training in scale construction and therefore possess the expertise required. All raters had an account on at least one social media and most of them were actively sharing information online, hence they represented the population for which the scale was designed. This is important for adequate evaluation of the items (MacKenzie, Podsakoff, & Podsakoff, 2011).

The experts were asked to rate each item on a scale from 0-10 on each of the 3 following aspects: how sensitive the item is to other people, if it is easy to understand and how often the expert performed the behavior himself or herself (an elaborate instruction was provided). Also, open-ended questions were asked to get comments and suggestions. Based on the ratings and feedback, the items were slightly modified (for instance, some words replaced by more simple ones, some explanations were added). Furthermore, we chose to drop two items.

Privacy protection

Clearly, admitting deceptive behavior is prone to social desirability bias, thus for the 8 selected in the previous step, we applied privacy protection mechanism as specified in equations (1) and (2).

The 8 items were then administered to 1,005 participants from the United States through the Amazon Mechanical Turk platform (see Paolacci, Chandler & Ipeirotis, 2010 for a more detailed description). The MTurk platform allowed us to test the items on a non-student sample and in a different cultural context. The survey was programmed by Survey Sampling International, a global data solution provider. An electronic coin built into the survey was tested, which excluded the possibility of forced-response non-adherence (the software would not allow the respondent to answer the next question unless the coin is flipped; the software would not allow to choose the option “no” in case of a forced-response “yes”).

Respondents were assigned to one of the 3 conditions (60% of the sample – randomized response (RR), 20% - direct questioning (DQ) and 20% were asked to evaluate item sensitivity). Comparing the RR and DQ condition allowed us to assess social desirable responding. In the DQ condition, the scale performed well: Cronbach’s alpha is 0.9 and exploratory factor analysis suggests a single factor (explaining 62% variance). In the RR condition, an item randomized response model was estimated (De Jong et al., 2010), and the results suggested local independence once a common factor was specified, again attesting to the unidimensionality of the items.

Furthermore, the differences between the RR condition and DQ condition suggested that the effect of the administration mode is non-negligible: consumers admit deceptive disclosures significantly more when their privacy is protected through RR. The sensitivity ratings also confirmed that the items are “somewhat sensitive”, suggesting that some form of socially desirable response prevention is needed. After a thorough final review of the scale, 6 items with the highest discrimination parameters were selected for the final version. We use a short scale to ensure efficient implementation across varying cultures (Burisch, 1984).

Model Estimation

Due to the model complexity, the model requires an iterative estimation procedure. We rely on Markov Chain Monte Carlo (MCMC) algorithms, in particular the Gibbs sampler with several Metropolis-Hastings steps. The sampling procedure consists of 25 steps, which all entail sampling from one set of parameters conditional on the other parameters. The steps combine full conditionals specified in De Jong, Pieters, and Fox (2010), Fox, and Glas (2003), De Jong, Steenkamp, Fox, and Baumgartner (2008), and De Jong, Steenkamp, and Fox (2007), De Jong, Pieters, and Stremersch (2012), resulting in the following full conditionals:

1. $\tilde{y}_{ijk} | \, y_{ijk}, \theta_{ij}, a_{kj}, b_{kj}$
2. $Z_{ijk} | \, \tilde{y}_{ijk}, \theta_{ij}, a_{kj}, b_{kj}$
3. $\theta_{ij} | \, Z_{ijk}, a_{kj}, b_{kj}, \sigma^2, \beta_j, \delta$
4. $Z_{ijks} | \, X_{ijk}, \xi_{ijs}, a_{kjs}, \gamma_{kjs}$
5. $\xi_{ijs} | \, \theta_{ij}, X_{ijk}, a_{kjs}, \gamma_{kjs}, Z_{ijks}, \beta_j, \delta$
6. $a_{kj} | \, \theta_{ij}, \bar{a}_k, \sigma_a^2, Z_{ijk}$
7. $\bar{a}_k | \, a_{kj}, \sigma_a^2$
8. $\sigma_a^2 | \, a_{kj}, \bar{a}_k$
9. $a_{kjs} | \, \xi_{ijs}, \bar{a}_{ks}, \sigma_{a,s}^2$
10. $\bar{a}_{ks} | \, a_{kjs}, \sigma_{a,s}^2$
11. $\sigma_{a,s}^2 | \, a_{kjs}, \bar{a}_{ks}$
12. $b_{kj} | \, \theta_{ij}, \bar{b}_k, \sigma_b^2, Z_{ijk}$
13. $\bar{b}_k | \, b_{kj}, \sigma_b^2$
14. $\sigma_b^2 | \, b_{kj}, b_k$
15. $\gamma_{kjs} | \, a_{kj}, \xi_{ij}, \sigma_{\gamma 1s}^2, \sigma_{\gamma 2s}^2$
16. $\bar{\gamma}_{ks} | \, \gamma_{kjs}, \sigma_{\gamma 1s}^2, \sigma_{\gamma 2s}^2$

17. $\sigma^2_{\gamma 1s} | \gamma_{kjs}, \bar{\gamma}_{ks}$

18. $\sigma^2_{\gamma 2s} | \gamma_{kjs}, \bar{\gamma}_{ks}$

19. $\sigma^2_{\xi s} | \xi_{ijs}, \bar{\xi}_{js}$

20. $\bar{\xi}_{js} | \xi_{ijs}, \sigma^2_{\xi s}$

21. $\bar{\xi}_{s} | \bar{\xi}_{js}, \sigma^2_{X,s}$

22. $\sigma^2_{X,s} | \bar{\xi}_{js}, \bar{\xi}_{s}$

23. $\delta | \theta_{ij}, \beta_j, X_{ij}, W_{ij}$

24. $\beta_j | T, \sigma^2, X_{ij}, W_{ij}, \theta_{ij}, V_j$

25. $\gamma | \beta_j, T, V_j$

Latent variable models are not identified, unless specific restrictions are imposed (Fox & Verhagen, 2010). Otherwise, the scale of the latent variable is not defined. For the dependent variable, we restrict the sum of country-specific difficulties to be zero in each country. That is, $\sum_k b_{kj} = 0 \quad \forall j$. This resolves the indeterminacy between the latent country mean and the location of the country-specific item difficulties. Similarly, for the latent predictors, we restrict the sum of the third threshold across each construct's items to be zero in each country. That is, $\sum_k \gamma_{kj(s),3} = 0 \quad \forall j$. The variance of the latent scale is set either by imposing a restriction on the variance of the latent variable, or by imposing restrictions on the international item discrimination parameters. We chose the latter option.

Priors

$\tilde{a}_k \sim N(0,1)$
$\tilde{b}_k \sim N(0,1)$

$$(\sigma_a^2)^{-1} \sim Gam(1,1)$$
$$(\sigma_b^2)^{-1} \sim Gam(1,1)$$

$$(\xi_{ij,1}^{MAT}, \xi_{ij,2}^{MAT}, \xi_{ij,3}^{MAT})' \sim MVN((\xi_{ij,1}^{MAT}, \xi_{ij,2}^{MAT}, \xi_{ij,3}^{MAT})', \Sigma_j^{MAT})$$
$$(\xi_{ij,1}^{SOCCOM}, \xi_{ij,2}^{SOCCOM})' \sim MVN((\xi_{ij,1}^{SOCCOM}, \xi_{ij,2}^{SOCCOM})', \Sigma_j^{SOCCOM})$$
$$(\xi_{ij,1}^{PRA}, \xi_{ij,2}^{PRA})' \sim MVN((\xi_{ij,1}^{PRA}, \xi_{ij,2}^{PRA})', \Sigma_j^{PRA})$$

The Multi-Item Measure used in 25 countries

Below, we provide the translation of our multi-item measure in 20 languages in our study.

ENGLISH

On [...], I have made it appear as if I…

1: paid a higher price for a product or service than I actually did.

2: owned products that I actually did not own.

3: owned more expensive brands than I actually did.

4: paid for a product or service that I actually got for free.

5: had a holiday or (short) trip that I actually did not have.

6: used services (such as sport clubs, dining, hotels, spa, etc.) that I did not use.

ARABIC

على [] جعلت الأمر يبدو وكأنني..

1: دفعت سعرًا للمنتج أو الخدمة أعلى مما دفعته بالفعل.

2: امتلكت منتجات ليست لدي بالفعل.

3: امتلكت منتجات من علامات تجارية ثمنها أعلى مما دفعته بالفعل.

4: دفعت سعرًا لمنتج أو خدمة حصلت عليها مجانًا بالفعل.

5: حصلت على عطلة أو رحلة (قصيرة) لم أحصل عليها بالفعل.

6: استخدمت خدمات (مثل، النوادي الرياضية، والمطاعم، والفنادق، والمنتجعات الصحية، إلخ.) لم أستخدمها بالفعل.

BULGARIAN

В [], направих да изглежда, като че ли …

1: съм заплатил по-висока цена за продукт или услуга, от действително платената от мен.

2: съм притежавал продукти, които в действителност не са били моя собственост.

3: съм притежавал по-скъпи марки от тези, които в действителност са били моя собственост.

4: съм заплатил за продукт или услуга, които в действителност съм получил безплатно.

5: съм изкарал почивка или (кратка) екскурзия, на която в действителност не съм бил.

6: съм използвал услуги (като спортни клубове, вечери, хотели, спа процедури и др.), които в действителност не съм използвал.

CHINESE

在 [], 上，我让我看起来像……

1: 花高价购买了产品或服务，实际并没有花那么多。

2: 拥有了某些产品，实际并没有。

3: 拥有了很多昂贵的品牌产品，实际并没有那么多。

4: 花钱购买了产品或服务，实际是免费获得的。

5: 度假或（短途）旅行了，实际并没有。

6: 享受了服务（例如运动俱乐部、晚餐、酒店、水疗等），实际并没有享受。

DUTCH

Op [], heb ik het doen lijken alsof ik…

1: een hogere prijs heb betaald voor een product of dienst dan ik daadwerkelijk heb gedaan.

2: producten bezat die ik in werkelijkheid niet bezat.

3: duurdere merken bezat dan ik in werkelijkheid bezat.

4: heb betaald voor een product of dienst die ik in werkelijkheid gratis heb gekregen.

5: op een vakantie of (korte) reis ben geweest waar ik dit in werkelijkheid niet heb gedaan.

6: gebruik heb gemaakt van diensten (zoals sportclubs, diners, hotels, spa’s, etc.) die ik niet heb gebruikt.

FILIPINO

Sa […], pinalabas kong parang ako ay...

1: nagbayad ng mas mahal na presyo para sa isang produkto o serbisyo kaysa sa talagang binayaran ko.

2: nagmamay-ari ng mga produkto na wala naman talaga ako.

3: nagmamay-ari ng mas mamahaling mga brand kaysa sa talagang mayroon ako.

4: nagbayad ng isang produkto o serbisyo na nakuha ko lang nang libre.

5: nagbakasyon o (sandaling) namasyal na hindi ko naman talaga ginawa.

6: gumamit ng mga serbisyo (tulad ng mga sports club, kumain sa labas, mga hotel, spa, atbp.) na hindi ko naman ginamit.

FRENCH

Sur [], j'ai donné l'impression que je…

1: avais acheté un produit ou service plus cher que ce que je l'ai réellement acheté.

2: possédais des produits qu'en réalité je ne possède pas.

3: possédais des produits de marques étant plus chères que les marques de ceux que j'ai réellement.

4: avais payé pour un produit ou service qu'en réalité j'ai obtenu gratuitement.

5: avais pris des vacances ou fait un (court) voyage qu'en réalité je n'ai jamais pris ou fait.

6: utilisais des services (comme des salles de sports, des restaurants, des hôtels, des SPA, etc.) qu'en réalité je n'ai pas utilisé.

GERMAN

Auf [], habe ich den Anschein erweckt, als ob ich ...

1: einen höheren Preis für ein Produkt oder einen Service gezahlt habe, als es tatsächlich der Fall war.

2: Produkte besitze, die ich in Wirklichkeit nicht besitze.

3: teurere Markenprodukte besitze, als es in Wirklichkeit der Fall ist.

4: für ein Produkt oder einen Service gezahlt habe, das/den ich in Wirklichkeit umsonst bekommen habe.

5: einen Urlaub oder Kurztrip gemacht habe, den ich in Wirklichkeit nicht gemacht habe.

6: einen Service genutzt habe (wie z.B. Sportverein, Essen gehen, Hotels, Wellness, usw.), den ich in Wirklichkeit nicht genutzt habe.

INDONESIAN

Di [], saya telah berbuat agar terlihat seolah-olah saya...

1: membayar harga yang lebih tinggi untuk suatu produk atau jasa dari harga yang sebenarnya saya bayar.

2: memiliki produk yang sebenarnya tidak saya miliki.

3: memiliki merek yang lebih mahal dari yang sebenarnya saya miliki.

4: membayar untuk produk atau jasa yang sebenarnya saya dapatkan secara gratis.

5: pergi liburan atau melakukan perjalanan (singkat) yang sebenarnya tidak saya lakukan.

6: menggunakan layanan (seperti klub olahraga, makan, hotel, spa, dll.) yang tidak saya gunakan.

ITALIAN

Su [], ho fatto finta di...

1: pagare per un prodotto o servizio un prezzo più elevato di quello che effettivamente avevo pagato.

2: avere prodotti che effettivamente non possiedo.

3: possedere marche più costose di quanto effettivamente possiedo.

4: avere pagato per un prodotto o servizio che effettivamente ho ricevuto a titolo gratuito.

5: avere fatto una vacanza o un breve viaggio che effettivamente non ho fatto.

6: avere utilizzato servizi (per esempio palestre, ristoranti, alberghi, terme, ecc.) che effettivamente non ho utilizzato

JAPANESE

[],で…

1: 商品やサービスに実際に払った金額よりも高い金額を払ったように見せかけたことがある。

2: 持っていない商品を持っているように見せかけたことがある。

3: 実際に持っているものよりも高いブランドのものを持っているように見せかけたことがある。

4: 実際はただで手に入れた製品やサービスをお金を払って手に入れたように見せかけたことがある。

5: 実際には行っていないのに長期旅行や短期旅行に出かけたように見せかけたことがある。

6: 実際には利用していないサービス (スポーツクラブ、外食、ホテル、スパなど)のどれか を利用したように見せかけたことがある。

POLISH

W serwisie [], próbowałem(-am) wywołać wrażenie, że…

1: zapłaciłem(-am) za produkt lub usługę więcej niż w rzeczywistości.

2: posiadałem(-am) produkty, których w rzeczywistości nie miałem.

3: posiadałem(-am) produkty droższych marek niż w rzeczywistości.

4: zapłaciłem(-am) za produkt lub usługę, które w rzeczywistości otrzymałem(-am) za darmo.

5: wybrałem(-am) się na urlop lub (krótki) wyjazd, choć nie było to zgodne z prawdą.

6: korzystałem(-am) z pewnych usług (takich jak siłownie, usługi gastronomiczne, hotelowe, spa itd.), choć nie było to zgodne z prawdą.

PORTUGUESE BRAZIL

Em [], eu dei a entender que eu

1: paguei um preço mais alto por um produto ou serviço do que realmente paguei.

2: possuía produtos que na verdade não possuía.

3: possuía marcas mais caras do que as que realmente possuía.

4: paguei por um produto ou serviço que na verdade obtive grátis.

5: saí em um feriado ou (breve) viagem em que na verdade não saí.

6: usei serviços (como clubes esportivos, jantares, hotéis, spa, etc.) que na verdade não usei.

PORTUGUESE PORTUGAL

No [], fiz com que parecesse que ...

1: …tinha pago um preço mais alto por um produto ou serviço do que aquele que realmente paguei.

2: …possuía produtos que na verdade não possuía.

3: …possuía marcas mais caras do que as que realmente possuía.

4: …tinha pago por um produto ou serviço que na verdade obtive grátis.

5: …tinha ido de férias ou feito uma (breve) viagem que na verdade não fiz.

6: …tinha usado serviços (como clubes desportivos, jantares, hotéis, spa, etc.) que na verdade não usei.

RUSSIAN

В сети [], я создал(а) видимость как будто бы я...

1: заплатил(а) более высокую цену за товар или услугу, чем на самом деле.

2: владел(а) товарами, которых у меня на самом деле нет.

3: владел(а) товарами более дорогих марок, чем на самом деле.

4: заплатил(а) за товар или услугу, хотя на самом деле это досталось мне даром.

5: ездил(а) на отдых или в (короткое) путешествие, хотя на самом деле это не так.

6: пользовался(ась) услугами (например, спортклубами, ресторанами, гостиницами, спа и т.д.), которыми я не пользовался(ась).

SPANISH CASTELLANO

En [], he aparentado...

1: pagar un precio más alto por un producto o servicio del que pagué realmente.

2: tener productos que en realidad no tenía.

3: tener marcas más caras de las que en realidad tenía.

4: pagar por un producto o servicio que en realidad recibí gratis.

5: tener unas vacaciones o viaje (corto) que en realidad no tuve.

6: usar servicios, como clubes deportivos, cenas, hoteles, spás, etc. que en realidad no usé.

SPANISH MEXICO

En [], he hecho parecer como si...

1: hubiera pagado un precio más alto por un producto o servicio del que pagué realmente.

2: tuviera productos que en realidad no tenía.

3: tuviera marcas más caras de las que en realidad tenía.

4: hubiera pagado por un producto o servicio que en realidad recibí gratis.

5: hubiera tenido unas vacaciones o viaje (corto) que en realidad no tuve.

6: hubiera usado servicios, como clubes deportivos, cenas, hoteles, spás, etc. que en realidad no usé.

SWEDISH

På [], har jag fått det att framstå som att jag …

1: betalat ett högre pris för en produkt eller tjänst än jag faktiskt gjort.

2: ägt produkter som jag egentligen inte ägde.

3: ägt dyrare varumärken än jag egentligen ägde.

4: betalat för en produkt eller tjänst som jag fick gratis.

5: åkt på en semester eller (kortare) resa som jag egentligen inte åkte på.

6: använt tjänster (t.ex. sportklubbar, middagar, hotell, spa osv.) som jag egentligen inte använt.

THAI

ใน [], ฉันแกล้งทำเป็นว่าฉัน...

1: ซื้อผลิตภัณฑ์หรือบริการในราคาแพงกว่าความเป็นจริง

2: มีผลิตภัณฑ์ที่จริงๆ แล้วไม่ใช่ของฉัน

3: มีสินค้าแบรนด์หรูที่จริงๆ แล้วฉันไม่มี

4: จ่ายเงินซื้อผลิตภัณฑ์หรือบริการที่จริงๆ แล้วฉันได้มาฟรี

5: ไปเที่ยวพักผ่อนในวันหยุดยาวหรือท่องเที่ยว(ในช่วงเวลาสั้นๆ) แต่จริงๆ แล้วไม่ได้ไป

6: ใช้บริการต่างๆ (เช่น เข้าฟิตเนส ดินเนอร์ พักโรงแรม เข้าสปา ฯลฯ) โดยที่จริงๆ แล้วไม่ได้ไปใช้บริการเหล่านั้น

TURKISH

[], üzerinden, kendimi sanki ... gibi gösterdim

1: bir ürün veya hizmet için aslında ödediğimden daha yüksek bir ücret ödemiş

2: aslında sahip olmadığım ürünlere sahip olmuş

3: aslında sahip olduğum markalardan daha pahalı markalara sahip olmuş

4: aslında bedava edindiğim bir ürün veya hizmet için ücret ödemiş

5: aslında yapmadığım bir tatili veya (kısa) seyahati yapmış

6: kullanmadığım hizmetleri (ör. spor kulüpleri, akşam yemeği, oteller, spa vs.) kullanmış

Summary

The dissertation provides insights into consumer's willingness to truthfully disclose their personal data on social media platforms based on a large-scale dataset that spans 25 countries and 5 continents. The data provide evidence that a significant proportion of consumers worldwide deliberately choose to present misleading information about themselves on social media platforms in order to enhance their online image, or in order to protect their privacy.

Dissertation chapters 2 and 4 provide tools to assess the proportions of deceptive disclosures on social media platforms. A self-report method to assess the truthfulness of consumers' social media disclosures is applied to estimate self-enhancing deception in the domains of physical appearance, personal achievement, and consumption across 25 countries. The estimated proportions, as well as the revealed sociographic and psychographic antecedents of self-enhancing deception, can be readily used by marketeers for prognostic purposes. Furthermore, the dissertation provides a novel econometric model for analysis of cross-cultural data on sensitive topics. The model can be used in combination with the aforementioned method for further research of the nomological network of deceptive disclosures on social media.

Chapter 3 of the thesis discusses consumer's willingness to disclose information on social media from yet another angle – the angle of consumers' privacy perceptions. The data suggest that consumers are motivated to provide deceptive disclosures on social media if they believe that their data are not used fairly. The chapter examined a managerially practical remedy to consumers' fairness concerns: offering consumers the choice to pay a monetary fee for their social media use instead of paying with their data. The global dataset revealed which consumer segments are likely to consider social media

data monetization practices unfair, and who would be willing to pay for the use of social media platforms instead of having their data used for commercial purposes. Managers can use these results to estimate the financial feasibility of offering consumers a fee-paying option given the consumer composition of their social media platform.

Taken together, the dissertation expands the theoretical body of knowledge on the prevalence and antecedents of deceptive consumer disclosures, and offers tools that allow marketers to refine the way in which they deal with consumer disclosures on social media platforms.

Nederlandse samenvatting

Het proefschrift geeft inzicht in de bereidheid van consumenten om hun persoonlijke gegevens naar waarheid vrij te geven op sociale mediaplatforms op basis van een grootschalige dataset die 25 landen en 5 continenten omvat. De gegevens leveren het bewijs dat een aanzienlijk deel van de consumenten wereldwijd er bewust voor kiest om misleidende informatie over zichzelf te verstrekken op sociale mediaplatforms om hun online imago te versterken of om hun privacy te beschermen.

Proefschrift hoofdstukken 2 en 4 bieden hulpmiddelen om de proporties van misleidende informatievrijgave op sociale mediaplatforms te beoordelen. Een zelfrapportagemethode om de waarheidsgetrouwheid van de informatievrijgave van consumenten op sociale media te beoordelen wordt toegepast om zelfverbeterende misleiding in te schatten op het gebied van uiterlijk, persoonlijke prestaties en consumptie in 25 landen. De geschatte proporties, evenals de onthulde sociografische en psychografische antecedenten van zelfverbeterende misleiding, kunnen door marketeers gemakkelijk worden gebruikt voor prognostische doeleinden. Verder biedt het proefschrift een nieuw econometrisch model voor analyse van interculturele gegevens over gevoelige onderwerpen. Het model kan in combinatie met de eerder genoemde methode gebruikt worden voor verder onderzoek naar het nomologische netwerk van misleidende informatievrijgave op sociale media.

Hoofdstuk 3 van het proefschrift bespreekt de bereidheid van consumenten om informatie op sociale media vrij te geven vanuit nog een andere invalshoek: de invalshoek van de privacypercepties van consumenten. De gegevens suggereren dat consumenten gemotiveerd zijn om misleidende informatie op sociale media te verstrekken als ze denken dat hun gegevens niet eerlijk worden gebruikt. Het hoofdstuk onderzocht een praktische middel voor managers om de bezorgheid van consumenten over eerlijkheid te verhelpen: consumenten de keuze bieden om een geldelijke vergoeding te betalen voor hun gebruik van sociale media in plaats van te betalen met hun gegevens. De wereldwijde dataset onthulde welke consumentensegmenten het genereren van inkomsten via sociale mediagegevens waarschijnlijk als oneerlijk beschouwen en wie bereid zou zijn om te betalen voor het gebruik van sociale mediaplatforms in plaats van dat hun gegevens voor commerciële doeleinden worden gebruikt. Managers kunnen deze resultaten gebruiken om de financiële haalbaarheid in te schatten om consumenten een betalende optie te bieden door middel van de consumentensamenstelling van hun sociale media platform.

Alles bij elkaar vergroot het proefschrift de theoretische kennis over de prevalentie en antecedenten van misleidende informatievrijgave van consumenten, en biedt het tools waarmee marketeers de manier kunnen verfijnen waarop ze omgaan met de informatievrijgave van consumenten op sociale mediaplatforms.

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