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Who are mobile app users from healthy lifestyle websites? Analysis of patterns of app use and user characteristics

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Abstract

The use of online communities and websites for health information has proliferated along with the use of mobile apps for managing health behaviors such as diet and exercise. The scarce evidence available to date suggests that users of these websites and apps differ in significant ways from non-users but most data come from US- and UK-based populations. In this study, we recruited users of nutrition, weight management, and fitness-oriented websites in the Czech Republic to better understand who uses mobile apps and who does not, including user sociodemographic and psychological profiles. Respondents aged 13–39 provided information on app use through an online survey ($n = 669$; M age = 24.06, SD = 5.23; 84% female). Among users interested in health topics, respondents using apps for managing nutrition, weight, and fitness ($n = 403$, 60%) were more often female, reported more frequent smartphone use, and more expert phone skills. In logistic regression models, controlling for sociodemographics, web, and phone activity, mHealth app use was predicted by levels of excessive exercise (OR 1.346, 95% CI 1.061–1.707, $p < .01$). Among app users, we found differences in types of apps used by gender, age, and weight status. Controlling for sociodemographics and web and phone use, drive for thinness predicted the frequency of use of apps for healthy eating ($\beta = 0.14$, $p < .05$), keeping a diet ($\beta = 0.27$, $p < .001$), and losing weight ($\beta = 0.33$, $p < .001$), whereas excessive exercise predicted the use of apps for keeping a diet ($\beta = 0.18$, $p < .01$), losing weight ($\beta = 0.12$, $p < .05$), and managing sport/exercise ($\beta = 0.28$, $p < .001$). Sensation seeking was negatively associated with the frequency of use of apps for maintaining weight ($\beta = -0.13$, $p < .05$). These data unveil the user characteristics of mHealth app users from nutrition, weight management, and fitness websites, helping inform subsequent design of mHealth apps and mobile intervention strategies.

Keywords

Mobile app users, Smartphones, Healthy lifestyle websites, Individual differences

Implications

Practice: Any potential intervention efforts utilizing mobile apps and targeting users of healthy lifestyle websites should consider underlying user characteristics such as gender, age, and weight status in selection of mHealth apps as well as consider the underlying psychological needs of users. App designers should incorporate user profiles in the design of mHealth apps to facilitate tailoring of app features to maximize their effectiveness as well as minimize any possible negative impact on users with different predispositions.

Policy: Standards for development of mHealth apps should include evaluation for potential to lead to psychological or behavioral vulnerabilities to avoid causing or exacerbating any maladaptive health behaviors in predisposed users.

Research: There are differences between app users and non-users of mHealth apps. Whereas some user characteristics such as excessive exercise or drive for thinness may help motivate app use, they should also be evaluated for potential to interact with mHealth app use in terms of leading to psychological harm or maladaptive health behaviors.

The popularity of using the internet as a source of health information has been increasing in tandem with increased access to the internet. In the USA, 59% of adults say that they have searched for information about health online [1], and similarly, nearly two thirds of Europeans say that they have looked for ways to improve their health online in the past 12 months [2]. This is encouraging and has been lauded for its potential to empower individuals to take charge of their own health and lifestyle choices. Individuals can now seek health information online [3], obtain online support from peers (e.g., via online health forums) [4, 5], or take part in intervention programs delivered fully online [6]. This, combined with internet access now readily available to most on their mobile devices and the explosion in the development of mobile health (mHealth) apps, means that the potential reach and impact of health promotion efforts have never been greater.

Indeed, mobile apps are now commonly incorporated in the design of health promotion programs (both face to face as well as online) and the mobile app market has been growing exponentially [7]. Resulting from this boom are efforts to carefully evaluate the "science" behind mobile apps to ensure their components reflect evidence- and theory-based principles of behavior change to maximize their effectiveness [8–10]. Less encouraging, nonetheless, are statistics regarding the actual use (especially sustained use) of mobile apps to track health and related behaviors. Case in point, although seven in ten Americans track some data about their health, few (9%) actually use online tools or mobile apps for the tracking, with half tracking information in their heads and third in pen and paper instead [11]. Additionally, when individuals have mobile apps on their phone, only 68% say that they use them and most are used just once and then deleted [12]. Unfortunately, research into who the app users are, how they differ from non-users, their patterns of app use, and factors that may predict app use is limited, although such data could prove valuable in the process of app development and tailoring of mHealth intervention efforts [13, 14]. More concretely, knowledge of factors that make one more likely to use apps such as level of digital literacy should be taken into account when designing and marketing mHealth apps to target audiences [2, 14]. Similarly, understanding personal characteristics that could predispose one to benefit more from specific app content or that could put one at risk for harmful effects from specific app content would be useful in tailoring app content for optimal effectiveness [15]. One can hypothesize, for example, that personality traits such as conscientiousness may facilitate compliance with mHealth apps and higher responsiveness to features that support planning and goal attainment. On the other hand, individuals high in neuroticism or having high drive for thinness could be at potential risk for negative outcomes from app features emphasizing behavioral goals such as weight loss [16, 17]. In this study, we specifically focus on users of nutrition, weight-management, and fitness-related websites (later referred to as healthy lifestyle websites) from the Czech Republic to addresses two key limitations in the existing mHealth literature: (1) a limited understanding of general user (sociodemographic) and psychological characteristics linked to mHealth app use and (2) homogenous data sources limiting the generalizability of findings beyond the Anglo-American context.

Generally speaking, mobile app users tend to be young, have above average education and income levels, and reside mostly in urban or suburban areas [12]. The profiles of mHealth app users more specifically are mapped mostly through industry analysis of mHealth consumers with the intent to size up the mHealth market as opposed to increasing understanding about the population of app users and their app use behavior. These reports are also rarely accessible to non-industry audiences or without paying a fee. We found only few scientific studies that have attempted to directly profile mHealth app users. In a survey of adult mobile phones users in the USA [18], 58% have downloaded an mHealth app at some point with the most common goals being to track physical activity (53%), eating (48%), for weight loss (47%), or learning to exercise (34%). Although respondents in this survey reported being interested in a number of app features including behavior goal tracking, medical monitoring, and consultation, few used all these features and the discontinuation rates were high (46%). Only few associations with user characteristics were reported with those downloading mHealth apps being younger, Latino/Hispanic, with higher income and education, and obese [18]. Whether there were differences in user characteristics by type of mHealth app or in preferred features was not investigated in this study.

Recently, Bhuyan et al. [19] have used data from the Health Information National Trends Survey (HINTS) conducted by the National Cancer Institute to evaluate mHealth use across different health-related behaviors among US adults. They found that nearly 36% of smartphone or tablet owners had an mHealth app, using it for achieving health-behavior goals (60%), medical decision-making (35%), or using it to communicate with healthcare providers (38%). In terms of demographic profiles, mHealth app users resembled app users more generally by being younger, non-Latino White, married, educated, with higher income, having medical coverage and a healthcare provider, being relatively healthy, from urban areas, and having confidence to take care of themselves. Findings indicated differences in the use of different types of mHealth apps and key user characteristics. Specifically, older individuals were less likely to use apps to reach behavioral goals, but obese individuals were more likely to use such apps compared to underweight individuals. Individuals aged 35–44, African Americans, and non-smokers were more likely to use apps for medical decision-making as compared to those younger than 35, those being White, and smokers, respectively. Those aged 65 and above, African Americans, and those with a regular healthcare provider were more likely to use apps to seek physician's second opinion. Whether additional user factors such as psychological characteristics predispose individual to differential use of mHealth apps could not be ascertained from this study.

The scarcity of data on mobile app use patterns and app user characteristics is in contrast with the importance that is typically placed on user perspectives by technology acceptance and usability theoretical models that emphasize the involvement of user input and consideration of user characteristics along the app development process [20–22]. For example, in the Unified Theory of Acceptance and Use of Technology model [22], user characteristics such as gender, age, or experience level are hypothesized to moderate the effects of social cognitions such as performance and effort expectancy, social influence on intentions to use technology, or the effects of facilitating conditions on usage itself. Understanding more about user characteristics linked to mHealth app use could reveal important individual difference variables in receptiveness to different mHealth app features or intervention strategies [23]. In addition to sociodemographic factors

[24], psychological characteristics could either predispose individuals to benefit from their use or put them at risk for negative consequences by influencing what type of information/features one attends to, how one processes that information, and subsequently uses the information/features to self-regulate own behavior [25, 26]. For example, individual traits such as neuroticism could predispose one to benefit differentially from mHealth apps supporting weight loss or exercise behavior [16, 17]. Highly neurotic individuals are more likely to engage in problematic health behaviors such as extreme dieting or excessive exercise [27], which could be theoretically facilitated by use of mHealth apps. Unfortunately, there is little data on the associations between mHealth app use and psychological characteristics of its users, although different aspects of personality have been linked to different features of persuasive technologies [28, 29] and social cognitions (e.g., behavioral control, barriers, attitudes) being predictive of technology uptake outcomes (e.g., intention to use apps [30] or intensity of mHealth app use [23]).

Importantly, data on mHealth app use or user characteristics involve predominantly US- and UK-based populations, limiting the generalizability of the findings to contexts that may differ culturally in rates of technology use, societal support for use of technology towards achieving health outcomes, or more specifically in consumer behavior towards mHealth solutions. The 2016 Global Internet Report by the Internet Society [31] reports that there are now 3.2 billion internet users worldwide; nonetheless, the growth rates of internet penetration are slowing and use varies by region. For example, 82% of Europeans and 89% of individuals in the USA use the internet, compared to 60% in Brazil, 39% in Nigeria, or 22% in India [32, 33]. Corresponding figures for smartphone ownership are 67% in Europe, 72% in the USA, 42% in Brazil, 28% in Nigeria, and 17% in India. Specific information on user characteristics linked to mHealth use, in particular, is however scarce and limited largely to the US population (as per the reports by Bhuyan et al. [19], and Krebs et al. [18]).

To this end, we present data obtained from Czech users of healthy lifestyle websites to evaluate individual factors (sociodemographic and psychological) linked to mHealth app use. In the Czech Republic, located in central Europe, 82% of the population are internet users (figure representing the European average and a 14th ranking among the 28 European countries) [32]. The figure grows beyond 90% among those that are young, educated, or economically active. Four in ten Czech users access the internet via their cell phones. Although falling in the mid-range among European countries and lacking behind the US, the Czech Republic has the highest mobile phone penetration in central Europe [34], with rates of usage increasing dramatically in recent years [35]. In terms of health profile, the Czech Republic has comparable life expectancy with the US (82 for the Czech Republic versus 81.2 for the US), but on average, fewer Czechs self-rate their health as good or very good as compared to the US but on par with countries such as Hungary or Norway [36]. Obesity rates in the Czech Republic stand at 33%, the highest in Europe but it is comparable to the US, with 29% of the Czech population insufficiently active (compared to 32% in the region of Americas) [37].

As part of a study on the role that digital technologies play in supporting healthy lifestyles, Czech users from different healthy lifestyle websites were recruited for a survey on their website and mobile app use. The primary objective of this study was to examine the general pattern of mHealth app use among this population. To achieve this goal, we intend to (a) evaluate differences between mobile app users and non-users with respect to sociodemographic factors and selected psychological characteristics, (b) to examine the patterns of app use among app users, and (c) to examine associations between different aspects of app use and sociodemographic and psychological factors.

Method

Participants

Participants were recruited as part of study (THINLINE) examining the role digital technologies play in supporting healthy lifestyles including diet, weight loss, and exercise and sport behaviors among young adults. Individuals seeking information specifically on lifestyle choices, such as diet, nutrition, or physical activity, make up nearly three quarters (74%) of those looking for health information online [2] and represent a population with arguably at least some level of motivational readiness to seek information about their health, to actively sustain specific eating and exercising oriented lifestyle, and/or to undertake behavior change. By specifically targeting users of healthy lifestyle websites, i.e., those who are already using technology (i.e., the internet), we were able to reach individuals with sufficient digital literacy (e.g., to seek health-related information online) and who may thus be more inclined to use technology-mediated intervention strategies (including mobile apps) to improve their health or reach behavioral goals.

The inclusion criteria were age 13–39 and current use of websites targeting nutrition, weight loss, and exercise or sport. The online survey was initiated by 1143 users. Data from 141 respondents were discarded due to stating that they do not use the internet, phone, or websites we inquired about ($n = 11$), filling in only page one and providing low-quality data ($n = 107$), and having low-quality data (low number of items answered, conflicting responses, and suspect/unreliable times spend on answers) ($n = 23$). Out of the resulting 1002 users, for this study, we analyzed data from 669 respondents aged 13–39 who provided information on app use and reached the final page of the survey which contained some of the measures of individual characteristics used in this study. There were no differences in sociodemographic characteristics including age, income, or education between those included in the analysis and those excluded due to missing data. Slightly fewer males have reached the final page of the survey as compared to females (63% versus 71%, $p < .05$). The final sample ($n = 669$; M

age = 24.06, *SD* = 5.23) consisted of 403 self-identified app users (i.e., those stating they use apps on their smartphone related to healthy lifestyle such as dieting, weight management, sport/exercise, or for improving health status) and 266 non-users (i.e., those stating they do not use apps on their smartphone related to healthy lifestyle).

Measures

Background information—Basic demographic information was collected including age, gender, household income, education, and nationality. Given the mixed age sample, participants ranked household income level by selecting one of the following response options: "It is not enough to cover all expenses," "Just covers all expenses," "It covers all expenses, it is not a problem for me/us," and "It is high, we do not have to worry about expenses." We recoded that self-reported highest education attained for respondents younger than 26 to reflect parents' education level, except for cases in which respondents aged 18–26, had higher attained education than their parents.

Information on website and app use—Respondents rated the frequency of internet and smartphone use following two separate questions "How often do you use the *internet/smartphone*?," with response options never (=1), several times a month (=2), several times a week (=3), almost daily (=4), and daily (=5). Two separate questions "How much advanced a user are you of the internet/smartphones?" measured level of internet and smartphone use skills on a scale ranging from beginner (=1) to expert (=8).

The question "How often do you visit websites regarding nutrition, weight loss, or exercise and sport?" measured the frequency of website visits. Respondents answered with respect to three types of websites, i.e., those focused on "nutrition (e.g., relating to specific diets, and healthy meals)," "weight loss (e.g., diets or instructions on how to lose weight)," and "exercise or sport (regarding your exercise or sport, but not, e.g., following the results of professional athletes)." Respondents answered on a 6-point scale with the response options: never (=1), almost never (=2), several times a month (=3), several times a week (=4), almost daily (=5), and daily (=6). Additionally, respondents indicated their activity on these websites by answering yes/no to whether they add evaluations, add comments, share content on their profiles, add content to sites, or talk with other people. The yes responses were summed to indicate intensity of website activity.

With respect to apps use, we asked respondents if they use special applications/programs on their smartphone helping with the following goals: healthy eating, keeping a diet, losing weight, gaining weight, maintaining your existing weight, sport or exercise, and/or improving the status of their health. Respondents then rated their use on a 6-point scale with the response options: never (=1), almost never (=2), several times a month (=3), several times a week (=4), almost daily (=5), and daily (=6). Additionally, we also asked app users to rate how important general app features (monitoring activities, planning activities, sharing activities with others, competing with others, communicating with others) were to them on a scale ranging from completely unimportant (=1) to completely important (=6).

Individual characteristics—We assessed several individual characteristics to represent those that could impact app use beyond the sociodemographic variables:

Body mass index—Self-reported weight and height were collected to compute body mass index (BMI) (weight[kg] / height[m^2]) and derive categories of underweight, normal weight, and overweight/obese individuals based on WHO's international classification and adjusting based on gender and age for respondents 13–18 using the IOTF guidelines [38].

Drive for thinness—Seven items from the subscale Drive for thinness from the Eating Disorder Inventory-3 (EDI-3 [39]) answered on a 6-point scale ranging from never (=1) to always (=6) were used. The scale was computed by averaging the items, with higher scores indicating higher drive for thinness (internal consistency was good with Cronbach's $\alpha = .85$).

Excessive exercise—Five items from the subscale Excessive exercise from the Eating Pathology Symptoms Inventory Scales (EPSI [40]) answered on a 5-point scale ranging from never (=1) to very often (=5) were used. The scale was computed by averaging the items, with higher scores indicating greater tendency for excessive exercise (internal consistency was good with Cronbach's $\alpha = .87$).

Sensation seeking—Four items from the Brief Sensation Seeking Scale-4 (BSSS-4 [41]) were used. The items were "I would like to explore strange places," "I like to do frightening things," "I like new and exciting experiences, even if I have to break the rules," and "I prefer friends who are excitingly unpredictable." Items were rated on a 4-point scale ranging from definitely does not apply (=1) to definitely applies (=4). The scale was computed by averaging the items, with higher scores indicating higher sensation seeking (internal consistency was good with Cronbach's $\alpha = .81$).

Neuroticism—Three items from the short 15-item Big Five Inventory (BFI-S [42]) were used. The items were "I worry a lot," "I get nervous easily," and "I remain calm in tense situations" (reverse scored), answered on a 6-point scale ranging from definitely does not apply (=1) to definitely applies (=6). The scale was computed by averaging the items, with higher scores indicating higher neuroticism (internal consistency was acceptable with Cronbach's $\alpha = .71$).

All psychological measures were translated by Ph.D. level psychology scientists with expert knowledge of English.

Procedure

The study utilizes data from visitors of websites focused on nutrition, weight loss, and exercise collected as part of a project on eating behaviors in the context of internet and technology use. The university Research Ethics Committee approved the study. The data were collected via online survey between May and October 2016. For participant recruitment, we approached Czech websites oriented on eating habits, exercising, dieting, and weight loss with a request to publish an invitation for study participation. Participants were motivated by the chance to win one of five vouchers for an e-shop in the amount of 40 euros each. In total, 65 websites agreed and published the invitation.

Statistical analysis

Basic descriptive statistics were run including means, standard deviations, and frequencies to describe the demographic and internet/app use patterns of the respondents in the resulting sample. To analyze differences between users and non-users of mobile apps, independent sample *t* tests and chi-square difference tests were conducted. Additionally, logistic regression was conducted to identify significant predictors of app use based on respondents' individual characteristics. To further describe the subgroup of app users, we conducted chi-square difference tests, *t* tests, and ANOVAs to analyze differences in app use based on age, gender, and weight status. Finally, we conducted hierarchical regression analyses to identify correlates of frequency of app use by type and different sociodemographic and psychological characteristics. Due to the non-normal distribution of the data, these analyses were conducted in Mplus.6 using maximum likelihood estimation with robust standard errors and a Satorra-Bentler scaled test statistic (MLM).

Results

Sample description

Among the 669 respondents who completed the survey, the majority were females (84%) with slightly

Table 1 | Demographic characteristics and general website use of the sample

Variable	Missing cases/%	Total sample (N = 669) Mean (SD)	App users (n = 403) Mean (SD)	App non-users (n = 266) Mean (SD)
Age	0/0	24.06 (5.23)	23.80 (5.25)	24.45 (5.19)
Self-rated internet skills	4/0.6	6.20(1.15)	6.22(1.16)	6.16(1.14)
Self-rated smartphone skills**	15/2.2	5.55(1.67)	5.97(1.25)	4.90(2.01)
Intensity of activity on websites*	17/2.5	1.79(0.71)	1.84(0.71)	1.71(0.71)
Body mass index*	32/4.8	23.08 (4.31)	22.79 (3.99)	23.52 (4.72)
Weight status category (age/gender matched based on BMI percentile)		%	%	%
Underweight	32/4.8	6.3	6.3	6.3
Normal weight		70.0	71.4	68.0
Overweight		16.8	17.2	16.2
Obese		6.9	5.2	9.5
Gender**	0/0	83.6 female	87.1 female	78.2 female
	Education			
Primary	7/1.0	0.3	0.3	0.4
Secondary		39.3	40.0	38.2
Tertiary		60.4	59.8	61.5
	Household income			
Not enough to cover all expenses	3/0.4	2.4	1.7	3.4
Just covers all expenses		29.9	29.2	30.9
Covers all expenses, not a problem		60.7	60.8	60.4
It is high, no worry about expenses		7.1	8.2	5.3
	Nationality			
Czech	0/0	91.9	92.3	91.4
Slovak		7.5	7.4	7.5
Other		0.6	0.2	1.1
	Daily/almost daily frequency of visits to websites			
Nutrition websites***	0/0	46.9	52.1	39.1
Weight loss websites***		16.9	20.8	10.9
Exercise or sport websites***		37.2	42.9	28.6
Daily frequency of internet use	0/0	88.6	90.6	85.7
Daily frequency of smartphone use***	0/0	80.1	89.8	65.4

Note. Statistically significant difference at *$p < .05$, **$p < .01$, ***$p < .001$

Table 2 | Psychological characteristics of the sample

Variable	Missing cases/%	Total sample (N = 669) Mean (SD)	App users (n = 403) Mean (SD)	App non-users (n = 266) Mean (SD)
Excessive exercise*	3/0.4	3.03 (0.95)	3.21 (0.88)	2.77 (1.01)
Drive for thinness*	16/2.4	3.19 (1.20)	3.34 (1.15)	2.97 (1.24)
Sensation seeking	3/0.4	2.75 (0.76)	2.76 (0.75)	2.74 (0.77)
Neuroticism	6/0.9	3.60 (1.18)	3.67 (1.19)	3.50 (1.15)

Note. Statistically significant difference at $^*p < .001$

more than half of the sample stating having achieved primary or secondary education (58%). The majority (60%) of the sample also stated having sufficient level of household income (i.e., covering most expenses), being Czech nationals (92%), and using the internet and smartphones on a daily basis (89 and 80%, respectively). The respondents self-rated their skill level with the internet and smartphone use relatively high ($M = 6.2$, $SD = 1.2$ and $M = 5.6$, $SD = 1.7$, respectively, on a scale ranging from 1 "*novice*" to 8 "*expert*"). The self-reported frequency of visits was the highest for nutrition websites with 47% of respondents visiting these sites almost daily or daily, 14% several times a week, and 29% several times a month (detailed overview of sociodemographic and web/app usage can be seen in Table 1).

App users versus app non-users

There were no statistically significant differences between app users and non-users relative to age, income, or education. Nonetheless, there were proportionately more women among app users compared to non-users (87% versus 78%; $\chi_1^2 = 9.241$, $p < .01$), and as expected, app users reported more frequent use of their smartphones ($\chi_4^2 = 105.193$, $p < .001$) and rated their smartphone skills as significantly better ($t_{652} = 8.395$, $p < .001$) as compared to non-users. There were no differences in the frequency of internet use or rating of internet skills between the two groups but app users were generally more frequent users of all types of websites (nutrition, weight loss, and sport/exercise) and were engaging in more activity on the websites as well (*See* Table 1). Although app users had slightly lower BMI than non-users ($t_{635} = 2.120$, $p < .05$), there were no differences among the groups based on representation in weight status categories reflecting age- and gender-specific norms [38].

When comparing app users and non-users in terms of psychological characteristics, app users scored significantly higher on scales assessing excessive exercise and drive for thinness than app non-users (*See* Table 2). To see whether psychological characteristics predict app use beyond sociodemographic factors, we conducted a logistic regression analysis. Controlling for gender, age, education, income, BMI, self-rated smartphone skills, frequency of website visits, and intensity of website activity, the use of apps for managing healthy lifestyle was predicted by levels of excessive exercise (OR 1.289, 95% CI 1.021–1.628, $p < .01$). Individuals with higher levels of excessive exercise were more likely to report using apps (Table 3).

Table 3 | Logistic regression predicting mobile app use

	B	S.E.	Sig.	Exp(B)	95% C.I. for EXP(B)	
					Lower	Upper
Block 1						
Gender	0.65	0.28	0.01	1.96	1.11	3.36
Age	0.00	0.02	0.99	1.00	0.96	1.04
Income	0.09	0.16	0.57	1.09	0.81	1.48
Education	− 0.06	0.20	0.75	0.94	0.64	1.38
BMI	− 0.04	0.02	0.09	0.96	0.91	1.01
Smartphones skill	0.40	0.06	0.00	1.49	1.31	1.68
Intensity of website activity	0.17	0.14	0.22	1.19	0.90	1.56
Frequency of website visits	0.25	0.11	0.02	1.29	1.04	1.60
Block 2						
Excessive exercise	0.25	0.12	0.03	1.29	1.02	1.63
Drive for thinness	0.08	0.10	0.42	1.08	0.89	1.31
Sensation seeking	− 0.11	0.13	0.42	0.90	0.69	1.17
Neuroticism	0.08	0.09	0.37	1.08	0.91	1.28
Block 1 Nagelkerke R = 0.20			Total Nagelkerke R = 0.22			

Table 4 | Types of apps used by app users (in %)

App for …	Never	Several times a month	Several times a week	Almost daily	Daily
Healthy eating	32.8	25.3	17.4	14.1	10.4
Keeping a diet	73.9	9.9	5.5	6.5	4.2
Losing weight	58.1	16.6	10.7	8.4	6.2
Gaining weight	90.6	5.2	1.7	1.5	1.0
Maintaining weight	68.5	13.6	8.9	4.7	4.2
Sport or exercise	9.9	27.5	27.3	21.1	14.1
Improving health status	55.1	16.4	13.6	8.4	6.5

Table 5 | Mean frequencies of use by different type of app and gender, age, and weight status categories

	Gender		Age			Weight status		
	Female $n = 322$ $M (SD)$	Male $n = 46$ $M (SD)$	13–18 $n = 68$ $M (SD)$	19–28 $n = 279$ $M (SD)$	29–39 $n = 56$ $M (SD)$	Under-weight $n = 24$ $M (SD)$	Normal weight $n = 274$ $M (SD)$	Overweight/obese $n = 86$ $M (SD)$
Healthy eating	2.50 (1.36)	2.08 (1.19)	2.53 (1.29)	2.46 (1.38)	2.23 (1.27)	3.17 (1.31)	2.41 (1.35)	2.33 (1.36)
Keeping a diet	1.61 (1.15)	1.33 (0.83)	1.60 (1.14)	1.59 (1.15)	1.41 (0.91)	1.71 (1.23)	1.52 (1.07)	1.67 (1.22)
Losing weight	**1.96 (1.29)**	**1.37 (0.84)**	1.75 (1.15)	1.94 (1.31)	1.73 (1.09)	1.92 (1.41)	1.82 (1.18)	2.03 (1.43)
Gaining weight	**1.15 (0.59)**	**1.35 (0.76)**	**1.41 (0.95)**	**1.14 (0.54)**	**1.05 (0.40)**	**1.58 (1.14)**	**1.15 (0.57)**	**1.09 (0.42)**
Maintaining weight	1.63 (1.11)	1.60 (1.05)	1.71 (1.05)	1.62 (1.12)	1.54 (1.04)	2.00 (1.47)	1.64 (1.07)	1.48 (1.06)
Sport or exercise	3.02 (1.19)	3.00 (1.33)	2.90 (1.10)	3.03 (1.24)	3.13 (1.19)	2.67 (1.09)	3.04 (1.21)	2.93 (1.20)
Improving health status	**1.89 (1.24)**	**2.31 (1.42)**	1.84 (1.15)	1.97 (1.28)	1.95 (1.34)	1.67 (1.01)	1.91 (1.24)	2.12 (1.38)

Note. Group comparisons highlighted in bold reflect statistically significant chi-square difference tests. Frequency values should be interpreted as corresponding to never (=1), almost never (=2), several times a month (=3), several times a week (=4), almost daily (=5), daily (=6)

App-user characteristics and patterns of app use

In the next set of analyses, we focus specifically on the subsample of app users. App users reported using apps for helping manage sport and exercise most often (35% using them almost daily or daily), followed by apps for healthy eating (25% using them almost daily or daily) and apps targeting weight loss and health (15% using them almost daily or daily) (*See* Table 4). The pattern of use relative to types of apps differed by gender for apps targeting losing and gaining weight, as well as improving health status. Females used weight loss apps more frequently than males ($\chi_4^2 = 13.717$, $p < .01$). Although the use of weight-gaining apps was overall relatively low, male users reported using them more frequently as compared to female users ($\chi_4^2 = 13.903$, $p < .01$) and were also more frequent users of apps for improving health status ($\chi_4^2 = 10.238$, $p < .05$). The use of weight-gaining apps also differed by age and weight status. Users aged 13–18 reported more frequent use of weight-gaining apps ($\chi_8^2 = 19.067$, $p < .05$) compared to the older groups and underweight app users were also using weight-gaining apps more frequently ($\chi_8^2 = 22.878$, $p < .01$). For ease of presentation, we report mean frequencies (not category percentages) of use by different types of apps by gender, age, and weight status categories to demonstrate these differences (*See* Table 5).

In terms of types of features valued the most, app users ranked monitoring as most important to them ($M = 4.2$, $SD = 1.7$ on a scale ranging from 1 "*completely unimportant*" to 6 "*completely important*") followed by planning of activities ($M = 3.3$, $SD = 1.7$). The importance of other activities such as sharing ($M = 1.8$, $SD = 1.2$), competing ($M = 1.7$, $SD = 1.2$), or communicating ($M = 2.0$, $SD = 1.4$) with others was rated as relatively unimportant. The rated importance of different activities on the apps did not differ by gender, weight status, or age category.

To evaluate whether psychological characteristics help predict different types of app use, hierarchical multiple regression analyses were conducted. Due to the low frequency of use of weight gaining apps, we did not include this category in the regression analysis. Sociodemographic characteristics (gender, age, income, education, and BMI) were entered in step one, followed by psychological characteristics in step 2. All models were statistically significant (*See* Table 6). Drive for thinness predicted the frequency of use of apps for healthy eating, keeping a diet, and losing weight, whereas excessive exercise predicted the use of apps for keeping a diet, losing weight, and managing sport/exercise. Sensation seeking was negatively associated with the frequency of use of apps for maintaining weight.

Discussion

This study aimed to uncover the differences between mHealth app users and non-users based on their sociodemographic and psychological characteristics and to identify factors that predict app use or are

Table 6 | Predicting frequency of app use by type of app

	Healthy eating		Keeping a diet		Losing weight		Maintain weight		Sport/ exercise		Improve health	
	β	p	β	p	β	p	β	p	β	p	β	p
Gender	**.11**/.08	.034/.151	.09/.02	.105/.712	**.18**/.08	.001/.144	.01/− .01	.847/.889	.03/.03	.553/.640	− **.13**/− **.13**	.015/.021
Age	− .07/− .06	.234/.291	− **.12**/− .08	.034/.143	− .11/− .05	.052/.311	− .03/− .03	.641/.579	.09/**.11**	.114/.047	.01/− .01	.896/.852
Income	− .05/− .06	.359/.251	.03/.02	.543/.726	.01/.01	.785/.831	− .05/− .06	.371/.265	− .02/− .04	.747/.456	− **.14**/− **.15**	.007/.005
Education	− .08/− .07	.159/.195	.01/.03	.802/.511	− .07/− .04	.204/.448	− .01/− .00	.919/.978	− .06/− .05	.288/.377	.08/.08	.124/.117
BMI	− .01/− .03	.855/.667	**.12**/.11	.035/.054	**.17**/**.13**	.002/.014	− .07/− .08	.223/.179	− .07/− .04	.181/.521	**.11**/**.12**	.039/.040
Excessive exercise	.09	.084	**.18**	.000	**.12**	.019	.10	.066	**.28**	.000	.08	.146
Drive for thinness	**.14**	.018	**.27**	.000	**.33**	.000	.08	.186	.09	.117	.02	.734
Sensation seeking	− .08	.155	− .02	.679	− .01	.924	− **.13**	.020	− .04	.411	− .06	.241
Neuroticism	− .07	.195	− .08	.156	− .00	.944	− .04	.501	− .05	.344	− .02	.753
R^2	.03/.06		.02/.12		.06/.18		.01/.04		.01/.10		.05/.06	

Note. Each model run separately by type of app. Presented are standardized regression coefficients and p level; the coefficients from steps 1 and 2 are divided by slash; all analyses were conducted on data from respondents with no missing data on all variables ($n = 369$), significant associations ($p < .05$) are in bold associated with use across different types of apps. In a sample of Czech youth and adults (13–39) recruited from healthy lifestyle websites (i.e., representing individuals already engaged with technology for health-related goals), we showed that those who also use mHealth apps are more likely to be women, more frequent, and more skilled smartphone users visiting healthy lifestyle websites more frequently and engaging with them more (e.g., by adding comments, evaluations, or sharing content). More importantly, after controlling for key sociodemographic factors, we identified psychological variables that were associated with app use, suggesting that indices such as excessive exercise or drive for thinness may represent predisposing factors in mHealth app use among individuals using the internet to manage their healthy lifestyles.

App users versus app non-users

With respect to the comparisons between app users and non-users, we found no differences based on age, income, or education. This is in contrast with previous studies that found associations between younger age, higher education (more than high school), income and greater use of health-related apps [18, 19]. The lack of differences by age is most likely attributable to the restricted age range of our sample (13–39) and low average age (24 years) as compared to previous studies. In a report by Bhuyan et al. [19], the likelihood of having an mHealth app decreased with increasing age starting at age 35 and up. In a study by Krebs and Duncan [18], the average age of the sample was 40. The lack of associations with income and education could additionally reflect our assessment of these factors. Given the mixed age nature of our sample, we had to adapt measures to be easily completed by youth (13–18) as well as adults (19–39). Consequently, our assessment of education and income (in particular) is rather crude and may not have been sensitive enough to detect differences.

We also found that proportionately more women than men used mHealth apps. In the study by Bhuyan et al. [19], which was nationally representative, no differences by gender were found in the use of health-related apps as was the case in the study by Krebs and Duncan [18]. The gender differences in our study could reflect the unique nature of our sample (i.e., users of healthy lifestyle websites) but could also be due to the low overall number of males in our sample. The males in our sample may also represent those more motivated to complete the survey as proportionately fewer men than women reached the final page of the survey. It should be noted, nonetheless, that studies in other areas of app use such as e-commerce report higher app usage in females as compared to males [15]. Krebs and Duncan as well as Bhuyan et al. also report associations between BMI (obese status) and app use for health-related goals. Although we found app users to have slightly lower BMI than non-users, BMI did not predict app use in the logistic regression model in our study. mHealth app use was predicted by smartphone skills, frequent website use, and controlling for these and other sociodemographic factors, also by excessive exercise.

The links between self-rated smartphone skills, more frequent website use, and mHealth app use are to be expected given that these skills likely define the more digitally savvy users. Since these individuals also arguably represent the early adopters of new technologies [29], learning more about this group of users can help us design more effective and more broadly acceptable tech solutions. In our study, the proportion of (sample eligible) website users that utilized mHealth apps was relatively high (60%), compared to estimates from population-based data (Bhuyan et al. reporting 36% having a health-related app on their mobile device [19]), although this level is consistent with volunteer-based samples (Krebs and Duncan [18] reporting 58%). Importantly, our results indicate that users of healthy lifestyle websites that also use mobile apps not only are more digitally competent but also have specific psychological needs predisposing them to use apps for managing their lifestyles.

Specifically, individuals scoring higher on a measure of excessive exercise (measured by a subscale of the Eating Pathology Symptoms Inventory or EPSI) were more likely to use apps in our sample. This "phenotype" may represent users more reliant on tech solutions (as opposed to own self-regulation skills) for behavioral support, or it could suggest a profile consistent with a heightened risk for eating disorders. Exercise behavior, if pathologically motivated (e.g., consistent with exercise dependence) may contribute to the development of eating disorders and also negatively influences quality of life of patients with eating disorders [43, 44]. Future research should also evaluate whether excessive exercise may further heighten risk in the presence of other predisposing factors, especially in combination with high neuroticism and low agreeableness when it is likely to lead to impulsive behaviors [45]. From this perspective, it seems that mHealth apps can have both positive and negative impact, either as a tool for healthy lifestyle or a tool for disordered eating or excessive exercise behavior. Future research into any possible links between healthy lifestyle website and app use and the risk of pathological behaviors such as disordered eating is warranted.

App-user characteristics and patterns of app use

In our investigation of the patterns of use among app users only, we found that sport and exercise apps were used most frequently, followed by apps for healthy eating and apps targeting weight loss and health. The majority of users (90%) reported using sport and exercise apps at least some time, with 35% using them almost daily or daily. This is consistent with other studies reporting the highest use for exercise-related apps. For example, among app users from the Krebs and Duncan study [18], 53% used apps to track their physical activity, 48% used apps to track eating, and

47% to lose weight. We also identified gender differences in the type of apps used in directions one might hypothesize, with females utilizing apps for losing weight more frequently and males utilizing apps for gaining weight more often. Interestingly, males also used apps for improving health status more often, which may seem contrary to expectations. One reason for this may be the fact that the males in our sample tended to have slightly higher BMI as compared to females ($M = 23.7$, $SD = 0.49$ versus $M = 22.6$, $SD = 0.22$ for males and females, respectively). Although this difference only approached statistical significance, it could partially explain the difference in usage of apps for improving health status since we also found that higher BMI predicted more frequent use of apps for losing weight and improving health status in our regression models. This effect is consistent with previous work finding those who are obese to be more likely to use mHealth apps to attain health-related goals [18, 19]. It is also encouraging from an intervention standpoint as it suggests that users potentially in need of interventions could be open and responsive to intervention efforts utilizing mobile apps. An alternative interpretation for the gender differences may also be related to the fact that male users in our sample likely represent more motivated male users, with potentially stronger health awareness, the results should thus be interpreted with caution.

Youngest users and also those classified as underweight used apps for gaining weight more frequently than the two older age groups or those with normal weight or overweight/obese status. Nonetheless, the use of these types of apps was rather infrequent, inversely correlated with income, and not predicted by any of the psychological variables. Although, this set of results should be interpreted with caution due to the low numbers of respondents within some categories (e.g., underweight).

When evaluating the impact of individual characteristics, in addition to gender and BMI, excessive exercise and drive for thinness were identified as predictors of app use for healthy eating (drive for thinness only), keeping a diet, losing weight, and sport/exercise-oriented apps (excessive exercise only). These are novel findings and unveil potential individual difference variables that play a role in the adoption of different types of mHealth apps. Bhuyan et al. [19] and others [23, 29] have called for more research into identifying individual difference characteristics that could help explain motivation for mHealth app use. Although the particular set of characteristics that we evaluated in our study have the potential to motivate app use, one could also argue they may pose potential for harm if ultimately leading to or reinforcing maladaptive behaviors such as disordered eating or exercise dependence. Future studies of user factors should examine whether and which individual characteristics moderate mHealth app use and subsequent impact on behavior. It is also possible that the effects of these individual characteristics may interact with other person-level factors such as age. This possibility should be investigated in future studies.

Our findings must be interpreted within the context of our cross-sectional design and sample characteristics which are specific to volunteers from healthy lifestyle websites. The findings cannot be generalized to populations with low digital literacy, disinterest in using technologies, or poor access to technologies. Our sample was low in number of males, which could be perhaps expected given the nature of websites we recruited from (focus on nutrition, weight, and sport and exercise) and possibly reflects males with higher level of motivation. Although only few studies have investigated user characteristics in relation to mHealth app use, our data were limited in the selection of psychological variables available, possibly leading to omission of other important individual difference variables (also as indicated by the rather low variance explained in our models). More research into the user characteristics that motivate mHealth app use is needed.

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The authors have full control of all primary data and they agree to allow the journal to review their data if requested.

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Human and animal rights and informed consent: Informed consent (implied by survey submission) was obtained from all individual participants included in the study.

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1. Pew. PEW Research Center/CHCF Health Survey. 2013. http://www.pewinternet.org/2013/02/12/the-internet-and-health/.
2. European Commission D-G for C, Networks C and T. Flash Eurobarometer 404 "European Citizens' Digital Health Literacy." 2014. http://ec.europa.eu/public_opinion/flash/fl_404_sum_en.pdf.
3. Kontos E, Blake KD, Chou W-YS, Prestin A. Predictors of eHealth usage: insights on the digital divide from the Health Information National Trends Survey 2012. *J Med Internet Res.* 2014; 16(7):e172. https://doi.org/10.2196/jmir.3117.
4. Graham AL, Papandonatos GD, Erar B, Stanton CA. Use of an online smoking cessation community promotes abstinence: results of propensity score weighting. *Health Psychol.* 2015; 34(Suppl):1286–95. https://doi.org/10.1037/hea0000278.
5. Leist AK. Social media use of older adults: a mini-review. *Gerontology*. 2013; 59(4):378–84. https://doi.org/10.1159/000346818.
6. Antypas K, Wangberg SC. An internet- and mobile-based tailored intervention to enhance maintenance of physical activity after cardiac rehabilitation: short-term results of a randomized

controlled trial. *J Med Internet Res.* 2014; 16(3):78–95. https://doi.org/10.2196/jmir.3132.

7. Statista. Worldwide Mobile App Revenues 2020|Statistic. https://www.statista.com/statistics/269025/worldwide-mobile-app-revenue-forecast/.
8. Yang C-H, Maher JP, Conroy DE. Implementation of behavior change techniques in mobile applications for physical activity. *Am J Prev Med.* 2015; 48(4):452–5. https://doi.org/10.1016/j.amepre.2014.10.010.
9. Conroy DE, Yang C-H, Maher JP. Behavior change techniques in top-ranked mobile apps for physical activity. *Am J Prev Med.* 2014; 46(6):649–52. https://doi.org/10.1016/j.amepre.2014.01.010.
10. Middelweerd A, Mollee JS, van der Wal CN, Brug J, Te Velde SJ. Apps to promote physical activity among adults: a review and content analysis. *Int J Behav Nutr Phys Act.* 2014; 11:97. https://doi.org/10.1186/s12966-014-0097-9.
11. Pew Research Center. Few Americans Track Their Weight, Diet or Exercise Online | Pew Research Center. 2014. http://www.pewresearch.org/fact-tank/2014/01/08/few-americans-track-their-weight-diet-or-exercise-online/.
12. Purcell K. Pew Internet Research. Half of adult cell phone owners have apps on their phones Americans' appetite for apps continues to grow. 2011. http://www.pewinternet.org/files/old-media/Files/Reports/2011/PIP_Apps-Update-2011.pdf. Accessed December 1, 2016.¨.
13. European Commission. Green Paper on Mobile Health ("mHealth"); 2014. file:///C:/Users/SterianiElavsky/Downloads/GreenPaperonmobilehealth (1).pdf.
14. Schnall R, Rojas M, Bakken S, Brown W, Carballo-Dieguez A, Carry M, Gelaude D, Mosley JP, Travers J. A user-centered model for designing consumer mobile health (mHealth) applications (apps). *J Biomed Inform.* 2016; 60:243–51. https://doi.org/10.1016/j.jbi.2016.02.002.
15. Kim Y, Briley DA, Ocepek MG. Differential innovation of smartphone and application use by sociodemographics and personality. *Comput Hum Behav.* 2015; 44:141–7. https://doi.org/10.1016/j.chb.2014.11.059.
16. Peñas-Lledó E, Bulik CM, Lichtenstein P, Larsson H, Baker JH. Risk for self-reported anorexia or bulimia nervosa based on drive for thinness and negative affect clusters/dimensions during adolescence: a three-year prospective study of the TChAD cohort. *Int J Eat Disord.* 2015; 48(6):692–9. https://doi.org/10.1002/eat.22431.
17. Dobmeyer AC, Stein DMA. Prospective analysis of eating disorder risk factors: drive for thinness, depressed mood, maladaptive cognitions, and ineffectiveness. *Eat Behav.* 2003; 4(2):135–47. https://doi.org/10.1016/S1471-0153(03)00013-8.
18. Krebs P, Duncan DT. Health app use among US mobile phone owners: a national survey. *JMIR mHealth uHealth.* 2015; 3(4):e101. https://doi.org/10.2196/mhealth.4924.
19. Bhuyan SS, Lu N, Chandak A, et al. Use of mobile health applications for health-seeking behavior among US adults. *J Med Syst.* 2016; 40(6) https://doi.org/10.1007/s10916-016-0492-7.
20. Talmon J, Ammenwerth E, Brender J, de Keizer N, Nykänen P, Rigby M. STARE-HI—statement on reporting of evaluation studies in health informatics. *Int J Med Inform.* 2009; 78(1):1–9. https://doi.org/10.1016/j.ijmedinf.2008.09.002.
21. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* 1989; 13(3):319. https://doi.org/10.2307/249008.
22. Venkatesh V, Smith RH, Morris MG, Davis GB, Davis FD, Walton SM. User acceptance of information and technology: toward a unified view. *MIS Q* 2003; 27(3):425–478.
23. Kwon M-W, Mun K, Lee JK, Mcleod DM, D'angelo J. Is mobile health all peer pressure? The influence of mass media exposure on the motivation to use mobile health apps. *Convergence: Int J Res New Media.* 2016. https://doi.org/10.1177/1354856516641065.
24. Higgins O, Sixsmith J, Barry MM. A literature review on health information- seeking behaviour on the web: a health consumer and health professional perspective. A literature review on health information-seeking behaviour on the web. Stockholm: ECDC; 2011.https://doi.org/10.2900/5788.
25. Viswanath K, Finnegan JR Jr, Gollust S. Communication and health behavior in a changing media environment. In: Glanz K, Rimer BK, Viswanath K, editors. *Health Behavior: Theory, Research, and Practice.* San Francisco, CA: Jossey-Bassy A Wiley Brand; 2015:327–48.
26. Baumgartner SE, Hartmann T. The role of health anxiety in online health information search. *Cyberpsychol Behav Soc Netw.* 2011; 14(10):613–8. https://doi.org/10.1089/cyber.2010.0425.
27. Lahey BB. Public health significance of neuroticism. *Am Psychol.* 2009; 64(4):241–56.
28. Kelders SM, Kok RN, Ossebaard HC, Van Gemert-Pijnen JE. Persuasive system design does matter: a systematic review of adherence to web-based interventions. *J Med Internet Res.* 2012; 14(6):e152. https://doi.org/10.2196/jmir.2104.
29. Ginters N. A review: how user characteristics affect the effectiveness of persuasive strategies in the health promotion domain of online interventions. (Master´s Thesis). The Netherlands: University of Twente, Positive Psychology and Technology; 2016.
30. Verkasalo H, López-Nicolás C, Molina-Castillo FJ, Bouwman H. Analysis of users and non-users of smartphone applications. *Telematics Inform.* 27:242–55. https://doi.org/10.1016/j.tele.2009.11.001.
31. The internet society. The global internet report. https://www.internetsociety.org/globalinternetreport/2016/wp-content/uploads/2016/11/ISOC_GIR_2016-v1.pdf. Accessed 1 April 2017.
32. Eurostat data. http://ec.europa.eu/eurostat/statistics-explained/index.php/Internet_access_and_use_statistics_-_households_and_individuals. Accessed 1 April 2017.
33. PEW data. http://www.pewglobal.org/2016/02/22/smartphone-ownership-and-internet-usage-continues-to-climb-in-emerging-economies/. Accessed 1 April 2017.
34. Czech Republic Just Tops Russia for Mobile Penetration—eMarketer. https://www.emarketer.com/Article/Czech-Republic-Just-Tops-Russia-Mobile-Penetration/1012047. Accessed 14 Dec 2016.
35. Lupac P, Chrobakova A, Sladek J. Internet in the Czech Republic 2014. Prague; 2015. http://worldinternetproject.com/_files/_//234_report_wip_czr2014_eng_fin.pdf. Accessed 12 Dec 2016.
36. Organisation for Economic Co-operation and Development (OECD). 2014. OECD Statistics. http://stats.oecd.org/Index.aspx?DataSetCode=HEALTH_STAT#. Accessed 1 April 2017.
37. World Health Organization. Nutrition, physical activity, and obesity: Czech Republic; 2013. http://www.euro.who.int/__data/assets/pdf_file/0005/243293/Czech-Republic-WHO-Country-Profile.pdf?ua=1. Accessed 1 April 2017.
38. Cole TJ, Lobstein T. Extended international (IOTF) body mass index cut-offs for thinness, overweight and obesity. *Pediatr Obes.* 2012; 7(4):284–94. https://doi.org/10.1111/j.2047-6310.2012.00064.x.
39. Garner DM. Eating Disorder Inventory-3. Professional Manual. In: Lutz FL, ed. Psychological Assessment Resources, Inc. 2004.
40. Forbush KT, Wildes JE, Pollack LO, et al. Development and validation of the Eating Pathology Symptoms Inventory (EPSI). *Psychol Assess.* 2013; 25(3):859–78. https://doi.org/10.1037/a0032639.
41. Stephenson MT, Hoyle RH, Palmgreen P, Slater MD. Brief measures of sensation seeking for screening and large-scale surveys. *Drug Alcohol Depend.* 2003; 72(3):279–86. http://www.ncbi.nlm.nih.gov/pubmed/14643945. Accessed 22 Dec 2016
42. Lang FR, John D, Lüdtke O, Schupp J, Wagner GG. Short assessment of the Big Five: robust across survey methods except telephone interviewing. *Behav Res Methods.* 2011; 43(2):548–67. https://doi.org/10.3758/s13428-011-0066-z.
43. Cook B, Engel S, Crosby R, Hausenblas H, Wonderlich S, Mitchell J. Pathological motivations for exercise and eating disorder specific health-related quality of life. *Int J Eat Disord.* 2014; 47(3):268–72. https://doi.org/10.1002/eat.22198.
44. Cook B, Hausenblas H, Crosby RD, Cao L, Wonderlich SA. Exercise dependence as a mediator of the exercise and eating disorders relationship: a pilot study. *Eat Behav.* 2015; 16:9–12. https://doi.org/10.1016/j.eatbeh.2014.10.012.
45. Claes L, Vandereycken W, Luyten P, Soenens B, Pieters G, Vertommen H. Personality prototypes in eating disorders based on the big five model. *J Personal Disord.* 2006; 20(4):401–16. https://doi.org/10.1521/pedi.2006.20.4.401.