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From self-reliers to expert-dependents: identifying classes based on health-related need for autonomy and need for external control among mobile users

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ABSTRACT

Mobile health apps are seen as promising tools to support autonomous consumers in their quest for better health. However, individual differences in the need for autonomy and need for external control may impact the degree to which individuals perceive mobile health apps to be useful in their daily life. Using data from a representative sample of the Dutch population (*N* = 1,027), we applied latent class analysis to identify subtypes among mobile users based on their need for autonomy and need for external control, and to examine differences among these subtypes. We identified four subgroups: the self-reliers, confirmation-seekers, expert-dependents, and indifferents. Next to demographic differences, self-reliers and confirmation-seekers were generally more e-health literate and expressed more privacy concerns than the expert-dependents and indifferents. Our findings demonstrate that subgroups of people express different degrees of health-related need for autonomy and need for external control, which should be taken into account in online and mobile health communication efforts.

Unhealthy lifestyle behaviors such as not being sufficiently physically active, smoking, and the consumption of too much alcohol, are an important cause of chronic illnesses such as cancer and cardiovascular diseases (World Health Organization, 2017). As a consequence, an unhealthy lifestyle reduces quality of life, decreases labor productivity, and largely increases healthcare associated costs (Scarborough et al., 2011). As healthcare budgets are becoming more and more limited, effective yet low-cost strategies are needed that yield healthier lifestyles and fewer detrimental consequences for both the individual and society. A promising strategy to promote and support healthy lifestyles is the use of mobile health apps, given their widespread adoption

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This manuscript features Online Supplementary Material (OSM), which includes the data of the study, the syntaxes of the analyses, and the output files of the Mplus latent class analyses. The OSM can be accessed here: https://osf.io/8qra2/?view_only=161cc86c7a3b4ec38bc02531d6b17090.

and technical possibilities. Mobile health apps are computer programs designed to run on a mobile device (e.g., smartphone, tablet) with the purpose of supporting health and health-related behavior. Examples are apps for fitness (i.e., apps to track and monitor activity and workouts), nutrition (i.e., apps to track and monitor nutrition and weight), and self-care (i.e., apps to support and give active control to an actual or potential health situation or condition) (Bol, Helberger, & Van Weert, 2018). Since mobile devices are always on and people tend to carry them with them everywhere (Klasnja & Pratt, 2012), mobile health apps could be used as a powerful tool to intervene in people's daily lives and promote healthy lifestyle behaviors.

To positively change lifestyle associated behaviors, with positive health outcomes as a result, self-determination theory (SDT: Ryan & Deci, 2000) suggests that an autonomous form of motivation is needed and that every person should perceive support for autonomy to form such autonomous motivation for health behavior change (Ng et al., 2012; Resnicow et al., 2008, 2014; Ryan & Deci, 2000). A claim that has typically been made, is that mobile health apps can provide autonomy support and help people to achieve autonomous motivation in their health-related decision making, i.e., the cognitive process through which people select a course of action from several alternative possibilities when it concerns their health and health-related behaviors (e.g., Bradway, Årsand, & Grøttland, 2015; Fogg, 1999; Schnall, Bakken, Rojas, Travers, & Carballo-Dieguez, 2015). Especially in a society where people are increasingly expected to take responsibility for their own health, mobile health apps thus seem to provide a viable way to support autonomous consumers in their quest for better health.

Against the optimistic backdrop of mobile technology supporting managing one's healthy lifestyles lies the question whether mobile health is effective for all individuals, if at all. Although SDT suggests that everyone has a basic need for autonomy, individual differences are profound when it concerns health decisions (Resnicow et al., 2008, 2014). Therefore, mobile health apps that do not take into account such individual differences and do not match individuals' preferences in need for autonomy and need for external control might not be perceived as autonomy supportive. Although such individual differences have been recognized (Deci & Ryan, 1985; Ng et al., 2012; Ryan & Deci, 2000), no research to date has acknowledged the complexity of these individual differences to help understand for whom and under what conditions mobile health apps could be helpful.

Therefore, this paper presents a *person-oriented* technique (i.e., latent class analysis) to provide a better understanding of the individual differences in need for autonomy and need for external control regarding health-related decisions among users of mobile technologies. Such an understanding is needed to inform theory, practice, and policy about how to tailor mobile health apps to specific user types based on people's need for autonomy and need for external control. To address this aim, we focused on (1) identifying whether subtypes exist among mobile users based on their need for autonomy and need for external control, and (2) examining differences among these subtypes in terms of mobile health app use, and demographic and other relevant background variables.

Need for autonomy and need for external control regarding health-related decisions

According to SDT (Ryan & Deci, 2000), an autonomous form of motivation is imperative for successfully initiating and maintaining changes in health-related behavior. In the context of health behavior change, people perceive themselves to be autonomous in their motivation when they experience volition and choice around attempting to change their health behavior. In other words, when the behavior is complemented with an experience of psychological freedom of choice. To date, evidence has been accumulating that autonomous motivation is an important predictor of health behavior change as well as positive health outcomes (Ng et al., 2012; Resnicow et al., 2008, 2014). According to SDT, autonomous motivation can be facilitated by fulfilment of the needs for autonomy, relatedness and competence. The need for autonomy refers to the idea that all individuals have the desire to perceive freedom and to feel volitional in one's behavior, for instance by being able to independently decide when and how to change their health-related behaviors (Ryan & Deci, 2000). The need for relatedness refers to an individual's need to feel connected with his or her social environment by receiving social support or normative feedback. The need for competence is related to the concept of self-efficacy, referring to individuals perceiving themselves to be skilled to perform certain tasks and activities (Bandura, 1998).

Many health behavior change interventions provide suggestions for managing (sustained) behavior change, in order to enhance the individual's self-efficacy and satisfy the need for competence (Ng et al., 2012; Rooke, Thorsteinsson, Karpin, Copeland, & Allsop, 2010). Moreover, many of such interventions target the need for relatedness through providing normative feedback and the affirmation of feelings (Boon, Risselada, Huiberts, Riper, & Smit, 2011; Friederichs et al., 2014; Rooke et al., 2010; Smit, de Vries, & Hoving, 2010). Contrastingly, there is a lack of evidence for the fulfilment of the need for autonomy in health behavior change interventions (Ng et al., 2012), providing the rationale for the present study specifically focusing on this basic psychological need.

Yet, whereas theory suggests that everyone has a basic need for autonomy, differences in this need exist among individuals when it concerns their health-related decisions. That is, while some people prefer to choose their own path towards lifestyle improvement (i.e., autonomy orientation), others prefer to be guided by clear-cut expert advice from professionals or peers (i.e., control orientation) – or report high or low levels of both types of orientation simultaneously (Resnicow et al., 2008, 2014). While SDT scholars have recognized these individual differences in the need for autonomy and need for external control (Deci & Ryan, 1985; Ng et al., 2012; Ryan & Deci, 2000), only few have taken them into account when developing health communication strategies. Two studies that investigated the influence of the need for autonomy in the context of printed health communication found that newsletters that were framed to be autonomy-supportive were more effective for people that preferred autonomous communication than newsletters that were framed in a more directive manner (Resnicow et al., 2008, 2014). Although previous research has shown that peers can be an influential source of support when it comes to health-related decision-making (Smith, Banting, Eime, O'Sullivan, & Van Uffelen, 2017), previous studies have only considered external control as coming from an expert source, like a doctor (Resnicow et al., 2008, 2014). These results not only suggest that individual differences in the needs for autonomy and external control should be considered for health communication to be effective, and for mobile technologies to effectively support users' health, but also make a distinction between experts and peers as being the source of external control. As mobile health apps often encourage the constant self-tracking of personal data (Consolvo, McDonald, & Landay, 2009; Fogg, 2003), they are well able to generate data-driven tailored and personalized feedback about individuals' health behavior (Fanning, Mullen, & McAuley, 2012; Piwek, Ellis, Andrews, & Joinson, 2016). As such, these new technologies are also able to assess and rather easily take into account individual differences in the need for autonomy and need for external control, improving their effectiveness in supporting their users' health behavior.

However, to be better able to create personalized mobile health technologies tailored to the individual's need for autonomy and need for control, we first need to better understand the individual differences in these needs. This calls for a more individualized approach, using person-oriented techniques, such as latent class analysis. Using latent class analysis, we will be able to identify subgroups of people who share common characteristics within subgroups, but are distinctively different from other subgroups (Kongsted & Nielsen, 2017). This way, we will be able to better understand the complexity of the interplay between individuals need for autonomy and need for control in health-related decisions. Such knowledge could help us better understand for whom mobile health apps could be more or less helpful. We formulate the following research question (RQ):

RQ1: Which subtypes can be identified among mobile users based on their need for autonomy and need for external control regarding health and health-related decisions?

Factors associated with need for autonomy and need for external control

As a second part of our aim, we explore the differences between the subtypes in terms of mobile users' mobile health app use, demographic characteristics, e-health literacy, information privacy concerns and preference for personalized advertisements in the context of mobile health apps. Differences in the subtypes based on these characteristics could help us understand not only for whom mobile health apps could be potentially useful in terms of people's need for autonomy and need for external control, but also in terms of characteristics not used as a basis for the class formation that might otherwise be relevant in determining the potential acceptance and usefulness of personalized communication via mobile health apps.

The first variable of interest relates to media use, more specifically mobile health app use. Although, to our knowledge, we are the first to investigate the relationship between need for autonomy and need for external control on the one hand, and mobile health app use on the other hand, we could argue that differences exist based on the individual's need for autonomy and need for control. It has typically been claimed that mobile health apps provide autonomy-support in people's health-related decision making (Bradway et al., 2015; Fogg, 1999; Schnall et al., 2015). Thus, it could be argued that those with a higher need for autonomy are especially likely to use mobile health apps to fulfil their need for autonomy. On the other hand, we could also give reason to believe the opposite: as mobile health apps enable users to receive expert feedback and peer support (Conroy, Yang, & Maher, 2014), it could also be argued that those with a higher need for external control are especially attracted to using mobile health apps. It could therefore be expected that both those with a higher need for autonomy and those with a higher need for external control frequently engage in mobile health apps.

The second set of factors we will look at are demographic variables, that is age, gender and educational level. Earlier research has suggested that need for autonomy and need for external control may vary across these demographics. For instance, previous research has demonstrated that people with a preference for directive communication are more likely be older and lower educated than people with a preference for autonomy-supportive form of communication (Resnicow et al., 2014). This study suggests that those with a higher need for autonomy are more likely to be younger and higher educated, whereas those with a higher need for external control are more likely to be older and lower educated. Earlier research has not reported on differences in need for autonomy and need for control based on gender, but we could draw upon health information seeking behavior literature to discuss potential gender differences as similar patterns for age and educational level have been demonstrated in the field of online health information seeking. That is, consistent patterns have been found that those who seek health information online are more likely to be younger, higher educated, and female (e.g., Kontos, Blake, Chou, & Prestin, 2014; Rutten, Squiers, & Hesse, 2006). As we could expect the display of more health information seeking behavior associated with a higher need for autonomy, based on these research findings we may expect people with a higher need for autonomy to be younger, higher educated, and more likely to be female than people with a lower need for autonomy.

Another variable that could help us understand and interpret the differences in need for autonomy and need for external control is the concept e-health literacy. E-health literacy refers to the ability to seek out, find, evaluate and appraise, integrate, and apply what is gained in online environments to solve a health problem (Norman & Skinner, 2006a). Despite the lack of literature linking need for autonomy and need for external control to e-health literacy, these two are expected to be related, also in the context of mobile health. For instance, a higher need for autonomy could suggest a higher need to be actively involved in one's own health-related decision making. This desire for active involvement requires adequate health literacy skills to be able to understand one's own health situation (Légaré & Witteman, 2013) and act upon this using relevant resources, such as mobile health apps, to support their health. We could therefore expect that higher levels of e-health literacy positively correlate with subtypes of people that report relatively higher levels of need for autonomy.

In addition to understanding differences in need for autonomy and need for external control by means of (in)adequate e-health literacy skills, we look at privacy concerns. As mobile technologies often require users to share personal health data to provide personalized health advice, factors that hinder mobile health technology use are often related to informational privacy (e.g., Abdelhamid, Gaia, & Sanders, 2017; Authors, 2018a). Informational privacy refers to the ability to control the aggregation and dissemination of information (Burgoon, 1982). As the need for autonomy is concerned with the feeling of having active control over one's own decisions and freedom of choice, it could be argued that privacy concerns related to mobile health apps are higher among those with higher levels of need for autonomy. On the contrary, those with a higher need for external control are potentially more open to surveillance from other parties, which could characterize them as having lower levels of privacy concerns. Following the same line of reasoning, it could be argued that a higher need for autonomy may be related to a lower preference for personalized ads. Mobile devices collect huge amounts of personal data from their users, and such personal data collection allows advertisers to present in-app personalized ads (Meng, Ding, Chung, Han, & Lee, 2016). Although mobile apps, such as health apps, can be provided for "free" in turn for personalized ads, they come with the price of potential privacy concern. We may therefore expect that a preference for such personalized ads is more pronounced in those with a higher need for external control and less pronounced in those with a higher need for autonomy.

As our first RQ is explorative of nature, we do not know yet which subgroups of people based on need for autonomy and need for external control we will discover. As a consequence, it is difficult to formulate specific hypotheses concerning the differences between the subgroups in terms of the above-mentioned variables. We therefore also formulate the following RQ rather exploratory:

RQ2: What differences exist between the different subtypes of mobile users in terms of their mobile health app use, demographic characteristics, e-health literacy, information privacy concerns and/or preference for personalized advertisements?

Methods

Recruitment and procedure

A representative sample of the Dutch population was recruited through CentERdata's LISSPANEL, as part of a larger panel wave study. A total of 1,288 panel members (90.0%) responded positively to our invitation to participate in the online survey, which started with questions on e-health literacy, health causality orientations, and the use of smart devices (i.e., smartphones, tablets and wearables). Respondents who did not report to have a smart device were excluded from further participation in the survey (n = 234, 18.2%). The questionnaire continued with questions on respondents' privacy concerns about and use of mobile health apps. Of the eligible sample (i.e., those with a smart device, n = 1,054, 81.8%), 27 respondents (2.6%) were excluded as they skipped a substantial part of the questionnaire to get to the end (n = 15) or reported having mobile health apps on their smart device, though filled out other types of apps when they were asked what kind of health apps they referred to (n = 12). This resulted in a final sample of 1,027 adults included in the statistical analyses. Ethical approval for the study was obtained from the institutional review board of the first author's university.

Measurements

Respondents answered all items on a 7-point scale ranging from 1 = *strongly disagree* to 7 = *strongly agree*, unless indicated otherwise. Factor validity was tested via confirmatory factor analyses for each scale variable separately. Referring to common fit criteria (e.g., Kline, 2016), all measures showed good model fit and reliability (see Table 1). All items are listed in the Online Supplementary Material.[1]

Need for autonomy and need for external control

The need for autonomy and need for control were measured with the health causality orientations scale (HCOS), which was developed based on the general causality orientation scale and adjusted to a health context (GCOS: Deci & Ryan, 1985). As part of the HCOS, respondents were provided with four scenarios (e.g., "You want to make a change to your health [such as changing your diet or

Table 1. Descriptives and factorial validity of all scale variables.

	M	*SD*	χ^2 (df)	*p*-value	CFI	TLI	RMSEA	SRMR	Alpha
Health causality orientation			205.07 (49)	< .001	.967	.956	.056	.045	
Autonomous	5.86	0.96							.79
Controlled (professionals)	3.42	1.36							.81
Controlled (peers)	3.18	1.38							.85
E-health literacy	5.04	1.24	30.95 (13)	.003	.998	.995	.037	.013	.95
Information privacy concerns			67.85 (22)	< .001	.995	.992	.045	.013	
Perceived surveillance	4.69	1.52							.83
Perceived intrusion	4.49	1.63							.89
Secondary use of personal data	4.66	1.70							.95
Preference for personalized ads	3.22	1.85							

CFI = Comparative Fit Index; TLI = Tucker Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; Alpha = internal consistency (Cronbach's alpha).

exercising more]. How likely are you to…"). Each of these scenarios were accompanied by three statements that represented an action representing an autonomy orientation (4 items, e.g., "Decide for yourself which type of changes you would like to make"), control (professionals) orientation (4 items, e.g., "Look for an expert who will tell you what to do") and control (peers) orientation (4 items, e.g., "Ask your friends what they do"). Respondents were asked to indicate the likelihood of these three potential actions on a 7-point Likert scale (1 = "very unlikely," 7 = "very likely"), given the described scenario.

Mobile health app use

Respondents were asked to look at their smart device(s), and to indicate which mobile health apps they had installed on their smart device(s). For each mobile health app, respondents were asked to indicate on a scale from "almost every day" to "never" how often they used each app. Mobile health app use was categorized into use (i.e., indicating to use mobile health apps to some extent) and non-use (i.e., reporting to not have mobile health apps installed as well as indicating to have mobile health apps installed but never using them).

E-health literacy

E-health literacy was measured using the e-health literacy scale (eHEALS: Norman & Skinner, 2006b). The eHEALS is an 8-item scale with items such as "I know how to use the Internet to answer my health questions."

Information privacy concerns

Respondents' information privacy concerns when using mobile health apps were assessed with the mobile users' information privacy concerns questionnaire, including three subscales with three items each: perceived surveillance, perceived intrusion, and secondary use of personal information (MUIPC: Xu, Gupta, Rosson, & Carroll, 2012). Sample items involved "I am concerned that mobile health apps are collecting too much information about me," "I feel that as a result of my using mobile health apps, others know about me more than I am comfortable with," and "I am concerned that mobile health apps may use my personal information for other purposes without notifying me or getting my authorization."

Preference for personalized ads

Respondents' preference for personalized ads in the context of mobile health apps was assessed with one item, i.e., "I prefer personalized advertisements."

Background variables

Demographic data (i.e. age, gender and educational level) were extracted from the LISSPANEL database. Educational level was categorized as follows, based on guidelines from CBS Statistics Netherlands (2013): low level of education (i.e., primary education, preparatory secondary vocational education), middle level of education (i.e., higher secondary general education or pre-university education, secondary vocational education), and high level of education (i.e., higher vocational education, university).

Statistical analyses

First, we conducted descriptive analyses to determine the sample's characteristics. To address our first research question, i.e., whether subgroups exist based on respondents need for autonomy and need for control (RQ1), we performed latent class analysis (LCA) based on the following continuous variables derived from the HCOS: autonomy orientation, control orientation (professionals), and control orientation (peers). LCA is a statistical method that can be used to identify a set of mutually exclusive latent classes, thereby classifying individuals from a heterogeneous group into smaller more homogeneous subgroups, and it has been claimed to be an important analytical method for testing a theoretically posited typology (McCutcheon, 1987). Moreover, LCA differs from other clustering techniques, such as principal component analysis or cluster analysis, by fitting "a model to the data rather than providing an ad hoc classification of the given data" (Van de Pol, Holleman, Kamoen, Krouwel, & De Vreese, 2014, p. 402). When using continuous variables for clustering, LCA is also often referred to as latent profile analysis (LPA, see also Masyn, 2013; Wang & Wang, 2012) or latent class cluster analysis (LCCA, see also Masyn, 2013). Using Mplus software (version 6), we performed the LCA six times to determine which class solution fitted our data best. To determine the model fit of each solution, we used several commonly used fit indices: the log likelihood (LL), Bayesian Information Criterion (BIC), Akaike's Information Criterion (AIC), Vuong-Lo-Mendell-Rubin Likelihood Ratio Test (LRT), the bootstrap likelihood ratio test (BLRT), the average posterior class probability (AvePP), and the entropy score. LL examines whether the fit of a larger model is significantly better than that of a smaller one, without regard to model parsimony; for BIC and AIC, a decrease in values indicates that a model with more subgroups (e.g., four-subgroup model) has a better trade-off between model fit and model complexity than a three-subgroup model; the LRT and BLRT compare whether a model with K classes is significantly better than a model with K-1 classes with a significant p-value indicating a better model fit; and the AvePP and the entropy score indicate how well the cluster variables predict membership of the latent classes, where a value closer to 1 means a better fit and the classes being distinct from each other (Hagenaars & McCutcheon, 2002). To test the robustness of the obtained class solution, we also performed LCA among a random subsample of approximately 50% respondents from the original sample (see Online Supplementary Material). After determination of the most optimal class solution, a new variable was stored in SPSS (version 22) that indicated the class membership for each individual case in the dataset. To address our second research question, i.e., whether subgroups differed in terms of mobile health app use and other relevant variables (RQ2), we conducted one-way analyses of variance (ANOVAs) with Tukey-Kramer post hoc tests for unequal sample sizes to compare the means of classes in terms of age, education level, e-health literacy, information privacy concerns, and the preference for personalized ads. Chi-square tests with Bonferroni-corrected z-tests were used to compare the column proportions of the classes based on mobile health app use and gender.

Results

Sample characteristics

Respondents' age ranged from 19 to 88 years, with an average age of 51.30 (SD = 15.95). Of them, 53.0% were female, 39.6% had a high level of education, 35.2% a middle level of education and 25.1% a low level of education. The majority of our sample reported not to use mobile health apps and was thus classified as non-users (67.9%). The remainder of the sample consisted of users (32.1%), who had, on average, three mobile health apps installed on their smart device (M = 2.58, SD = 2.37), of which they used two on average (M = 2.19, SD = 1.98). See Table 1 for full details on the sample's demographic characteristics.

Latent class analysis

To identify whether subgroups exist based on respondents' need for autonomy and need for external control (RQ1), we examined the number of latent classes in the data. We found that a two-class and four-class solution offered the best fit in comparison with a one-class and three-class solution, respectively, as their model fit indices were most optimal while at the same time having significant LRT p-values (p-values of .000 and .001 respectively). A five-class or six-class solution did not significantly increase the fit of the data, compared to a four-class

Table 2. LCA results with different fit indices.

# of classes	LL	BIC (LL)	AIC (LL)	# par	LRT *p*-value	BLRT *p*-value	AvePP	Entropy
1	−4965.76	9973.12	9943.51	6	n.a.	n.a.	n.a.	n.a.
2	−4888.93	9847.19	9797.85	10	.000	.000	.878	.587
3	−4832.14	9761.37	9692.28	14	.113	.000	.836	.650
4	−4785.13	9695.08	9606.27	18	.001	.000	.824	.714
5	−4755.58	9663.71	9555.15	22	.201	.000	.814	.747
6	−4734.14	9648.57	9520.27	26	.525	.000	.866	.816

LL = Log Likelihood. BIC = Bayesian Information Criterion. AIC = Akaike's Information Criterion. # par. = number of parameters. LRT = Vuong-Lo-Mendell-Rubin Likelihood Ratio Test. BLRT = bootstrap likelihood ratio test. AvePP = average posterior class probability. n.a. = not applicable. These LCA results remained the same after a robustness check (i.e., running the LCA models for a random subsample of approximately 50% of the total sample; see Online Supplementary Material).

Table 3. Estimated means (with standard errors between parentheses) for autonomy orientation, control orientation (experts), and control orientation (peers) for the four-class solution.

	Self-reliers (n = 483)	Confirmation-seekers (n = 344)	Expert-Dependents (n = 190)	Indifferents (n = 10)	F-test (df)	p-value
Autonomy orientation	6.31 (0.03)[d]	6.08 (0.03)[c]	4.52 (0.04)[b]	2.33 (0.31)[a]	552.06 (3)	< .001
Control orientation-experts	2.85 (0.06)[b]	3.98 (0.07)[c]	3.94 (0.08)[c]	1.55 (0.20)[a]	76.89 (3)	< .001
Control orientation-peers	2.13 (0.04)[a]	4.57 (0.04)[c]	3.41 (0.07)[b]	1.58 (0.16)[a]	602.24 (3)	< .001

Different superscripts indicate statistically significant differences between figures in a row at p < .05. Lowest figures in a row are assigned "a," then "b," etc.

and five-class solution, respectively (with LRT *p*-values of .201 and .525, respectively). Since lower LL and BIC scores and higher entropy score represent a better model fil, the four-class solution was preferred over the two-class solution. See Table 2 for full details on the results from our LCA.

Building on the four-class solution, we distinguished four unique groups of mobile app users based on their need for autonomy and need for external control. We provide a concise description of each of the four classes in the following. Each class' estimated means for autonomy orientation, control orientation (professionals), and control orientation (peers) can be found in Table 3.

Class 1

The first class of respondents was labelled as *self-reliers* (n = 483). As Table 3 shows, the self-reliers had a relatively high autonomy orientation (M = 6.31, SE = 0.03), while their scores for control orientation were – compared with the other classes – less than average (control orientation – professionals: M = 2.85, SE = 0.06; control orientation – peers: M = 2.13, SE = 0.04). The self-reliers covered the largest subsample in our study population (47.0%).

Class 2

The second class of respondents was labelled as *confirmation-seekers* (n = 344). This class of respondents covered the second largest group in our sample (33.5%) and reported relatively high scores for both autonomous (M = 6.08, SE = 0.03) and control orientation (control orientation – professionals: M = 3.98, SE = 0.07; control orientation – peers: M = 4.57, SE = 0.04).

Class 3

The third class of respondents was labelled as *expert-dependents* (n = 190). While this class of respondents reported a less than average score for autonomy orientation (M = 4.52, SE = 0.04), both scores for control orientation were above average relative to the total sample (control orientation – professionals: M = 3.94, SE = 0.08; control orientation – peers: M = 3.41, SE = 0.07). The expert-dependents encompassed the second smallest group in our sample (18.5%).

Class 4

The fourth class of respondents was labelled as *indifferents* (n = 10) and comprised the smallest subsample of our sample (1.0%). Although small in number, the indifferents presented a class very distinct from other classes, as they reported relatively low scores for both autonomous (M = 2.33, SE = 0.31) and control orientations (control orientation – professionals: M = 1.55, SE = 0.20; control orientation – peers: M = 1.58, SE = 0.16).

Differences between classes

To identify whether subgroups differed in terms of their mobile health app use, demographic characteristics, e-health literacy, information privacy concerns, and/or preference for personalized ads (RQ2), the data revealed several differences between the four classes, yielding support for the four-class solution. Table 4 presents an overview of the differences between the four classes.

With regard to mobile health app use, we found significant differences between the classes, χ^2 (3) = 9.44, p = .024. However, subsequent Bonferroni-corrected z-tests did not show significant differences in column proportions, leading us to conclude that no differences were found between the classes with regard to their mobile health app use.

Furthermore, we found significant differences between the different classes in terms of demographics, including age, $F(3, 1023) = 21.03$, $p < .001$, $\eta^2 = .06$, gender, χ^2 (3) = 9.73, p = .021, and educational level, $F(3, 1022) = 3.39$, p = .018, η^2 = .01. With regard to age, the self-reliers were significantly older (M = 55.16, SD = 14.68) than the confirmation-seekers (M = 46.86, SD = 15.89; mean diff. = 8.30, SE = 1.09, p < .001), expert-dependents (M = 49.97, SD = 16.74;

Table 4. Comparison of the four classes concerning mobile health app use, demographics, e-health literacy, information privacy concerns, and preference for personalized ads.

	Self-reliers (n = 483)	Confirmation-seekers (n = 344)	Expert-Dependents (n = 190)	Indifferents (n = 10)	F-test (df)/χ^2 (df)	p-value
Mobile health app use, *n* (column %)					9.44 (3)	.024
Yes	141 (29.2)	130 (37.8)	58 (30.5)	1 (10.0)		
Age, Mean (*SD*)	55.16 (14.68)^{b}	46.86 (15.89)^{a}	49.97 (16.74)^{a}	42.10 (15.77)^{a}	21.03 (3)	< .001
Gender, *n* (column %)					9.73 (3)	.021
Female	247 (51.1)^{a,b}	204 (59.3)^{b}	89 (46.8)^{a}	4 (40.0)^{a,b}		
Educational level, Mean (*SD*)	2.14 (0.79)^{a,b}	2.22 (0.80)^{b}	2.04 (0.77)^{a}	1.70 (0.82)^{a,b}	3.39 (3)	.018
E-health literacy, Mean (*SD*)	5.16 (1.31)^{c}	5.18 (1.06)^{c}	4.60 (1.15)^{b}	3.10 (1.73)^{a}	20.37 (3)	< .001
Information privacy concerns, Mean (*SD*)						
Perceived surveillance	4.79 (1.64)^{b}	4.67 (1.35)^{b}	4.53 (1.45)^{b}	3.07 (1.61)^{a}	5.30 (3)	.001
Perceived intrusion	4.59 (1.78)^{b}	4.46 (1.48)^{a,b}	4.35 (1.47)^{a,b}	3.20 (1.71)^{a}	3.19 (3)	.023
Secondary use of personal data	4.76 (1.85)^{a}	4.64 (1.53)^{a}	4.47 (1.56)^{a}	3.43 (1.68)^{a}	3.17 (3)	.024
Preference for personalized ads, Mean (*SD*)	3.02 (1.94)^{a}	3.51 (1.80)^{b}	3.17 (1.61)^{a,b}	4.20 (2.04)^{a,b}	5.77 (3)	.001

One-way analyses of variance (ANOVAs) with Tukey-Kramer post hoc tests for unequal sample sizes and Chi-square tests with Bonferroni-corrected z-tests were conducted. Significant differences at $p < .05$ are indicated by the figures in a row having no superscripts in common. For gender, educational level, and preference for personalized ads, Class 4 shows observable lower (for the former two) or higher (for the latter one) values, but does not significantly differ from other classes whereas other classes with higher or lower values do. These anomalous outcomes can be a result of insufficient power to detect meaningful differences when comparing Class 4 (n = 10) with other classes.

mean diff. = 5.19, $SE = 1.33$, $p = .001$), and indifferents ($M = 42.10$, $SD = 15.77$; mean diff. = 13.06, $SE = 4.95$, $p = .042$). In terms of gender, the confirmation-seekers were more likely to be female (59.3%) than the expert-dependents (46.8%). With regard to education, the confirmation-seekers were more likely to be higher educated ($M = 2.22$, $SD = 0.80$) than expert-dependents ($M = 2.04$, $SD = 0.77$; mean diff. = 0.19, $SE = 0.07$, $p = .045$).

In terms of e-health literacy, the four classes differed significantly on their reported level of e-health literacy, $F(3, 1023) = 20.37$, $p < .001$, $\eta^2 = .06$. The self-reliers ($M = 5.16$, $SD = 1.31$) reported to have higher e-health literacy skills than the expert-dependents ($M = 4.60$, $SD = 1.15$; mean diff. = 0.57, $SE = 0.10$, $p < .001$) and the indifferents ($M = 3.10$, $SD = 1.73$; mean diff. = 2.06, $SE = 0.39$, $p < .001$). The confirmation-seekers ($M = 5.18$, $SD = 1.06$) also reported to have higher e-health literacy skills than the expert-dependents (mean diff. = 0.58, $SE = 0.11$, $p < .001$) and the indifferents (mean diff. = 2.08, $SE = 0.39$, $p < .001$). Furthermore, the expert-dependents reported higher e-health literacy skills than the indifferents (mean diff. = 1.50, $SE = 0.39$, $p = .001$).

Regarding privacy concerns, the four classes differed significantly with respect to their concerns related to perceived surveillance, $F(3, 1023) = 5.30$, $p = .001$, $\eta^2 = .02$, privacy concerns regarding intrusion, $F(3, 1023) = 3.19$, $p = .023$, $\eta^2 = .01$, and privacy concerns regarding secondary use of information, $F(3, 1023) = 3.17$, $p = .024$, $\eta^2 = .01$. More specifically, the indifferents reported significantly less privacy concerns ($M = 3.07$, $SD = 1.61$) than the other three classes in terms of perceived surveillance (self-reliers: $M = 4.79$, $SD = 1.64$; mean diff. = −1.73, $SE = 0.48$, $p = .002$; confirmation-seekers: $M = 4.67$, $SD = 1.35$; mean diff. = −1.61, $SE = 0.49$, $p = .005$; expert-dependents: $M = 4.53$, $SD = 1.45$; mean diff. = −1.47, $SE = 0.49$, $p = .015$), and the self-reliers in terms of their perceived intrusion (indifferents: $M = 3.20$, $SD = 1.71$, self-reliers: $M = 4.59$, $SD = 1.78$; mean diff. = −1.39, $SE = 0.52$, $p = .039$).

Lastly, we found significant differences between classes regarding their preference for personalized ads, $F(3, 1023) = 5.77$, $p = .001$, $\eta^2 = .02$. Confirmation-seekers reported a significantly higher preference for personalized ads ($M = 3.51$, $SD = 1.80$) than the self-reliers ($M = 3.02$, $SD = 1.94$; mean diff. = 0.49, $SE = 0.13$, $p = .001$).

Discussion

The aim of this study was to identify whether subgroups exist based on mobile users' health-related need for autonomy and need for external control (RQ1), and to determine whether the subgroups found differed in terms of their mobile health app use, demographic characteristics, e-health literacy, information privacy concerns, and/or preference for personalized ads (RQ2). Four subgroups were identified: the self-reliers, confirmation-seekers, expert-dependents, and indifferents. The *self-reliers* represented almost half of the respondents in our sample and had relatively high levels of need for autonomy, but relatively low levels of need for external control. The *confirmation-seekers* were the second largest group, reporting relatively high scores for both the need for autonomy and need for external control. The *expert-dependents* scored relatively low on need for autonomy, though high on external control. The smallest group in our sample, the *indifferents*, reported low scores for need for autonomy as well as external control.

In addition to their distinct patterns in need for autonomy and need for external control, several differences were found between subgroups with regard to demographic characteristics, e-health literacy, information privacy concerns and preference for personalized ads – giving confidence in the classes truly representing heterogeneous sets of people. In terms of demographic differences, our data showed that the self-reliers were relatively old, while the confirmation-seekers and expert-dependents were relatively young. This finding is somewhat contradictory with previous research that suggested that people with a preference for autonomy-supportive communication are generally more likely to be younger (Resnicow et al., 2014). The study by Resnicow and colleagues, however, only considered the need for autonomy-supportive communication when determining people's preferences, whereas we also considered two different needs for external control, i.e., the need for external control from professionals, such as doctors, and from peers, such as family and friends. Using latent class analysis, we were able to account for the complexity and different underlying distributions among the need for autonomy and need for external control (Kongsted & Nielsen, 2017), thereby providing a more nuanced understanding of what these needs mean, how they interact, and how they together inform preferences regarding the communication styles used in health communication efforts.

Furthermore, in line with earlier research (Resnicow et al., 2014), we found that the expert-dependents reported a lower level of education than the confirmation-seekers, indicating that people with a preference for directive communication are more likely to be lower educated than people with a preference for autonomy-supportive communication (Resnicow et al., 2014). Yet, a similar difference between the expert-dependents and the self-reliers, i.e., the other subgroup scoring relatively high on need for autonomy, was not found. Moreover, the findings of this paper shed new light on the relationship between the need for autonomy and need for external control, and gender. That is, we found that the confirmation-seekers were more likely to be female than expert-dependents. We could argue that this finding is consistent with earlier research, as earlier studies have shown that information seekers are more likely to be female versus male (e.g., Kontos et al., 2014; Rutten et al., 2006), and information seekers conceivably score high on both the need for autonomy and need for external control. To be more specific, a high need for autonomy is needed to take active control over one's own health, while a high need for external control is needed to be open to receive health-related advice from external sources. Given the lack of previous research linking the need for autonomy and need for external control to demographic variables, our findings and conclusions should be interpreted with caution.

Regarding e-health literacy, we found that self-reliers and confirmation-seekers had higher e-health literacy skills than expert-dependents and indifferents. In other words, our data confirmed that subgroups with higher levels of need for autonomy reported higher levels of e-health literacy than subgroups with lower levels of need for autonomy. Self-reliers and confirmation-seekers thus seem to be more skilled to make their own health-related decisions. Our findings further demonstrated that the indifferents were less concerned about their privacy than the self-reliers and – to some extent – the confirmation-seekers and expert-dependents. In combination with their lower scores on e-health literacy, indifferents may thus not only be less capable of making their own health-related decisions, but also less concerned about their privacy, making them an especially vulnerable group.

Lastly, self-reliers displayed lower preferences for personalized ads than confirmation-seekers. Although self-reliers and confirmation-seekers appeared similar with respect to their relatively high e-health literacy skills and privacy concerns, confirmation-seekers seem more open for support from external sources, such as their peers, professionals, and advertisers. Interestingly, despite their relatively high privacy concerns, confirmation-seekers are open to in-app personalized ads, which at first sight seems counterintuitive. One explanation could be that confirmation-seekers place the benefits of receiving personalized expert advice through mobile health apps before privacy costs associated with personalized ads. As this is, to the best of our knowledge, the first study to explore relationships between the need for autonomy and need for external control on the one hand and e-health literacy, privacy concerns and preference for personalized ads on the other hand, our findings warrant replication and further research.

Implications

This study adds to previous work by showing that health-related need for autonomy and need for external control differ among individuals and display a complex pattern of interaction. Our findings thereby confirm results from scarce previous research, which has demonstrated individual differences in the general need for autonomy (Deci & Ryan, 1985), and when it concerns health-related need for autonomy (Resnicow et al., 2008, 2014). We confirm that some people prefer to have autonomy over their choice to change their lifestyle associated health behaviors, while others have a higher need for external control, preferring to be guided by clear-cut expert advice from professionals or peers. Furthermore, some people prefer to have autonomy over their health decision and, simultaneously, prefer to be guided by expert advice and, vice versa, some people concurrently have low scores for both the need for autonomy and need for external control. Thus, although SDT posits that everyone has a basic need for autonomy, our findings confirm that individual differences are profound when it comes to health-related need for autonomy and need for control, at least in a rather individualist culture like the one present in the Netherlands. Yet, we are uncertain whether these findings hold under all conditions – for instance, it is conceivable that the need for autonomy is less high amongst respondents from more collectivist cultures, whereas the need for external control might be higher in such cultures. To advance and specify theoretical assumptions within SDT, we therefore suggest that a more nuanced understanding of if, when, and how people want to have choices regarding health-related decisions is needed.

Moreover, our findings contribute to the fields of communication and media psychology as they further and nuance our understanding of the potential role of mobile health apps in health-related behavior change. Mobile health technologies are especially suitable for personalization and tailoring strategies (Fanning et al., 2012; Piwek et al., 2016). However, our findings indicate that mobile health apps are currently reaching only about one third of the population. Therefore, we should first better understand how to achieve wider, more consistent use of mobile health apps to reap their benefits for health outcomes. At the same time, research and practice should collaboratively invest in developing mobile health apps that are evidence and theory-based, matching the needs of their users. There is a substantial gap between merely providing mobile health apps and actual behavior change, and there is hardly any evidence supporting the claim that current mobile health technologies are bridging that gap (Patel, Asch, & Volpp, 2015). Systematic knowledge about how to engage people to keep using mobile health apps is needed to take next steps, and conduct studies that will yield information about the effects of mobile health apps on associated health outcomes. To this end, we also encourage future studies to take a more in-depth perspective and take into account for what specific activities people use their mobile health apps. A recent study demonstrated that the use of specific mobile health apps was differently related to factors such as privacy concerns than general use of mobile health apps (Authors, 2018a). Future research should therefore distinguish between different stages of adoption and use as well as between the specific activities mobile technologies are being used for, and consider the role of need for autonomy and need for control in explaining the use and effectiveness of mobile health apps.

The results of our research also have a number of implications for practice. First, our findings help understand for whom mobile health apps could be most effective. Because of their relatively high levels of e-health literacy, which has been found a prerequisite for mobile health app use (Authors, 2018a), we could argue that these apps could be especially useful for confirmation-seekers. Despite the willingness and ability of confirmation-seekers to engage in their own health using electronic sources, this group also reports high privacy concerns. Drawing on psychological reactance theory (Brehm, 1966), such privacy concerns might increase mobile health app users' sense of their autonomy being threatened, resulting in increased feelings of reactance and ultimately message rejection, which could be detrimental for health interventions (Rains, 2013). As privacy concerns as such may negatively impact technology use (Abdelhamid et al., 2017), the confirmation-seekers may in fact not be effectively reached by mobile technologies on the long run. Further research may need to focus on providing more thorough insight into the privacy concerns held by (potential) users of mobile health apps, as well as on identifying strategies to overcome concerns to reduce reactance and widen the use and effectiveness of, especially evidence-based, mobile technologies aimed at improving healthy lifestyles, and ultimately health.

Second, the results also add to our understanding of how mobile health apps could be effective for different target audiences. The results imply that it might be beneficial to tailor mobile health apps to specific user types based on people's need for autonomy and need for external control. Tailoring based on individuals' need for autonomy and need for external control by categorizing them in different classes (i.e., self-reliers, confirmation-seekers, expert-dependents, indifferents), and adapting communication styles accordingly, is potentially also a more cost-efficient than tailoring on a more detailed, individual level. To illustrate, the self-reliers and expert-dependents currently do not seem the best target group for mobile health apps, thus strategies need to be developed to broaden the reach and effectiveness of mobile health apps. For example, mobile health apps could individually tailor the message frames of health information presented through apps. Message framing refers to taking a certain perspective when formulating a message (Entman, 1993), thus, message frame tailoring refers to adjusting the message's perspective based on people's individual needs (Smit, Linn, & Van Weert, 2015). For the expert-dependents, this may imply that a more directive communication style needs to be used, in contrast to using a more autonomy-supportive communication style for self-reliers, and a combination of styles for confirmation-seekers. As a last illustration, a previous study on the effect of message content and format features on the selection of health information (Kim, Forquer, Rusko, Hornik, & Cappella, 2016) showed that the use of a directive communication style – in this study operationalized as verbs in the imperative form – can indeed have positive effects. It is our hypothesis that especially people high in need for external control, such as the expert-dependents and confirmation-seekers, might in fact benefit from such way of communication. Yet, when testing the effectiveness of tailoring communication styles based on the need for autonomy and need for external control within the context of a certain mobile health app – or other specific health technology – it should be taken into account that a generalization of findings to *all* mobile health apps should be considered impossible, as these apps, like media in general (Reeves, Yeykelis, & Cummings, 2016), tend to vary largely in terms of content and form.

Third, in terms of specific mobile health app features, mobile health apps for those with a high need for autonomy may be designed to leave much room for users to make their own decisions. For example, strategies like customization – the ability to self-tailor the mediated environment (Kalyanaraman & Sundar, 2006; Sundar, Bellur, & Jia, 2012) – in mobile health apps could be particularly effective for those with a higher need for autonomy, such as the self-reliers and confirmation-seekers. A recent study showed that customization increased intentions to engage in physical activity for those with a greater need for autonomy (Bol, Høie, Nguyen, & Smit, 2019), but not for those with a lower need for autonomy. On the other hand, system-driven tailoring strategies, based on an assessment of individual characteristics, might be more effective for those with a low need for autonomy and a high need for external control from experts (i.e., expert-dependents), as such mobile health app strategies do not require a lot of effort from its users but at the same time offer the opportunity for personalized expert advice (Sundar & Marathe, 2010). For those with a high need for external control from peers (i.e., confirmation-seekers and expert-dependents), social support features within mobile health apps could be an interesting venue to explore further. As such features are already commonly included in mobile health apps (e.g., Direito et al., 2014), future research could explore whether subgroups with a high need for external control from peers would especially benefit from social support features in apps.

Fourth and last, the group of indifferents warrants attention in health communication, both in practice and future research. Although this seems only a small group in the population, our sensitivity analysis (see Online Supplementary Material) showed that this group is truly distinct from other subgroups and thus worthy of analysis. This subgroup of people may not likely perceive themselves in need for health behavior change, but in case they do, they are not very capable of and willing to successfully use online or mobile health information. Moreover, they may not be aware of any possible – and likely – violations of their privacy. Health communication efforts targeting indifferents could potentially use strategies that have been found most effective for people with low (e-)health literacy skills, such as using noncomplex text and illustrations (Meppelink, Smit, Buurman, & Van Weert, 2015). Moreover, policy recommendations should focus on protecting this vulnerable subset of the population, who tend to not care or now know about privacy risk and its potential negative consequences.

Conclusion

Based on mobile users' health-related need for autonomy and need for external control, we identified four subgroups: the self-reliers, confirmation-seekers, expert-dependents, and indifferents. These subgroups differed from each other in terms of several demographics, e-health literacy, perceived privacy concerns, and preference for personalized ads. Our study provides evidence for the prevalence of four subgroups truly being distinct and heterogeneous, and suggests that differences in the need for autonomy and need for external control should be taken into account to optimize the impact of online and mobile health communication efforts.

Note

1. This manuscript features Online Supplementary Material (OSM), which includes the data of the study, the syntaxes of the analyses, and the output files of the Mplus latent class analyses. The OSM can be accessed here: https://osf.io/8qra2/?view_only=161cc86c7a3b4ec38bc02531d6b17090.

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