Differences in mobile health app use: A source of new digital inequalities?

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ABSTRACT

This article provides a more differentiated understanding of mobile health consumers, and considers whether health app use may contribute to new digital inequalities. It focuses on factors associated with mobile health app use, and identifies which factors explain the use of different types of health apps. Data from a large representative sample of the Dutch population ($N = 1,079$) show that mobile health app users were generally younger, higher educated, and had higher levels of e-health literacy skills than non-users. Interestingly, different usage patterns were found for specific types of health apps. Theory and policy implications are discussed.

Mobile health apps are increasingly gaining popularity: of the 3,195,204 active mobile apps available in the iTunes app store and the 3,612,250 active apps in the Google Play store, 95,851 and 105,912, respectively, were categorized as Health and Fitness (AppBrain 2018; Pocketgamer.biz 2018). Not surprisingly, current research has focused on the potential benefits of mobile health apps for preventive health and healthcare (e.g., DiFilippo et al. 2015; Arora et al. 2012; Fanning, Mullen, and McAuley 2012) and also the potential harms and challenges stemming from the use of mobile apps for health purposes (e.g., Dayton 2014; Steinhubl, Muse, and Topol 2015).

Mobile health has also become relevant from a legal and public policy point of view (see, e.g., WHO 2011; European Commission 2012). In the European Commission's e-health digital market strategy, mobile health apps play a central role. In its e-health Action Plan 2012–2020, the European Commission (2012) explicitly mentions that, "e-health – when applied effectively— delivers more personalized 'citizen-centric' healthcare, which is more targeted, effective and efficient and helps reduce errors, as well as the length of hospitalization. It facilitates socio-economic inclusion and equality, quality of life and patient empowerment through greater transparency, access to services and information and the use of social media for health." A question that remains largely unaddressed is to what extent and under which circumstances personalized e-health care promotes equality, inclusion, and empowerment (see also Council

of the European Union 2006), or reinforces existing, or even creates new digital inequalities. European Commission (2012) merely hints at possible inequalities as the result of regional differences, limited access in deprived areas, and differences in the legal and healthcare systems, but does not touch upon possible inequalities as a result of, for example, differences in socio-demographic background, skills, and use of e-health solutions.

To assess whether mobile health apps may be contributing to potential new digital inequalities or divides, a better understanding is needed of the differences between people who use and people who not use mobile health apps, and which factors are associated with the use of different types of health apps. Some earlier studies have already focused on the users (e.g., Gimpel, Nißen, and Görlitz 2013; Yuan et al. 2015; Lee and Cho 2016) and non-users (e.g., Peng et al. 2016) of mobile health apps. However, these studies typically rely on non-representative samples, and usually focus on one specific health app to explore more in-depth or aggregate different types of health apps into one measure of mobile health app use. These methodological choices make it difficult to understand who are using which mobile health apps and to identify important trends.

This article is directed at gaining a more differentiated understanding of mobile health app use by: (1) explaining differences in mobile health app use based on the demographic background of the user, their e-health literacy skills, and privacy concerns, and (2) disaggregating

mobile health app use by specific type of health apps to see whether we can predict use of one type of health app over another. It contributes to a more in-depth exploration of the potential individual and social benefits of health app use and also the potential risks of exclusion for particular categories of users. Moreover, a better understanding of users of mobile health apps is needed to evaluate which populations are being reached through mobile health interventions, as well as to better fine-tune health and consumer protection policies for mobile health.

Explaining differences in mobile health app use

Mobile technologies have unique qualities that make them a powerful tool to promote healthy lifestyles: mobile devices are always on, widely adopted, and people tend to carry them with them everywhere (Klasnja and Pratt 2012). Yet, some people are more likely to benefit from mobile health technology because of digital divides. While earlier research on digital divides has focused mostly on inequalities based on difference in access to and quality of Internet access (first level digital divide), the subsequent literature looks at inequalities based on digital literacy and skills (second level divide), and different ways of using digital technology (third level divide) (DiMaggio and Hargittai 2001; Hargittai 2010; Livingstone and Helsper 2007; Scheerder, Van Deursen, and Van Dijk 2017; Van Deursen and Van Dijk 2014; Van Deursen and Hesper 2015; Van Dijk and Hacker 2003). The third level divide is also referred to as the "digital usage gap," which reorients the discussion from that of gaps between "haves" and "have nots" in terms of access to equipment to that of gaps in tangible outcomes as a results of digital technology use (Scheerder, Van Deursen, and Van Dijk 2017; Van Deursen and Van Dijk 2014). We seek to understand the digital usage gap for mobile health apps by understanding differentiating patterns of mobile health use by focusing on individual differences in demographic factors, e-health literacy skills, and motivational factors, most notably privacy concerns.

Many widely used theoretical frameworks for understanding user adoption of new technology, such as TAM (Technology Acceptance Model) (Davis 1989), UTAUT (Unified Theory of Acceptance and Use of Technology) (Venkatesh et al. 2003), and the diffusion of innovations theory (Rogers 2003), acknowledge potential individual differences by considering demographic variables such as age, gender and education. In the case of mobile technologies, there is evidence that certain population segments such as younger, higher educated men are more likely to have access to them (Statistics Netherlands

2016; Rice and Pearce 2015; Carroll et al. 2017). On the other hand, it has been argued that mobile technology use may be less associated with the old digital divides than Internet use because it is more affordable (Rice and Katz 2003; James 2009). However, whether or not mobile *health* technology use is associated with the digital divides remains understudied.

Besides demographic factors, skills for using mobile health apps could potentially foster digital inequalities as well. The ability to seek out, find, evaluate and appraise, integrate, and apply what is learned in online environments to solve a health problem, referred to as e-health literacy (Norman and Skinner 2006a), is directly related to the extent to which users engage with online technology (DiMaggio and Hargittai 2001; Mackert et al. 2016). Earlier research has shown that individuals with limited health and e-health literacy skills not only consume less online information sources, but also gain less positive outcomes (e.g., less self-management of healthcare needs) from online sources (Neter and Brainin 2012), creating new inequalities in the domain of digital health information. The lack of e-health skills might also translate into mobile health app use, such that people with limited e-health literacy skills might make less use of mobile apps for health-related purposes and, in turn, are less able to exploit the potential of mobile health technologies. This is problematic since this group of vulnerable healthcare consumers are often most in need of effective interventions to manage and maintain their health (Kreps and Neuhauser 2010).

Additionally, the level of control people have over technology can be a factor contributing to inequality of use (DiMaggio and Hargittai 2001). Mobile health apps automatically collect large amounts of real-time personal data, which could erode the level of control people experience, resulting in potential privacy concerns (Prasad et al. 2014). Communication privacy management theory (Petronio 2002) suggests that privacy concerns include three dimensions, namely, perceived surveillance (i.e., the feeling of online activities being watched, recorded, and the data shared with various entities), perceived intrusion (i.e., unwanted incursion of another's presence or activities), and secondary use of personal information (i.e., the concern of information collected for one purpose getting used for another without authorization from the user) (Xu et al. 2012). Concerns about the possible loss of privacy as a result of information disclosure has been found to result in self-protective behaviors such as selective sharing of certain type of content and discontinuation in use of technology (Kruikemeier, Boerman, and Bol 2018). In the case of mobile health apps, privacy concerns can also be expected to shape usage, such that people with high levels of concerns might decide not to

use mobile apps for health-related purposes (Prasad et al. 2014). Thus, the level of privacy concerns (or lack thereof) could be an indicator of consumer vulnerability, as it could result in "an increased probability of making unfortunate consumer choices" (Berg 2015).

Given the possibility that mobile health apps may instead of reducing the existing disparities in healthcare deepen them (Robinson et al. 2015), we examine whether the factors that have been shown to be related to use of online technologies in general also have a bearing on use of mobile health apps. We address the following research question:

RQ1: Which factors – demographic characteristics (gender, age and education level), e-health literacy, and privacy concerns (surveillance, intrusion, and secondary use of information) – are associated with differences in mobile health app use?

Differentiated usage patterns of specific mobile health apps

A major reason for the scarcity of research focusing on mobile health app users and non-users is the methodological challenge in measuring mobile health app use. Because individuals' mobile activities and motivations to use mobile health apps are extremely varied, it is challenging to investigate their use through traditional surveys. Consequently, research has primarily measured mobile health app use by examining one specific health app in depth or by looking at aggregated mobile health use, for instance by assessing general usage of health apps as one outcome variable (e.g., Lee and Rho 2013; Carroll et al. 2017). Although different mobile health apps might provide similar features, they also offer distinct features addressing different goals and targeting different groups that could affect usage.

Beyond our first question regarding the differences in mobile health app use *in general*, we also look at whether specific categories of health apps might attract (or turn away) different types of health consumers. Regarding demographic characteristics, specific types of health apps may attract different populations than we would expect based on general user statistics (i.e., younger, higher educated men). Differences in adoption of specific types of mobile health apps could also be predicted by one's e-health literacy skills and level of privacy concerns. Although skills might play a more prominent role in the adoption of mobile health apps in general, one could also argue that certain types of health apps require more skills than others. While some mobile health apps rely on automatically generated health data (e.g.,

pedometers), others require manual input of data (e.g., calorie meters), which requires certain skills.

With regard to privacy concerns, the perceived control over the data resulting from health apps use may vary strongly across different types of health apps (Prasad et al. 2014). Active control over automatically generated health data is obviously lower compared to manually registration of one's health data, which might lead to higher privacy concerns. Moreover, some types of mobile health apps might collect more sensitive health data than others, which may also raise privacy concerns. Although research has demonstrated evidence for the "privacy paradox" wherein people often do not act upon their privacy concerns (Norberg, Horne, and Horne 2007), taking into account the sensitivity of health data might make people more reluctant to share their personal data with mobile health apps.

Therefore, we look at use of specific mobile health apps and examine whether we can predict use of one type of health app over another based on the demographic characteristics of the user, e-health literacy skills, and privacy concerns. We address the following research question:

RQ2: Which factors – demographic characteristics (gender, age and education level), e-health literacy, and privacy concerns (surveillance, intrusion, and secondary use of information) – are associated with differences in use of specific types of mobile health apps?

Methodology

Study sample

Respondents were recruited through CentERdata's LISSPANEL, which comprised of a representative sample of the Dutch population. In total, 1,545 panel members were invited to participate, of which 1,389 fully completed the survey. The eligible subsample, that is those who possessed a smart device, consisted of 1,106 adults. Of those respondents, three skipped a substantial part of the questionnaire to get to the end and 24 respondents indicated that they had mobile health apps on their smart device but filled out other types of apps when they were asked what kind of health apps they owned. These 27 respondents were excluded from the dataset, resulting in a final sample of 1,079 adults. Respondents' age ranged from 18 to 89 years, with an average age of 50.32 (SD = 16.35), and 54.1% were female. Most respondents owned a smartphone ($n = 947$, 87.8%), followed by a tablet ($n = 779$, 72.2%), and a minority also owned a wearable ($n = 40$, 3.7%).

Procedure

As part of a larger panel wave study, respondents were invited to participate in an online survey. The survey started with questions on e-health literacy and respondents' use of smart devices (i.e., smartphone, tablet, wearable). Individuals who did not have a smart device were screened out before questions about privacy concerns about and use of mobile health apps were introduced. Demographic questions were extracted from the LISS-PANEL database. The institutional review board of the university granted permission for this study.

Measures

Mobile health app use. Respondents were asked to take their smart device(s) and report which health apps they had installed on their device(s). Thereafter respondents were asked to indicate how often they used each of these mobile health apps. They were given eight options ranging from "almost every day" to "never."

E-health literacy. It was measured using the e-health literacy scale (eHEALS: Norman and Skinner 2006b), which has 8 items such as 'I know how to use the Internet to answer my health questions' that are reported on a 5-point scale (1 = 'strongly disagree,' 7 = 'strongly agree,' $\alpha = .94$).

Information privacy concerns. They were measured using the 9-item MUIPC (Mobile Users' Information Privacy Concerns) scale (Xu et al. 2012). Confirmatory Factor Analysis (CFA) confirmed the three-factor structure of the MUIPC, resulting in a good fit with $\chi^2 (21) = 63.88$, $p < .001$, RMSEA = 0.044, SRMR = 0.011, TLI = 0.992, CFI = 0.996. Reliability analysis confirmed three reliable subscales, i.e., perceived surveillance (3 items, $\alpha = .78$), perceived intrusion (3 items, $\alpha = .90$), and secondary use of personal data (3 items, $\alpha = .93$). Sample items were, respectively, as follows: '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 more about me 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.' All items were measured on a 7-point Likert scale (1 = 'strongly disagree,' 7 = 'strongly agree').

Background variables. Respondents' age, gender, and educational level were measured as part of a previous wave, and thus extracted from the LISSPANEL database. Educational level was based on the categories used by CBS Statistics Netherlands (2013): primary education, preparatory secondary vocational education, higher secondary general education or pre-university education, secondary vocational education, higher vocational education, and university.

Statistical analysis

Logistic regression analysis was conducted to assess the relationships between aggregated mobile health app use and demographic background, e-health literacy, and privacy concerns (RQ1). We distinguished users from non-users, using the non-users group as reference category. Furthermore, logistic regression analyses were conducted to associate disaggregated mobile health app use (i.e., categories of specific mobile health app use) with demographic background, e-health literacy, and privacy concerns (RQ2). All independent variables were entered into the model as continuous covariates, except for gender, which was included as a dichotomous factor. We included aggregated mobile health app use as a control variable in the logistic regression models to be able to predict use of a specific type of mobile health app rather than aggregated use, since a large number of people belonging to the non-user groups of specific types of health apps also belong to the non-user group of aggregated mobile health apps. The results, described in the next section, present 'odds ratios'—any number greater than 1 suggests a higher likelihood to use mobile health apps (e.g., an odds ratio of 2 means that this group is two times *more* likely to use health apps than the reference group), whereas a number less than 1 suggests a lower likelihood of mobile health app use (e.g., and odds ratio of 0.5 means that this group is two times *less* likely to use health apps than the reference group).

Results

Mobile health app classification

Mobile health apps reported by the respondents were coded into categories of health apps to assess what kinds of health apps were being used by the people in our sample. Two coders worked together on establishing a codebook for categorizing the health apps. After consensus was reached about the categories, 10% of the total 368 unique health apps were double coded with good intercoder reliability ($n = 37$, $\kappa = .843$). Health app categories included fitness, nutrition, self-care, vitals, sleep, mindfulness, reproductive health, health information, and health dashboards (see Table 1 for an overview and examples of the categories). Since many apps have multiple functions (e.g., tracking activity and logging weight), apps were coded on their primary category (e.g., A fitness app providing the opportunity to also log food intake was coded as fitness app. Apps that overviewed health

Table 1. Description, examples, and user statistics of the different mobile health app categories.

	Description	Examples	% using such apps	Average number of apps in use
Fitness	Apps to track and monitor activity and workouts	Endomondo, Sworkit	52.3 (15.0)	0.86 (1.30)
Nutrition	Apps to track and monitor nutrition and weight	Food, Fatsecret	27.7 (8.0)	0.40 (0.80)
Self-care	Apps to support and give active control to a (potential) health situation or condition	MedAlert, Reanimation	12.9 (3.7)	0.19 (0.57)
Vitals	Apps to monitor vital signs, i.e., blood pressure, heart rate, body temperature, respiratory rate	Heart rate, Spo2	6.1 (1.8)	0.08 (0.34)
Sleep	Apps to track and monitor sleep patterns	SleepCare, Sleepcycle	5.8 (1.7)	0.07 (0.37)
Mindfulness	Apps for meditation, mental health, self-esteem	7 s Meditation, Headspace	5.5 (1.6)	0.11 (0.72)
Reproductive health	Apps for pregnancy, ovulation, menstruation	Love Cycles, Pregnancy+	5.5 (1.6)	0.09 (0.42)
Wearables	Apps that are connected to an activity bracelet	Fitbit, UP Jawbone	2.9 (0.8)	0.04 (0.22)
Health dashboards	Apps where you can store health data from other apps to get a complete overview of your health	S-Health, Lifelog	34.8 (10.0)	0.38 (0.55)
Health information	Apps to access health information and news	VascularDementia, Brain3D	1.6 (0.5)	0.02 (0.13)
Health insurance	Apps to access your health insurance information	Ohra, Menzis	1.0 (0.3)	0.02 (0.19)
Other	Apps that were too uncommon to categorize, e.g., apps for sports events	Strongmanrun, Mindbody	3.2 (1.4)	0.05 (0.28)

Notes. Percentages are relative to users of all mobile health apps ($n = 310$) and percentages within parentheses are relative to the full sample ($N = 1,079$). Means are based on the mobile health app users ($n = 310$) with standard deviations within parentheses.

data from other apps, were categorized as health dashboards). Health apps that could not be categorized as health apps (e.g., undefinable app names or letters) were coded as missing values.

Mobile health app user and non-user descriptives

Of this sample, 394 (36.5%) indicated that they had mobile health apps installed on their smart device versus 685 (63.5%) who had not. Of those who reported to have mobile health apps, 310 (28.7% of the total sample) actually used their mobile health apps; thus, 84 (7.8% of the total sample) individuals indicated that they had mobile health apps installed but never used them. Those who reported having mobile health apps had three health apps on their smartphone on average ($M = 2.65$, SD $= 3.43$), of which they on average used two ($M = 1.81$, SD $= 2.07$). Table 2 reports the demographics, e-health literacy skills, and privacy concerns of mobile health app users and non-users, first in the full sample ($N = 1,079$) and then by users ($n = 310$), and non-users ($n = 769$).

Explaining differences in mobile health app use (RQ1)

The findings presented in Table 3 show that numerous factors are associated with mobile health app use. Users of mobile health apps were generally younger (OR $= 0.97$; 95% CI 0.96–0.98) and more highly educated (OR $= 1.12$; 95% CI 1.01–1.24) than non-users. No significant differences between users and non-users were found for gender (OR $= 1.25$; 95% CI 0.94–1.66). Furthermore, users of mobile health apps had higher levels of e-health literacy skills than non-users (OR $= 1.46$; 95% CI 1.28–1.66). No significant differences between users and non-users were found for privacy concerns (OR$_{surveillance} = 1.22$; 95% CI 0.97–1.52; OR$_{intrusion} = 0.81$; 95% CI 0.66–1.01; OR$_{secondary use} = 0.90$; 95% CI 0.73–1.12). The results regarding RQ1 are visualized in Figure 1.

Explaining differences in use of specific types of mobile health apps (RQ2)

While the data in Table 3 suggests that age, education level, and e-health literacy are associated with mobile

Table 2. Descriptive statistics for the sample demographics, e-health literacy skills, and privacy concerns.

	Full sample ($N = 1,079$)		Health app users ($n = 310$)		Health app non-users ($n = 769$)	
Women (*n*, %)	584	54.1	167	53.9	417	54.2
Age (*M* [SD], range)	50.32 (16.35)	18–89	43.61 (15.20)	18 – 84	53.02 (16.03)	18 – 89
Education level						
Low (*n*, %)	274	25.4	48	15.5	226	29.5
Middle (*n*, %)	393	36.5	126	40.6	267	34.8
High (*n*, %)	410	38.1	136	43.9	274	35.7
E-health literacy (*M* [SD], range)	4.83 (1.24)	1–7	5.20 (1.04)	1–7	4.68 (1.28)	1–7
Privacy concerns						
Surveillance (*M* [SD], range)	4.53 (1.39)	1–7	4.38 (1.20)	1–7	4.58 (1.46)	1–7
Intrusion (*M* [SD], range)	4.32 (1.51)	1–7	4.05 (1.34)	1–7	4.43 (1.56)	1–7
Secondary use of information (*M* [SD], range)	4.48 (1.54)	1–7	4.26 (1.41)	1–7	4.58 (1.58)	1–7

Notes. Low level of education = primary education, preparatory secondary vocational education; middle level of education = higher secondary general education or pre-university education, secondary vocational education; high level of education = higher vocational education, and university.

Table 3. Logistic regression model explaining mobile health app use.

	b (SE)	OR	95% CI
Gender (male = 1)	0.22 (.15)	1.25	[0.94, 1.66]
Age	−0.03 (.01)***	0.97	[0.96, 0.98]
Education level	0.11 (.05)*	1.12	[1.01, 1.24]
E-health literacy	0.38 (.07)***	1.46	[1.28, 1.66]
Surveillance	0.20 (.11)	1.22	[0.97, 1.52]
Intrusion	−0.21 (.11)	0.81	[0.66, 1.01]
Secondary use of information	−0.10 (.11)	0.90	[0.73, 1.12]

Notes. R^2 = .16 (Nagelkerke). Model χ^2 (7) = 129.58, $p < .001$. OR = Odds ratio. * $p < .05$. *** $p < .001$.

health app use, the data in Table 4 suggests that these factors are not uniform across different types of health apps. Whereas gender was not associated with aggregated mobile health app use, gender was significantly related to using fitness apps, nutrition apps, self-care apps, and reproductive health apps. Men were more likely to use fitness apps than women (OR = 2.30; 95% CI 1.42–3.74), whereas women were more likely to use nutrition apps (OR = 0.28; 95% CI 0.16–0.50), self-care apps (OR = 0.43; 95% CI 0.20–0.90), and productive health apps (OR = 0.18; 95% CI 0.04–0.85) than men. With regard to age, only users of fitness and reproductive health apps were on average younger (resp. OR = 0.97; 95% CI 0.96–0.99 and OR = 0.95; 95% CI 0.90–0.99), while users of self-care and vitals apps were usually older (resp. OR = 1.04; 95% CI 1.01–1.06 and OR = 1.06; 95% CI 1.02–1.09). Although in most cases education level

did not relate to use of specific types of mobile health apps, it was associated with the use of mindfulness apps, such that more highly educated people were more likely to use these apps than lesser educated people (OR = 1.70; 95% CI 1.08–2.68). With regard to privacy concerns, we found that the use of health dashboards was significantly related to secondary use of information, a subdimension of privacy, such that those with less concerns about secondary use were more likely to use health dashboard than those with higher privacy concerns (OR = 0.66; 95% CI 0.46–0.94). On the other hand, higher levels of privacy concern regarding perceived surveillance were associated with the use of reproductive health apps (OR = 2.88; 95% CI 1.11–7.45), such that those with high privacy concerns about surveillance were more likely to use reproductive health apps than those with low concerns. The level of e-health literacy skills was not significantly related to the use of a specific type of mobile health app. The results regarding RQ2 are visualized in Figure 2.

Discussion

This article examined differences among users and non-users of mobile health apps by examining predictors of mobile health app use, with a particular focus on different types of health apps (i.e., fitness, nutrition, self-care, vitals, sleep, mindfulness, reproductive health, health

Table 4. Logistic regression models explaining use of specific types of mobile health apps.

	Fitness		Health dashboards		Nutrition		Self-care	
	b (SE)	OR [95% CI]	b (SE)	OR [95% CI]	b (SE)	OR [95% CI]	b (SE)	OR [95% CI]
Gender (male = 1)	0.83*** (.25)	2.30 [1.42, 3.74]	0.12 (.25)	1.12 [0.68, 1.85]	−1.26*** (.29)	0.28 [0.16, 0.50]	−0.85* (.38)	0.43 [0.20, 0.90]
Age	−0.03*** (.01)	0.97 [0.96, 0.99]	0.00 (.01)	1.00 [0.98, 1.02]	0.01 (.01)	1.01 [0.99, 1.03]	0.03** (.01)	1.04 [1.01, 1.06]
Education level	0.13 (.09)	1.14 [0.96, 1.36]	0.16 (.09)	1.17 [0.97, 1.41]	−0.00 (.10)	1.00 [0.82, 1.22]	0.02 (.14)	1.02 [0.78, 1.33]
E-health literacy	−0.14 (.12)	0.87 [0.69, 1.09]	0.06 (.12)	1.06 [0.84, 1.35]	−0.03 (.13)	0.97 [0.76, 1.24]	0.26 (.18)	1.30 [0.91, 1.85]
Surveillance	−0.16 (.19)	0.85 [0.59, 1.23]	0.23 (.20)	1.26 [0.86, 1.86]	−0.27 (.21)	0.76 [0.51, 1.15]	−0.29 (.26)	0.75 [0.45, 1.23]
Intrusion	0.17 (.18)	1.19 [0.84, 1.68]	−0.07 (.19)	0.93 [0.65, 1.34]	0.08 (.20)	1.09 [0.73, 1.61]	−0.25 (.26)	0.78 [0.47, 1.29]
Secondary use of information	0.05 (.17)	1.05 [0.75, 1.47]	−0.42* (.18)	0.66 [0.46, 0.94]	0.00 (.19)	1.00 [0.69, 1.46]	0.44 (.24)	1.56 [0.98, 2.49]
χ^2	507.73		318.61		258.51		120.11	
Nagelkerke R^2	.66		.54		.50		.39	

	Vitals		Sleep		Mindfulness		Reproductive health	
	b (SE)	OR [95% CI]	b (SE)	OR [95% CI]	b (SE)	OR [95% CI]	b (SE)	OR [95% CI]
Gender (male = 1)	1.02 (.57)	2.76 [0.91, 8.39]	−0.21 (.53)	0.81 [0.29, 2.27]	−0.48 (.55)	0.62 [0.21, 1.83]	−1.70* (.78)	0.18 [0.04, 0.85]
Age	0.05** (.02)	1.06 [1.02, 1.09]	−0.00 (.02)	1.00 [0.96, 1.03]	−0.01 (.02)	0.99 [0.96, 1.03]	−0.06* (.02)	0.95 [0.90, 0.99]
Education level	−0.20 (.19)	0.82 [0.57, 1.19]	0.11 (.19)	1.11 [0.76, 1.63]	0.53* (.23)	1.70 [1.08, 2.68]	0.19 (.21)	1.21 [0.80, 1.83]
E-health literacy	0.37 (.30)	1.44 [0.81, 2.57]	0.38 (.27)	1.46 [0.85, 2.50]	−0.08 (.24)	0.92 [0.57, 1.49]	−0.06 (.25)	0.94 [0.58, 1.54]
Surveillance	0.03 (.35)	1.03 [0.52, 2.05]	−0.10 (.38)	0.90 [0.43, 1.90]	0.47 (.42)	1.60 [0.71, 3.62]	1.06* (.49)	2.88 [1.11, 7.45]
Intrusion	−0.22 (.37)	0.80 [0.39, 1.66]	0.77 (.39)	2.16 [1.00, 4.66]	−0.12 (.39)	0.88 [0.42, 1.88]	−0.64 (.37)	0.53 [0.25, 1.10]
Secondary use of information	0.40 (.34)	1.49 [0.77, 2.88]	−0.59 (.37)	0.56 [0.27, 1.15]	−0.08 (.38)	0.93 [0.44, 1.95]	−0.28 (.40)	0.75 [0.35, 1.65]
χ^2	70.32		53.42		51.92		67.51	
Nagelkerke R^2	.39		.31		.31		.41	

Notes. OR = Odds ratio. * $p < .05$. ** $p < .01$. *** $p < .001$.

information, and health dashboards). Using a unique dataset from a large representative sample of the Dutch population including data on mobile health app use, coupled with demographic background information and measures on e-health literacy and privacy concerns, our analysis suggests that several individual characteristics differently contribute to use of specific types of mobile health apps. A person's gender, age, education, e-health literacy skills, and privacy concerns are all associated with use, but vary in predicting use of specific types of mobile health apps. When mobile health app use is considered in the aggregate, our results show that users compared to non-users are generally younger, more highly educated, and more e-health literate. However, when use of specific types of mobile health apps is considered, statistically significant relationships also emerge between mobile health app use, gender, and privacy concerns.

A person's age and education level are significantly related to mobile health app use, such that younger, more highly educated people were more likely to use mobile health apps than older, lesser educated people. Although these results are in line with current statistics on mobile device owners, the results on use of specific types of mobile health apps show a more refined analysis of the mobile health app user. These results show that, even though users of fitness apps and reproductive health apps are generally younger, users of self-care and vitals apps are typically older. This is in line with prior research findings that older populations are more at risk of chronic diseases (e.g., hypertension) and mobile health apps that enable monitoring of such diseases (e.g., by checking blood pressure) would be especially used by them (Lorenz and Oppermann 2009). Furthermore, disaggregated data analysis reveal that education level is especially associated with the use of mindfulness apps, such that more highly educated people were more likely to use such apps than their lesser educated counterparts. Although gender was not associated with general mobile health app use, our examination of specific mobile health app categories showed that while men are more likely to use fitness apps than women, women were more likely to use nutrition, self-care, and reproductive health apps. These findings on both aggregated and use of specific types of mobile health apps enhance our understanding of how different health apps are being used across various population segments.

The level of e-health literacy only contributed to mobile health app use in general, but not so much to use of specific types of health apps. Since e-health literacy is often a strong predictor of technology use (Neter and Brainin 2012), it is reasonable to expect that less variance exists in e-health literacy skills among users of online technologies. Based on our results, e-health literacy could be considered a prerequisite of mobile health app use in general. In contrast, although privacy concerns do not determine whether people use mobile health apps in general, they do predict use of certain types of health apps. We found that people with less concerns about their privacy over secondary use of information were more likely to use health dashboards than those with higher privacy concerns, whereas people with more privacy concerns about perceived surveillance were more likely to use reproductive health apps than those with lower privacy concerns. These findings indicate that specific types of health apps raise more privacy concerns than others, and that people consider certain types of health-related data more sensitive than others (Prasad et al. 2014). It therefore seems that people explicitly distinguish between different types of health apps, which further underscores the need to develop a more differentiated understanding of privacy in the context of health apps. Future research needs to further examine why exactly people are more or less concerned about particular health apps.

Interestingly, our findings suggest that different dimensions of privacy concerns are differently associated with mobile health app use. That is, concerns about secondary use of information were negatively related to use of health dashboards, whereas concerns about perceived surveillance were positively related to use of reproductive health apps. Theoretically, this is quite fascinating. While different subdimensions of the construct privacy concerns could be expected to predict use of different types of mobile health apps, it is striking that these subdimensions also differ in the direction of predicted outcomes. However, intuitively this makes sense. For instance, as users of health dashboards in our sample indicated low levels of privacy concerns about secondary use of information, it is likely that those worried about secondary use of personal information deliberately choose to stay away from such health apps. Conversely, those who choose to use health dashboards could be generally less concerned about secondary use of information, or simply do not understand the privacy risk. With regard to privacy concerns about perceived surveillance, which were in our sample generally high among users of reproductive health apps, it could be that a user might choose to use such an app even though the recording and collection of sensitive health data leads to surveillance related concerns.

Altogether, these findings show the importance of considering privacy concerns as a multidimensional construct and merits further investigation. They prompt questions about to what extent privacy concerns can be an obstacle for the use of particular health apps. As most
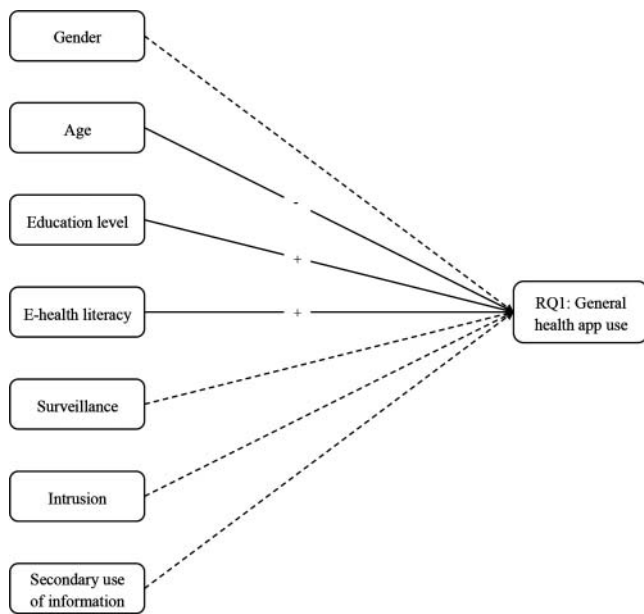
Figure 1. Visualization of the findings for RQ1: Which factors – demographic characteristics (gender, age, and education level), e-health literacy, and privacy concerns (surveillance, intrusion, and secondary use of information)—are associated with differences in mobile health app use? Lines with pluses (+) indicate positive relationships, lines with minuses (−) indicate negative relationships, and dashed lines indicate non-significant relationships with mobile health app use.

law (e.g., stricter rules for the secondary use of health-related data) in order to create an environment in which users can develop trust in the use of mobile health apps.

Two, our findings provide a critical backdrop against which to assess strategies, such as the European e-health strategies, which tend to differentiate little between different types of users. Here, it is important to bear in mind that certain consumers are probably better positioned to self-manage their health (e.g., the "average" e-health consumers who is young, highly educated, and e-health literate) than other more "vulnerable" consumers (for a more in-depth discussion on the notions of "average" and "vulnerable" consumer, see Baker, Gentry, and Rittenberg 2005; Duivenvoorde 2014; Hare, Law, and Brennan 2012; Incardona and Poncibò 2007; London Economics, VVA Consulting, and Ipsos Mori 2016). Moreover, with the increasing "datafication" and "commodification" of health data through online health platforms, users are increasingly challenged to identify trustworthy versus less trustworthy actors in this sector (Andrejevic 2014; Van Dijck and Poell 2016). Effective empowerment of users calls for a more differentiated perspective on the individual needs and potential of consumers to self-management, and this
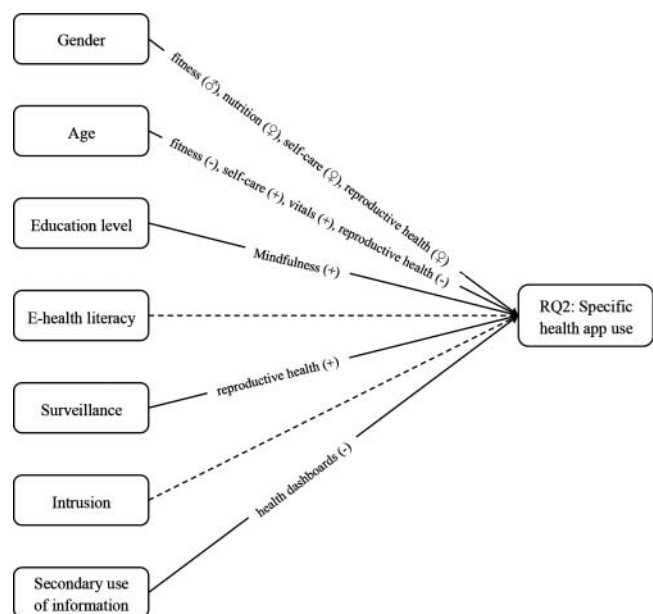
of the digital divides literature so far has focused on socio-demographic or socio-economic determinants (Scheerder, Van Deursen, and Van Dijk 2017), these findings provide new perspectives into the digital divides.

Our findings relate to the discourse on the digital divides in two ways. One, they prompt the question whether mobile health technologies are expanding digital divides, rather than closing them. For example, deepening of digital divides could be a result of creation of additional advantages for those using mobile health apps (e.g., young and educated individuals) and not for more vulnerable individuals (e.g., socially disadvantaged or elderly), who are more likely to be in need for new, cost-effective health-care solutions. Accordingly, if the goal is to ensure broad access to, and use of such apps also for other groups (e.g., as part of national health strategies), it is important to focus not only on the typical adopters. Instead, we should invest in informing and also addressing the concerns of those parts of the population, such as older and less educated individuals, that have shown lesser propensity to use mobile health apps. This could mean that e-health literacy strategies would need to be tailored to the different needs and levels of education and digital literacy in the population. It could also mean that there is a need to target more specifically privacy concerns through a more differentiated approach in data protection

Figure 2. Visualization of the findings regarding RQ2: Which factors—demographic characteristics (gender, age and education level), e-health literacy, and privacy concerns (surveillance, intrusion, and secondary use of information)—are associated with differences in use of specific types of mobile health apps? Text in lines indicates with which specific types of mobile health apps the factors have positive (+) or negative (−) relationships. For gender, male symbols (♂) indicate use by males, and female symbols (♀) indicate use by females. Dashed lines indicate non-significant relationships with mobile health app use.

study provides some first indications that such differences in society exist.

Previous research has shown that most digital tools are not well designed for vulnerable populations, such as older adults and adults with limited health literacy skills (Bol 2015; Bolle et al. 2016; Meppelink et al. 2015; Romano Bergstrom, Olmsted-Hawala, and Jans 2013). It is questionable whether development of solutions for socially and economically disadvantaged groups can be left to the market, as these groups typically are not an attractive market segment. Here, there is the need for the government or public institutions to stimulate the development of user-friendly e-healthy solutions for segments of society that are less likely to be served by the market.

One limitation of this study is the cross-sectional research design, which does not capture changes over time. Longitudinal studies are needed in the future. Moreover, our findings rely on self-reported data, which might have led to a biased measure of mobile health app use. For instance, not all people might be aware of health apps installed on their mobile device (e.g., preinstalled Apple's Health or Samsung's S Health app). We should also note that we did not ask the respondents about their goals and motivations for using their mobile health apps. Since most apps have multiple functions (e.g., tracking activity and logging weight), we could have categorized some of the reported apps differently than what respondents used them for. Furthermore, our data do not provide insight into potentially important differences between users' health-related activities "offline" and "online." For instance, although runners have been reported to benefit from health apps in terms of improved "offline" health behaviors such as increased physical activity (Dallinga et al. 2015), we cannot argue that all runners equally benefit from mobile health apps. In fact, not everyone who engages in health behaviors uses an app to support these behaviors, and different motivations may differently predict mobile health app use or non-use. Future research could provide more insight into the goals and behaviors behind mobile health app use and non-use.

Conclusions

To conclude, the main goal of this article was to compare mobile health app users and non-users by disaggregating use of specific types of mobile health apps; the findings suggest systematic differences in who chooses to use mobile apps for health and who does not. Specifically, a person's age, education level, and e-health literacy skills were found to be predictors of mobile health app use in general. Importantly, the findings also suggest that different populations select different types of mobile health apps such that gender, age, education levels, and privacy concerns are differently associated with use of specific types of mobile health apps. These findings pose a challenge to research that aggregates use of all mobile health apps. Our findings suggest different gradations of mobile health app users, differentiated either by their demographic background and/or their level of privacy concern for mobile health apps use. This article contributes to a better, more differentiated understanding of mobile health app use, which could enable the development of more nuanced strategies for bridging the digital divides.

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