Article

Trading Data for Health

How Social Comparison Orientation and Privacy Attitudes Impact on mHealth App Use

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Abstract

mHealth apps are growing in popularity among smartphone users. Such apps often contain social features that enable users to compare their behaviour with others but to function, mHealth apps require users to share health information which is considered a threat to individuals' privacy. Building on social comparison theory and research on privacy decision-making, we investigate the effects of users' social comparison orientation and privacy attitudes as well as the potential mediating effect of health information disclosure on users' intention to use a dietary app. Relying on a PLS-based structural-equation model in a sample of N = 528 participants, our study supports claims of a positive effect of social comparison orientation on intention to use a mHealth app. Further, the negative effect of privacy attitude and the positive mediation of information disclosure were supported as well. The study also demonstrated that findings were stable when the context of information disclosure is changed.

Keywords

mHealth, health apps, social comparison, privacy, experiment, SEM.

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Recent years witnessed the growing importance of smartphone apps that support users' health and health-related lifestyles (Alessa et al., 2018; Becker et al., 2017; Park & Shin, 2020), with application ranging from the management of chronic diseases (Robbins et al., 2017) to apps supporting psychological conditions (Sprenger et al., 2017) to more general fitness or dietary apps (Klenk, et al., 2017). Even though empirical evidence on the quality and effectiveness of mHealth apps is sparse (McKay et al., 2018; Holmen et al., 2017; Brannon & Cushing, 2015) such apps become more and more widespread (Krebs & Duncan, 2015).

An important feature of mHealth apps is that they allow users to compare themselves with others (Gupta et al., 2020; Arigo et al., 2020). Part of the appeal, particularly of fitness and dietary apps, lies in the fact that they provide features such as leader boards where individual performances are evaluated and compared with others as well as features that allow users to directly compete against and/or compare themselves with friends (Li et al., 2019; Zhu et al., 2021). The Fitbit app, for instance, allows users to compare their weekly exercise with friends, running apps such as Runtastic compare individual performance with an undisclosed comparison group, and the Chinese Mi Fit app compares sleep, exercise, and weight profiles with other users in the same region. A recent scoping review of research on physical activity apps found that 31% of apps use one form or another of social comparison features (Arigo et al., 2020), underlining findings of an earlier systematic review that argued that competitive and cooperative social features are commonly used in mHealth interventions, but that their effects on behaviour need further investigation (Lee et al., 2018).

To compare their data with peers or 'relevant' others, users are required to share their personal information with the app provider. Sax, Helberger, and Bol (2018) point out that on part of the consumer, the use of mHealth apps is a double-edged sword as most mHealth apps provide users with tailor-made health solutions, either through user-driven customization or provider-driven personalization (Nguyen et al., 2020). The app economy, however, often necessitates the monetization of users' personal data (Cecere et al., 2020). Personal health data is considered particularly sensitive and its protection has become a major challenge for app users, providers, and regulatory bodies (Zhang et al., 2018; Martínez-Pérez et al., 2015; Dehling et al., 2015). This is particularly problematic because mHealth apps often request more data than they actually need in order to function properly (Brandtzaeg et al., 2019; Huang & Bashir, 2017).

The goal of this paper is to scrutinize in how far participants' intention to use mHealth apps (in our case a dietary app) is influenced by social comparison orientation and privacy attitudes as well as health consciousness. We argue that intention to disclose information to a dietary app with a social comparison functionality acts as a mediator and we also expect that contextual factors, e.g. cues on other people's health information disclosing patterns moderate participants' intention to use such an app. Empirically we test this by relying on an online survey with an experimental manipulation of the disclosing behaviour by others.

Social Comparison and App Use

Social comparison orientation has gained prominence in social science since Festinger's (1954) social comparison theory, investigating how social comparison processes occur and what effects they have, particularly with respects to individuals' self-esteem. Broadly speaking, social

comparison is understood as individuals' tendency to compare themselves with others in order to reduce uncertainty and to manage their self-concept (Festinger, 1954). More recent approaches employing social comparison orientation have started to investigate the relationship between social media use and social comparison processes (Feinstein et al., 2013). On a theoretical level, studies increasingly see social comparison processes as driven by individuals' characteristics and preferences (Schneider & Schupp, 2011). These approaches (for instance Buunk & Mussweiler, 2001) analyse in how far individuals vary in their frequency of self-comparison with others or even see differences in psychological predispositions for social comparison (Schneider & Schupp, 2014). Gibbons and Buunk (1999) understand social comparison as a two-factored construct, with a tendency to compare oneself based on one's abilities, and on orientations towards others' opinions.

Even though this and comparable approaches (Schneider & Schupp, 2014) have been employed to understand differences in social comparison orientation, the concept has rarely been applied towards the use of mHealth apps (Zhu et al., 2021). This is surprising, as Arigo and Suls (2018) highlight the importance of considering social comparison orientation to understand the use and effects of mHealth apps. In a related empirical study, Li et al. (2019) tested the continuous use of a fitness app by focusing on social comparison features (rank comparisons with others). They concluded that social rank expectations are the central driving force for continuous use, while upward comparisons may reduce usage intention. Further, there is some evidence that suggests a relationship between the use of social comparison features and the overall benefits users gain from using mHealth apps: Rockmann and Maier (2019) found that the use of social comparison features in mHealth apps was positively related to the overall benefit of use, but that this effect was stronger for users with high performance goals.

For our study we assume that higher levels of social comparison orientation will lead to a higher likelihood to use an mHealth app with social comparison features. Because these features are often enabled by users divulging their data, we have to consider the role of mobile privacy attitudes in the usage process.

Privacy Infringements as Usage Costs

The business model of contemporary apps, including mHealth apps, is that such apps are often free to use – or available for rather modest monetary prices – but require users to grant providers access to their personal data (Cecere et al., 2020; Sax et al., 2018). Becker et al. (2017) describe privacy concerns as perceived costs in the use of mHealth apps. Simply put, there seems to be a trade-off between users giving away personal data in order to use tailored mHealth apps. In addition, based on self-determination theory (Deci & Ryan, 2000), Joeckel and Dogruel (2020) outline that social connectedness functionalities in apps offer users the fulfilment of their need for relatedness while challenging their need for autonomy at the same time, via potential privacy infringements. Thus, users of mHealth apps need to evaluate the pros and cons of disclosing personal information on the one hand and protecting their privacy on the other.

This mirrors findings from research on the privacy-calculus model (Dinev & Hart, 2006; Dienlin & Metzger, 2016; Trepte et al., 2020). This rational decision-making model argues that users – more or less explicitly – base privacy decisions on cost-benefit calculations. Related, such

rational decision models argue that even though privacy attitudes are not the only explanatory factor for privacy decisions, a recent review (Kokolakis, 2017) and metareview (Baruh et al., 2017) underline their importance in privacy decision-making processes. Privacy attitudes can explain users' intention to disclose personal information (Dienlin & Trepte, 2015). Referring to the use of mHealth apps and following findings by Becker et al. (2017) such attitudinal factors are perceived as usage costs that are likely to reduce the intention to further use an app or act as an entrance barrier to start using mHealth apps (Brandtzaeg et al., 2019; Zhou et al., 2019). Similarly, mHealth apps are perceived as trustworthier, if they adhere to strict privacy policies and if users maintain control over their data (van Haasteren et al., 2019).

As such, privacy attitudes are a factor that – fully or partially mediated through intention to disclose private information – will reduce the likelihood to use a mHealth app with a social comparison feature. That is, while social comparison orientation is likely to booster app use, privacy attitudes act as a barrier to do so.

The Impact of Social Norms

Social comparison works through mechanisms that relate to social norm theory (Rimal & Lapinski, 2015). Dempsey et al. (2018) outline that health interventions need to take social norms into consideration and research since the 1980s found that one's health behaviour is influenced by perceived social norms (Perkins & Berkowitz, 1986). Here, not only norms of what should be done (injunctive norms) but descriptive norms, the actual observed behaviour of others (Cialdini & Trost, 1998), come into play. Other people's behaviour acts as a mental shortcut to guide one's actions, so if other people adhere to a certain behaviour, the tendency to do the same is increased. Empirical evidence shows that this pattern is also observed for mHealth apps (Lazard et al., 2020). Such orientations towards descriptive social norms are also one important context factor within privacy decision-making (Teutsch et al., 2018; Masur & Scharkow, 2016) and impact disclosing behaviour (Spottswood & Hancock, 2017). This means that particularly for a mHealth app with embedded social comparison features other users' disclosing behaviour and, as a consequence, intention to use such an app, is very likely not independent from how other users use such an app and disclose personal information. As a novel addition to current research, we therefore investigate the impact of such descriptive norms on the effects of privacy attitudes and social comparison orientation.

A Research Model of Social Comparison, Privacy Attitudes, and Information Disclosure on Intention to Use and Recommend Apps

The core of our research model (see Figure 1) is centred on the role of social comparison orientation and privacy attitudes on the use of a mHealth app with social comparison features. Following our literature review, we assume that the higher one's social comparison orientation, the higher the intention to use this app (H1 and path H1 in our model). At the same time, we propose H2 suggesting that the higher one's privacy attitudes are, the lower one's intention to use an app that requires giving away personal data for social comparison purposes will be (path H2). For H3, we expect that the relationship between privacy attitudes and intention to use is mediated

through users' intentions to disclose health-related information. Therefore, H3a states that the higher one's privacy attitudes the lower one's intention to disclose private information (path H3a) and, related in H3b we propose that the higher one's intention to disclose private information, the higher one's usage intention of an mHealth app with a social comparison feature (path H3b). To confirm H3, we expect the indirect effect of privacy attitudes on intention to use the app to remain significant after H3a and H3b were accounted for. As the disclosure of health-information is considered a cost that occurs for using the app, high levels of privacy attitudes will be interpreted as higher perceived usage costs. As privacy decisions are always a wagering of self-disclosure vs. self-protection (Joeckel & Dogruel, 2020) and as social comparison is likely to require disclosures of others, we also expect some kind of tit-for-tat behaviours such as that those high in social comparison orientation are also more likely to disclose more information needed for these social comparison processes. Therefore, in H4 we propose a positive effect of social comparison orientation on intention to disclose information (path H4). Consequentially, in H4a we also expect a potential mediation effect of information disclosure for social comparison orientation as well.

For a more complete picture, we have to take two contextual factors into consideration. First, as we are focusing on mHealth app use, information disclosure and usage intention of such apps are not independent from people's own health (Park & Shin, 2020). Therefore, attitudes towards one's health need to be accounted for. Second, as outlined above, social comparison as well as intention to disclose personal information are influenced by perceived social norms. Thus, our described research model might be impacted by the prevalent social norms in terms of other user's (disclosing) behaviour.
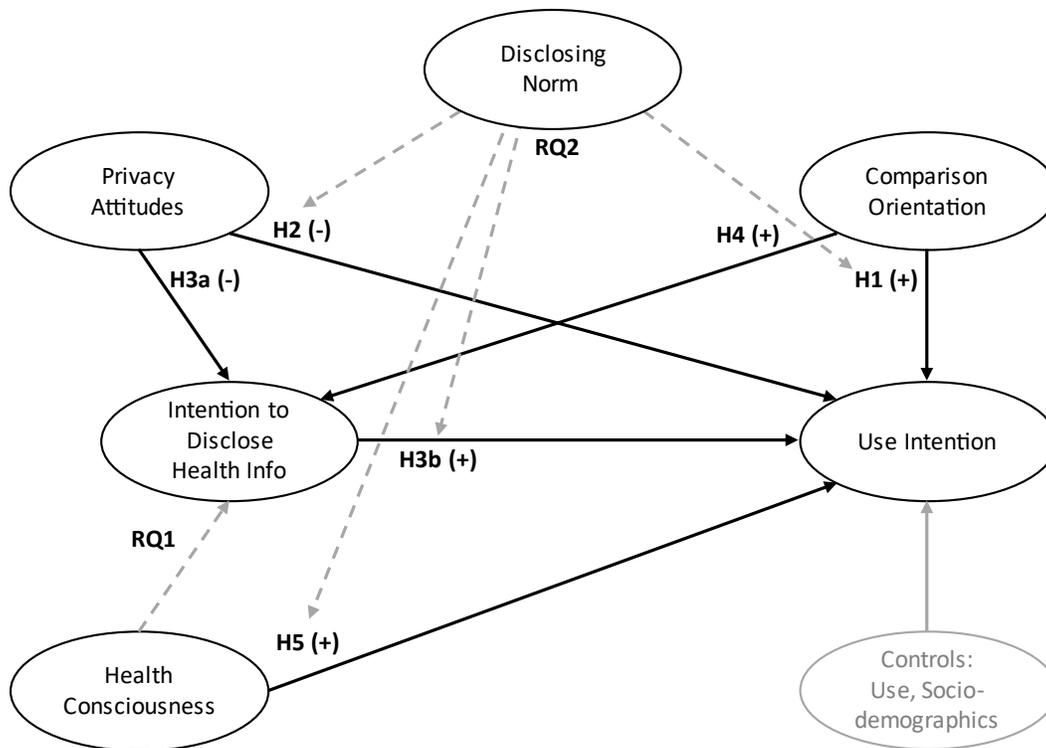

Figure 1.   Research Model Depicting Proposed Effects on Intention to Use a mHealth App.

Focusing on potential impacts from health attitudes, Chen and Lin (2018) argue that for inquiring about mHealth app usage, research models should be supplemented with aspects of health consciousness, which can be defined as the extent to which individuals take care of their health (Gould, 1990; Cho et al., 2014). That is, an individual high in health consciousness, will make choices that reflect this belief, for instance choosing healthier food or using an app that supports one's healthy lifestyle. Empirically, both Chen and Lin (2018) and Cho et al. (2014) found support that health consciousness has a positive impact on mHealth app usage. We can supplement our model with H5 that assumes that the higher one's health consciousness the higher one's intention to use the mHealth app with social comparison features usage (path H5). It seems plausible that if users are concerned about their health, they see the need to disclose health information as this allows an app to provide a more tailored user experience (c.f. Park & Shin, 2020). Still for mHealth app use, this relationship has not been theoretically undermined and/or empirically tested yet, so we put it up for debate, hence the dotted line in our model (path RQ1) which inquires on the following research question (RQ1): What is the relationship between health consciousness and the intention to disclose personal information for an mHealth app?

For the impact of social norms on our model, we investigate in how far different levels of social norms, manipulated through the perceivable disclosing behaviour of others, might moderate the effects in our model. Therefore, we manipulate social norms through the number of other users disclosing personal information and ask a second research question (RQ2): How does the number of other users disclosing private health information affect the research model described above, particularly with reference to the impact and strength of privacy attitudes and social comparison orientation? On an empirical level, we control for socio-demographic and usage related variables (prior app use, usage frequency).

Method

Participants

Participants were recruited in October 2018 through a commercial online access panel in Germany as part of a larger research project on mHealth app use and privacy. They had to qualify for the study by indicating whether they used a smartphone. After eliminating incomplete data, a total of $N = 528$ participants (48.2% female; 55.3% highly educated; $M_{age} = 46.17$; $SD = 13.30$) remained in the study's sample.

Study Design and Procedures

After answering some questions about their app use in general and health-related app use in particular, participants were asked about their privacy attitudes, social comparison orientation, and health consciousness. They were then told that they were going to be confronted with a description of an app targeting health-related issues. The original and translated study material is included in the appendix.

We created a description of a hypothetical food app, *FoodieEdu*. The main function of the app as described on an app introduction screen within the survey, was to provide users with tailored

dietary health information. This description contained information on how the app uses social comparison to provide better results, such as a statement in the app that read *"try not to eat after 8pm – 46% of users with eating habits such as yours have tried it and report feeling better"* or *"stay hydrated – 86% of users in your region drank more than you"*. On a second screen, users had to indicate which type of personal information they were willing to share with the app. This list contained eleven data points such as age, gender, current location, including five health-related information points, namely height, weight, blood pressure, dietary information (vegetarian, vegan, omnivore), and food allergies. To manipulate different levels of descriptive disclosing norms, each item on this list was accompanied by a percentage of other app users having provided this type of information. This number ranged from 1% to 100% of other users. Numbers were randomly generated based on the following criteria: one tenth of the sample (control group) received no information of other users indicating the data points, three out of ten received a number ranging from 1% to 33% for each type of information (condition: low), for another three out of ten the number ranged from 34% to 66% (condition: medium), and the remaining group received a number ranging from 67% to 100% (condition: high). This procedure allowed us to first analyse all groups combined and then to further investigate the impact of descriptive disclosing norms (RQ2).

Measures

Behavioural Intention to Use and Recommend an App. Following related research on the use and acceptance of mHealth apps (Sprenger et al., 2017), we employed two measures for users' behavioural intention to engage with the presented *FoodieEdu* app. First, participants rated their likeliness to use the app in the future, described as intention to use. Second, we employed an item inspired by Reichheld's (2003) net-promoter score and previously used as a measure for app evaluations (Dogruel et al., 2017), asking how likely participants are to recommend the app for a friend (i.e. intention to recommend). Intention to use and intention to recommend were both measured on a five-point rating scale and combined into a formative factor.

Social Comparison Orientation. We measured social comparison relying on the translated short version of the original Social Comparison Scale by Gibbons and Buunk (1999) as tested and applied by Schneider and Schupp (2011; 2014). The two-dimensional structure is measured with items such as "I often try to find out what others think who face similar problems as I face" for the comparison of abilities and items such as "I always pay a lot of attention to how I do things compared with others" used to measure comparison of abilities. In total, the scale consists of six items replicating the original two-factor structure comparing abilities (item 1 – 3) and opinions (items 4 – 5), each measured on a five-point rating scale. We employed these two additive mean indexes to generate a reflective factor for social comparison orientation.

Privacy Attitudes. We assessed participants' attitudes following the model promoted by Dienlin and Trepte (2015). They differentiate privacy attitudes into three dimensions: (1) using apps which rely on user data in order to function, (2) disclosing such information, and (3) personalized app user experiences. We presented participants with three incomplete statements related to privacy and app usage (i.e. "If mobile apps access my personal data that is…"). Participants were then asked to finish each statement on a 5-point semantic differential with six adjective pairs, which

was adapted from Dienlin and Trepte (2015). After recoding each variable so that high values on the differential indicated high privacy attitudes, we formed the three subdimensions as an additive mean index and used these as indicators for a reflective factor in the model.

Intention to Disclose Health Information. For each app, we asked participants whether or not they were willing to disclose a list of eleven different types of information (coded *yes* or *no*). We counted the number of health-related information (*none* to *five*) users were willing to disclose.

Health Consciousness. For measuring health consciousness, we employed five marker items from Gould's (1990) health consciousness scale that we translated into German and employed as a reflective factor.

Control Variables. As controls, we accounted for users' prior use of food-related apps (dietary apps, calorie/ fat and/or protein counter apps) by relying on a five-point rating scale, ranging from 1 = *never* to 5 = *regularly* as well as users' app usage frequency by inquiring about their time of daily app usage with a scale ranging from 1 = *never* to 5 = *more than 5 hours*.

We also accounted for participants' age, gender (*male/female*), and education (high = *A-Level* vs. low = *no A-Level*).

Results

Data Analysis Strategy

Data analysis was based on structure-equation models using the PLS-procedure in SmartPLS 3.0 (with consistent bootstrap of N = 5,000; Ringle et al., 2015). In contrast to covariance-based SEM, SmartPLS has lower requirements on sample size and measure properties and allows the use of reflective as well as formative latent factors at the same time (Hair et al., 2014). Even though, there is no procedure to accurately gauge the statistical power of PLS-based approaches, we can draw reference from related approaches, such as linear multiple regression analysis or mediation analysis. Based on Fritz and MacKinnon's (2007) analysis as well as a calculation for regression analysis in G-Power (Faul et al., 2007), our sample would yield sufficient power (>80%) even for low effect sizes.

Previously employed measures were used as reflective factors and our dependent variable. Behavioural intention to use and recommend the app was measured as a formative factor. We employed a first-order model for each of the measures employed as we did not set out to test the factor structure of previously tested sub-scales. Table 1 gives an overview on our measurement and latent factor structures.

As PLS-based SEM does not treat global fit indicators, particularly when models include formative factors, the same way as covariance-based SEM, such indicators should be treated cautiously (Hair et al., 2014) but are included in Table 1 as well.

Table 1. Scale Properties and Item List

(Latent) Construct	Subdimension & items (scale properties)	Loading [95% CI]	Measurement and scale	Source
Behavioural intention to use and recommend an app *r* = .83 [.79; .86]	"How much would you …" "… like to use the app" (M = 2.8 [2.7; 2.8], SD = 1.2 [1.2; 1.3]) "… recommend the app to a friend" (M = 2.6 [2.5; 2.7], SD = 1.2 [1.2; 1.3])	.99 [.96; 1.0] .91 [.84; .95]	1 = *not at all* 5 = *very much*	self-developed
Information disclosure	"Would you be willing to disclose your …?" (FE: *M* = 3.60 [3.46; 3.74], *SD* = 1.71 [1.60; 1.81]) "Height" (80.5% [77.1; 83.6]) "Weight" (75.1% [71.3; 78.6]) "Blood pressure" (59.1% [55.0; 63.7]) "Dietary preferences" (73.9% [70.3; 77.7]) "Food allergies" (71.6% [67.9; 75.6])		0 = *not selected* 1 = *selected*	self-developed
Social comparison orientation α = .78, *rho_A* = .80, CR = .79, AVE = .65	Abilities (Item 1, item 2, item 3) (*M* = 2.51 [2.44; 2.59], *SD* = 0.92 [0.87; 0.97], α = .66) Opinion (Item 4, item 5, item 6) (*M* = 2.83 [2.74; 2.91], *SD* = 0.98 [0.92; 1.02], α = .84)	.73 [.62; .84] .88 [.78; 1.0]	1 = *agree not at all* 5 = *agree very much*	Schneider & Schupp (2011; 2014)
Privacy attitudes α = .88, *rho_A* = .89, CR = .88, AVE = .70	"When mobile apps access personal data, I find that …" (*M* = 3.70 [3.63; 3.78], *SD* = 0.82 [0.78; 0.86], n = 495, α = .84) "Disclosing personal data to a mobile app to unlock all functions is …" (*M* = 3.68 [3.6; 3.746], *SD* = 0.82 [0.78; 0.87], n = 495, α = .86) "Personalized offerings based on my data are …" (*M*= 3.46 [3.39; 3.54], *SD* = 0.84 [0.79; 0.89], n = 495; α = .86)	.74 [.58; .86] .83 [.73; .92] .93 [.80; 1.0]	Rating scale *ranging* from 1 to 5 *very useful – not useful* *advantageous – disadvantageous* *worrying – not worrying*[*] *very dangerous – not dangerous*[*] *very careful – not careful* *very bad – very good*[*]	Self-developed based on Dienlin & Trepte (2015)
Health consciousness α = .85, *rho_A* = .87, CR = .85, AVE = .54	"How much do you agree with the following statements?" "I think a lot about my health" "I permanently monitor my health" "I deal a lot with my health" "I pay attention towards changes in my health" "In my everyday life, I take care of how I feel"	 .85 [.71; 1.0] .80 [.67; .96] .78 [.62; .93] .70 [.50; .86] .47 [.20; .67]	1 = *agree not at all* 5 = *agree very much*	Self-developed based on Gould (1990)

Note. Factor loadings based on PLS-Consistent bootstrap with *N* = 5,000 samples, 5% bias corrected confidence intervals. Properties of point estimates based on estimate with *N* = 1,000 bootstrap using, 5% confidence interval. Discriminant validity achieved for all constructs (HTMT < .85), SRMR = .05; NFI = .85. [*]Marked items reversed.

Hypothesis Testing

Overall, our research model explains 40.6% of total variance. This includes the influence of our control variables. Of these socio-demographic variables age ($b* = .05$, 95% CI [-.03, .14], $p = .197$), gender ($b* = -.03$, 95% CI [-.10, .05], $p = .492$), and education ($b* = .01$, 95% CI [-.06, .08], $p = .775$) did not contribute significantly to the model. Yet, prior app use ($b* = .21$, 95% CI [.13, .28], $p < .001$) and app usage intensity ($b* = .14$, 95% CI [.05, .22], $p = .002$) were significant positive predictors for behavioural intentions to use and recommend, our central dependent measure.

We can confirm H1 and H2 as we observe a significant positive effect of social comparison orientation on behavioural intentions to use and recommend (path H1; $b* = .18$, 95% CI [.08, .29], $p = .001$) and a significant negative effect of privacy attitudes on intentions to use and recommend (path H2; $b* = -.21$, 95% CI [-.29, -.13], $p < .001$). To test H3, we first tested H3a, the negative effect from privacy attitudes on intention to disclose heath information (path H3a) and then H3b, the positive effect of intention to disclose heath information on intentions to use and recommend (path H3b). We can confirm both H3a ($b* = -.17$, 95% CI [-.27, -.07], $p = .001$) and H3b ($b* = .26$, 95% CI [.19, .33], $p < .001$). With H3a and H3b confirmed, we can test the mediation effect proposed in H3. Here, we expected that part of the influence of privacy attitudes on intentions to use and recommend was mediated through the relationship of privacy attitudes with intention to disclose heath information. We can confirm this in the model. The specific indirect effect of privacy attitudes through intention to disclose heath information on intentions to use and recommend was weak but negative and significant ($b* = -.04$, 95% CI [.08, -.02], $p = .005$). Consequentially, the total effect of privacy attitudes on intentions to use and recommend was the combination of these two effects (direct, indirect) and also negative and significant ($b* = -.25$, 95% CI [-.33, -.16], $p < .001$).

In H4, we further expected that social comparison orientation positively impacted on intention to disclose heath information (path H4) and we can also confirm this effect ($b* = .13$, 95% CI [.03, .23], $p = .015$). For testing H4a, the mediation effect of social comparison orientation on behavioural intentions to use and recommend through intention to disclose heath information, we looked at the specific indirect effect, which was weak but positive and significant ($b* = .03$, 95% CI [.01, .06], $p = .022$), confirming H4a. The total effect of social comparison orientation on intentions to use and recommend was positive and significant ($b* = .22$, 95% CI [.11, .33], $p < .001$). All in all, we see that intention to disclose health information indeed partially mediates the effects of privacy attitudes and social comparison orientation on intention to use and recommend an app.

As expected in H5, health consciousness had a significant and positive effect on behavioural intentions to use and recommend (path H5; $b* = .17$, 95% CI [.08, .26], $p < .001$).

Investigating RQ1 and RQ2

In RQ1, we were wondering if health consciousness effected intention to disclose heath information, which would imply that intention to disclose heath information could also become a mediator for the relationship of health consciousness on behavioural intentions to use and recommend. Yet, the corresponding path health consciousness on intention to disclose heath

information) was not significant ($b^* = .10$, 95% CI [-.01, .19], $p = .056$). The same was found for the specific indirect effect of health consciousness on intentions to use and recommend through intention to disclose heath information ($b^* = .02$, 95% CI [-.00, .05], $p = .060$]. Still, the total effect of health consciousness on intentions to use and recommend is significant ($b^* = .19$, 95% CI [.10, .28], $p < .001$). In our study, we cannot confirm a mediation of health consciousness on intentions to use and recommend through intention to disclose heath information but due to confidence intervals that only marginally span into the negative, we do not rule them out for future studies and leave the question open for further exploration.

To investigate the potential impact of social norms on our model (RQ2), data analysis now looked at the effects of the three levels of disclosing norms, that is a low number of other users (Group 1), a medium number of users (Group 2) and a high number of other users (Group 3) disclosing personal information. As we were interested in analysing impacts of several effects at the same time, we carried out a multi-group-analysis following the Smart-PLS procedure comparing these three experimental conditions. Multi-Group-Analysis not only presents path-coefficients for each of the three groups as data subsets but compares if these path coefficients differ significantly from each other. We employed the PLS-MGA procedure. This test indicates if two effects differ significantly from each other on the 5% level, when the p-level is either below .05 or above .95 depending on the direction of the difference (Henseler et al., 2009). Testing for differences between all paths in these three subsets might lead to high alpha error inflation and we are not interested in all subtle changes within the model. Instead, we wonder if the overall strength of the effects of our predictors remained stable. Therefore, we focused on the total effects of our predictor variables on behavioural intentions to use and recommend. That is, we focused on the total effects of social comparison orientation, privacy attitudes, intention to disclose heath information (where direct and total effect are identical) as well as health consciousness on intentions to use and recommend.

Table 2.   Standardized Total Effects per Condition

	Condition					
	Low $n = 157$		Medium $n = 161$		High $n = 157$	
	b^*	95% CI	b^*	95% CI	b^*	95% CI
Social comparison orientation on intentions to use and recommend	.16	[-.01; .33]	.18	[.01; .33]	.19	[.01; .38]
Privacy attitudes on intentions to use and recommend	-.34	[-.48; -.20]	-.26	[-.40; -.12]	-.14	[-.28; .01]
Intention to disclose heath information on intentions to use and recommend	.28	[.13; .41]	.19	[.05; .35]	.38	[.26; .50]
Health consciousness on intentions to use and recommend	.12	[-.06; .25]	.27	[.12; .39]	.08	[-.08; .21]

Table 3.   Differences in Standardized Total Effects

	Differences (Δ)					
	Low vs. medium		Low vs. high		Medium vs. high	
	Δ	*p*	Δ	*p*	Δ	*p*
Social comparison orientation on intentions to use and recommend	.02	.586	.03	.606	.01	.528
Privacy attitudes on intentions to use and recommend	.08	.782	.20	**.968**	.12	.867
Intention to disclose health information on intentions to use and recommend	.09	.183	.10	.850	.19	**.976**
Health consciousness on intentions to use and recommend	.15	.933	.04	.360	.18	**.033**

Note. Significant differences on the 95%-level in **bold** (p < .05 or p > .95, based on PLS MGA significance test).

Table 2 presents these effects including the bias-corrected 95% confidence intervals for our three groups. Table 3 then depicts the results of the significance test for the group comparison following the PLS-MGA algorithm.

For the effects of social comparison orientation and privacy attitudes on behavioural intentions to use and recommend we see two opposing patterns: The more other people disclose health information, the more important social comparison orientation became as a predictor for intentions to use and recommend and the less important privacy attitudes gets. In the low disclosing condition, social comparison orientation was not a significant predictor for intentions to use and recommend but it became significant in the medium and high condition. Yet, this increase was subtle, and coefficients did not differ significantly (see Table 3). Privacy attitudes, in contrast, was a significant predictor in the low and medium condition but no longer in the high disclosing condition and here the difference in effect size between the low and the high condition became significant (see Table 3).

Even if the effect sizes for intention to disclose heath information on behavioural intentions to use and recommend between the medium and high condition differed significantly (see Table 3), the overall effect size was rather stable: intention to disclose heath information remained a significant positive predictor for intentions to use and recommend for all three groups – it simply became slightly more important in the high disclosing condition than in the medium condition.

For health consciousness, we see a more diverse picture. It only remained a significant predictor in the medium condition and effect sizes differed significantly between the low and the high condition. This finding is surprising and remains open for further inspection, as we have no theoretical assumption, why the effect of health consciousness should be influenced by other people's disclosing behaviour.

Summary

All in all, we could confirm all our hypotheses as we see health consciousness and social comparison orientation as significant positive predictors of intention to use and recommend a mHealth app and privacy attitudes as a negative one. We observed direct effects for all of these constructs but parts of these effects were mediated through their relationship with intention to disclose health information, which not only acted as a mediator but additionally added a significant part of variance explanation. Thus, the central role of intention to disclose health information in our model could be confirmed. This was also confirmed in our multi-group analysis which we carried out to examine the impact of different disclosing norms. Here, in answering, RQ2, we also saw that different disclosing norms are likely to impact the effects of social comparison orientation and privacy attitudes, increasing the first, when more users disclose personal information and increasing the latter when only few users disclose personal information.

Discussion

We set out to investigate the interdependence between social comparison orientation and privacy attitudes for users' intention to use an mHealth app with a social comparison functionality. Our central assumption was that mHealth app users 'pay with their privacy for using social comparison orientated apps. If users cherish their own privacy, they become reluctant to use an mHealth app but if they are high in social comparison orientation, this will increase their likelihood to use it. Even so, these two processes are well studied, for instance with respect to the privacy-calculus model for app use in general (Dienlin & Metzger, 2016; Trepte et al., 2020) and some few studies on the impact of social comparison on mHealth app use (Li et al., 2019; Arigo & Suls, 2018; Arigo et al., 2020, Zhu et al., 2021). To our understanding, no study has investigated both potential effects at the same time. Empirically, our study underlines that both concepts are crucial predictors for intention to use and recommend an mHealth app. More importantly, our results highlight the fact that the effects of both predictors are mediated by the intention to disclose personal health information, which itself becomes a stable – positive – predictor for usage intention. As a consequence, we can argue that the disclosure of personal information indeed is the 'price' (Becker et al., 2017) users who cherish their privacy have to pay to use mHealth apps.

We found these relationships to be stable when other crucial variables are controlled for, such as socio-demographic variables but also prior app use and app usage frequency. Further, we particularly focused on health consciousness as a relevant variable for mHealth app use. In line with previous research (Chen & Lin, 2018; Cho et al., 2014), we found it to be an additional predictor that is, however, less likely to be mediated by the intention to disclose private health information.

Both privacy decision-making as well as social comparison processes depend on other people's behaviour. Therefore, we also investigated changes in our proposed model resulting from changing in the app's decision-making environment.

Here, we manipulated the disclosing norms (Spottswood & Hancock, 2017) of other users. Relying on multi-group analysis, we tested in how far this change in the setting impacted on the (total) effect sizes of our model. Overall, we see a rather consistent picture: When contexts change

from few to many people disclosing personal health information in an app, privacy attitudes are more and more suppressed and social comparison orientations become more and more salient, so that for future research we may postulate these findings as new, testable hypotheses:

$H1_{new}$: When users observe that more people disclose health information, this will suppress the effect of privacy attitudes on intention to use and/or recommend a social comparison oriented mHealth app.

$H2_{new}$: When users observe that more people disclose health information, this will bolster the effect of social comparison orientation on intention to use and/or recommend a social comparison oriented mHealth app.

For other predictors, our findings are less stable: Health consciousness was only a significant predictor in the group with medium levels of others disclosing information. One possible explanation is that privacy attitudes and social comparison orientation were too important in the other groups. Only if a risk for one's privacy is not indicated by a small number of others disclosing information, or if social comparison becomes a dominant predictor, because an overwhelming majority of users disclose such information, users do rely on their health consciousness to decide. Similarly, the effect of intention to disclose health information on usage intention was weakest when a medium number of other users disclosed information. Again, this indicates that users might have difficulties to judge the costs and benefits of disclosing health information in such conditions. In other words, if only few others share data with an app, the app is perceived as costlier (i.e. sharing data might have detrimental consequences). On the other hand, if many users share their data, the app is perceived as more trustworthy and privacy attitudes take a backseat to social comparison. If, however, some data points are shared by slightly more than 50% of others and different data points by slightly less than 50%, users have a hard time to consider these cues in their decision-making process.

Limitations and Outlook

Despite this open field for debate, our findings are rather stable and underline our theoretical assumption. Nevertheless, we must note some limitations, both on a theoretical as well as a methodological level. On a theoretical level, we see that although our research model was based on existing theoretical assumption on the effects of privacy attitudes as well on some recent findings on the impact of social comparison orientation on the use and usage intention of apps, our research model is rather eclectic and not firmly rooted in one of the more prominent models of technology use and acceptances such as the technology acceptance model (Davis, 1989), or newer variations such as the technology readiness and technology acceptance model (TRAM; Lin et al., 2007) or the classical UTAUT2 (Venkatesh et al., 2012; Hoque & Sorwar, 2017) model. We do not see this as problematic for our approach, as we focus on the identification and interrogation of specific effects of privacy attitudes and social comparison orientation but we acknowledge the fact that future research is well advised to integrate our findings into more general models of technology use and acceptance to provide a more general perspective on the barriers and support factors of mHealth app use in general.

Related to this, our study was based on one, fictious app. Therefore, the generalization of our findings is limited, which calls out for a replication of our study with varied settings, such as

different user groups and different types of mHealth apps. In our study, we had focused on a dietary app, which is a prominent example of mHealth apps but do not cover the broad range of available offers and some apps, for instance apps for chronic disease management (Robbins et al., 2017) are likely to both increase perceived benefits as well as perceived costs of disclosing personal data. Future studies that seek to replicate our findings, or set out to test our newly proposed hypotheses, would benefit from pre-registering their predictions to further advance the intersection of health communication and privacy research following the ideals of open science research.

Comparable to other studies on mHealth app use and acceptance and moving more to the methodological level, another limitation of our study refers to the fact that we were only able to focus on behavioural intention and not actual usage. We only measured intention to disclose personal information as well as intention to use and recommend an app. For the latter, we relied on a two-item measure that had combined usage intention and intention to recommend. Although both items correlated highly and both loaded high onto our common factor, it still was a parsimonious measure that could account for some but perhaps not all aspects of behavioural intention. Such measures are always second-best choices, as we were not able to observe actual behaviour. However, this is a critique valid for a substantial amount of related research, as actual behaviour is hard to observe and even harder to systematically manipulate to allow for experimental-type research.

Conclusion

Taken together, our research has opened the ground for a better understanding of the interdependent relationship between privacy attitudes and social comparison orientation in the use of mHealth apps and underlines the importance of these factors for the use and acceptance of mHealth apps. Only if the impact of these two factors is fully accounted for, so we claim as a conclusion, will we understand how and why users choose to use or not to use mHealth apps that have the potential to provide them with tailored health solution which support them in their everyday life health management.

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Conflict of Interest

Authors declare no conflict of interest.

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Appendix

Stimulus Material

Page 1: Instructions

Original (German)

Gesünder leben

(…)

Bitte lesen Sie sich die Beschreibung der App jeweils in Ruhe durch. Auf der folgenden Seite sehen Sie einige Informationen, die Nutzerinnen und Nutzer angeben können, um die App zu personalisieren. Diese Personalisierung hilft Ihnen einerseits dabei, die App auf ihre Wünsche und Ansprüche einzustellen, Sie geben jedoch andererseits persönliche Informationen über sich preis.

Wir bitten Sie jeweils anzugeben, welche Informationen Sie der App zur Verfügung stellen würden. Je mehr Informationen Sie der App zur Verfügung stellen, desto genauer kann diese auf Ihre persönliche Situation eingehen. Wenn Sie gar keine Information auswählen, kann es sein, dass die App nicht ordnungsgemäß funktioniert.

English Translation

Healthier living

(…)

Please read the description of the app carefully. On the following page you will see some information that users can enter to personalize the app. On the one hand, this personalization helps you to adjust the app to your wishes and needs, but on the other hand, you also disclose personal information about yourself.

We ask you to indicate what information you would provide to the app. The more information you provide to the app, the more precisely it can respond to your personal situation. If you do not select any information at all, the app may not function properly.

Page 2: Stimulus Presentation

Original (German)

FoodieEdu

Haben Sie das Ziel, mehr auf Ihre Ernährung zu achten? Diese App hilft Ihnen dabei, sich Ihrem Ziel gemäß gesund zu ernähren – egal ob Sie abnehmen oder einfach darauf achten wollen, sich gesünder, etwa mit weniger Zucker, zu ernähren.

Hierfür finden Sie bei uns Tools wie ein Ernährungstagebuch und Ernährungspläne, die Ihren individuellen Vitamin-, Mineralstoff-, Proteinbedarf u.v.m. berücksichtigen. Gerade im stressigen Alltag hilft FoodieEdu Ihnen Ihre Ernährung immer im Blick zu behalten und auszuwerten. Auf lange Sicht will FoodieEdu Ihnen dabei helfen, täglich auf die Ernährung zu achten und diese bei Bedarf zu verändern. Zentraler Bestandteil ist eine Ernährungsdatenbank mit tausenden Grundnahrungsmitteln und Produkten aus dem Supermarkt, die so einfach protokolliert werden können.

Die App bietet:

- Individuelle Ziele: Egal, ob Sie abnehmen, zunehmen oder einen Marathon laufen möchten. FoodieEdu unterstützt Sie bei Ihren Zielen!
- Individueller Ernährungsplan: Erstellen Sie den passenden Ernährungsplan für Ihre Ziele.
- Individuelle Analysen: Die App bietet Ihnen eine Auswertung Ihrer gewählten Lebensmittel und Sie erhalten Tipps zur Optimierung.

Um das Angebot besser auf Sie zuzuschneiden, haben Sie in den Einstellungen der App die Möglichkeit, weitere persönliche Daten preiszugeben. Dadurch erhalten Sie und andere Nutzerinnen und Nutzer die Möglichkeit, Ihre Ernährungsgewohnheiten zu optimieren. Je nachdem welche Angaben Sie getätigt haben, erhalten Sie Informationen wie: **„Versuchen Sie mal nicht mehr nach 20 Uhr zu essen, 43% der Personen mit Ihrem Ernährungsprofil haben es ausprobiert und fühlen sich danach besser". „Achten Sie darauf mehr zu trinken, 86% der Nutzer in Ihrer Region haben heute mehr getrunken als Sie". Oder einfach „Sie liegen im Trend – Pasta ist das liebste Mittagessen von Personen in Ihrem Alter".**

English Translation

FoodieEdu

Do you have the goal of paying more attention to your diet? This app helps you to eat healthy according to your goals - no matter if you want to lose weight or if you just want to eat healthier, for example with less sugar.

For this purpose, we provide you with tools such as a nutrition diary and nutrition plans that take your individual vitamin, mineral and protein requirements and much more into account. Especially in stressful everyday life, FoodieEdu helps you to always keep an eye on and evaluate your nutrition. In the long run, FoodieEdu wants to help you to pay attention to your diet every day and to change it if necessary. The central component is a nutrition database with thousands of basic foods and products from the supermarket, which can be easily logged.

The app offers:

- Individual goals: Whether you want to lose weight, gain weight or run a marathon. FoodieEdu helps you to achieve your goals!
- Individual nutrition plans: Create a nutrition plan tailored to your goals.
- Personalized analysis: The app analyzes what you eat and helps you to optimize your grocery list.

In order to better tailor the offer to you, you have the option of disclosing additional personal information in the app's settings. This gives you and other users the opportunity to optimize your eating habits. Depending on the information you have entered, you will receive information such as: **"Don't try to eat after 8 pm, 43% of people with your nutritional profile have tried it and feel better afterwards". "Make sure you drink more, 86% of people in your area have drunk more than you have today". Or simply "You're trendy - pasta is the favorite lunch of people your age".**