Differences in mobile phone affinity between demographic groups: implications for mobile phone delivered interventions and programs

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Background: The impact of any intervention or program delivered through mobile phones (mHealth) may be influenced by the individual recipient's relationship with his or her mobile phone. However, few studies have assessed the attitudes and preferences of different demographic groups with respect to mobile phone use. This study assessed whether individuals' demographic characteristics [primary demographics (PD): race, ethnicity, gender and age] are influential factors in attitudes and behaviors associated with mobile use pattern, using the Mobile Phone Affinity Scale (MPAS). The MPAS examines six underlying constructs associated with mobile phone use: Connectedness, Productivity, Empowerment, Anxious Attachment, Addiction, and Continuous Use.

Methods: U.S. adults (n=1,055, mean age 32.5 years, 10% Hispanic, 86.3% white) completed the MPAS and provided information about PD (e.g., race, ethnicity, age) and social demographic (SocD) characteristics (e.g., having children, employment). Chi-square analyses and multivariate analyses were used to assess the relationships among the PD and SocD variables, and MPAS constructs.

Results: Significant differences were found between PD and SocD variables (all $P<0.01$). Specifically, whites were more likely than non-whites to be married and to be living with children, while non-Hispanics tended to report higher household income and education than Hispanics. Women were more likely to report living with children and less likely to have full-time employment than men (all $P<0.01$). There was a significant effect of PD characteristics on MPAS constructs in that whites and women tended to score higher on some MPAS constructs than non-whites and men (all $P<0.01$). Similarly, some SocD characteristics including employment status and living with children were differentially associated with some MPAS constructs (all $P<0.01$).

Conclusions: Results indicate that there are differences in attitudes and use preferences to mobile phone use based on some of the primary and SocD demographic characteristics. These findings provide important insights into mHealth intervention components that will increase appeal to different subgroups.

Keywords: Mobile phone affinity; mobile phone use patterns; demographic differences

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Introduction

Because of the ubiquity of mobile phone use among American adults, the mobile phone has become an increasingly popular platform for delivery of behavioral interventions and health-related programs and has shown promise for promoting health behavior change and disease management on a large scale (1-11). Surveys conducted from 2016 to 2018 by the Pew Research Center show that 95% of American adults now own a mobile phone of some kind (12,13). Demographic surveys show high rates of mobile phone ownership across race, ethnicity and gender groups including African Americans (94%), Whites (94%), Hispanics (98%), men (96%), and women (94%) (12,13). In general, similar rates of mobile phone ownership are evident across most age groups (12,13), with text messaging being the communication feature most commonly used among mobile phone owners between ages 18 to 64 (12,13).

While overall ownership is high, there are differences in mobile phone usage that vary by education, income and employment status (14,15). For example, individuals with lower levels of education and income tend to have a higher frequency of mobile phone use and report being more dependent on their phone compared to higher income and more highly educated individuals (14). Greater use of this technology has also been noted more among adults with children (parents or guardians) than those without children (15). These primary demographic (PD) and social demographic (SocD) characteristics may also differentially influence attitudes and cognitions related to mobile phone use.

Over the past 10 years, health-related programs and interventions delivered through mobile phones (mHealth) have been developed to address a wide variety of health behaviors including diabetes management (7-9), smoking cessation (4-6), and physical activity (1-3). While mHealth platforms have shown promise in health behavior interventions, research with different demographic groups are only emerging. So far, while these small pilot studies show evidence of acceptability and preliminary efficacy of mHealth approaches, their overall effect sizes are small (1,10,11). More research is needed to determine the particular mHealth intervention components that are beneficial to enhance behavior across various subpopulations. It has been suggested that the frequency with which an individual carries his or her mobile phone with them, and their patterns of use of various mobile phone features may impact their receptivity to, and engagement with, interventions delivered through the mobile phone, and may ultimately impact the efficacy of mobile phone-delivered programs (16). Further, attitudes toward mHealth and the ways in which mHealth tend to be used may guide choices of potential features when developing a mHealth intervention for a particular target population.

The Mobile Phone Affinity Scale (MPAS) is a recently developed 24-item instrument designed to assess both positive and negative cognitions and behaviors associated with mobile phone use (16). Previous measures of mobile phone and/or internet use tended to focus on problematic patterns of usage (17-22), suggesting that high use of these technologies may be indicative of an addictive or otherwise pathological usage pattern (17-22). This approach appears to disregard potential beneficial aspects of technology use. Positive functions associated with mobile phone use (and technology use, more broadly) may include increasing connections with family and friends (12-16), organizing work related activities, and tracking to improve health behaviors (e.g., tracking physical activity, managing diabetes) (1-6). The psychometric evidence of the MPAS has been previously demonstrated, showing that each subscale has good internal validity and internal consistency.

To our knowledge, no studies thus far have assessed whether subgroups differ in the relationships they have with their mobile phone. This information may help inform the development of mobile phone intervention approaches that would be most relevant for demographic subgroups varying in race, ethnicity, gender and age. Moreover, this study extends the knowledge of SocD characteristics (e.g., education and income) which underscore the nature of the relationship these groups have with this device.

Methods

Procedure and participants

Participants were registered users of the Amazon Mechanical Turk (MTurk). MTurk is reliable and inexpensive recruitment site that facilitates data collection from large, ethnically diverse samples (23-25). Eligible participants were 18 years old or older, resided in the United States, were fluent in English (reading and writing), and owned a mobile phone. To participate in the study, MTurk workers who clicked on our study link were redirected through the MTurk website to our project survey website, which presented detailed information about the study and an informed consent form. After providing electronically signed consent, participants completed the study surveys assessing attitudes and cognitions regarding mobile phone use and demographic information. The online survey was managed through a secure, web-based application, Research Electronic Data Capture (REDCap) (26) hosted by our institution's Information Services department. Informed consent, human subject protocols and the research were approved by the Institutional Review Board.

Measures

Demographics

Single items corresponding to the US Census were used to assess PD characteristics including participant race, ethnicity, gender and age. Participants also provided SocD information consisting of level of education, income, employment status, marital status, and whether they have children living at home.

MPAS

The MPAS is a 24-item instrument developed to assess both positive and negative behaviors and cognitions related to mobile phone use (16). Three positive subscales assess Connectedness, Productivity, and Empowerment/Safety associated with mobile phone use. These constructs measure individuals' use of this technology to: (I) to remain connected with friends and family (e.g., "My phone helps me stay close to family and friends"); (II) organize work/school schedule and/or related tasks (e.g., "My phone helps me stay up-to-date with work/school activities"); and (III) the ability to access help when in an unsafe situation (e.g., "Having my phone with me makes it easier to leave a risky situation"). The subscales that assess negative constructs related to mobile phone use are Anxious Attachment (e.g., "I feel anxious if I don't have my phone with me"), and Addiction (e.g., "I find myself occupied on my phone even when I'm with other people"). A sixth subscale examines Continuous Use (e.g., "I use my phone all day"). Participants respond to each item indicating how true each statement is for them using a 5-point Likert-type scale, ranging from 1 = "Not all true" to 5 = "Extremely True". Confirmatory factor analysis has previously demonstrated strong measurement structure with high item factor loadings for these respective factors, as well as good internal consistency for each factor (16).

Statistical analyses

Preliminary analyses of the primary and SocD characteristics

Frequency tests were used to assess the distribution of the sample (n=1,055). For race and ethnicity sample size constraints allowed only for comparison between white *vs.* non-white, and Hispanic *vs.* non-Hispanic subgroups, respectively. For analyses of age, a median split approach was used to create two age groups, ages 18–29 years and ages 30 and older. Participant responses for level of education included: less than 8^{th} grade, 12^{th} grade, some college, associate degree, bachelor's degree, and graduate/advanced degree. Employment status was coded into three groups: full-time, part-time, and unemployed or disabled. Marital status was coded into two categories: single or married. Annual income was reported by 747 participants' and was coded into three categories: (≤$32,000, $33,000–60,000, and ≥$61,000).

Chi-square tests of independence were conducted and compared proportional differences within each of the four PD categories (race, ethnicity, gender and age) for the five SocD factors (education, income, employment, marital status and living with children). Post-hoc tests using adjusted residuals and adjusted P values were conducted following significant chi-square results that included SocD variables with more than two levels (e.g., education) to determine the particular cell that had disproportionately more cases than others. The criterion for statistical significance was set to P=0.01 to reduce the likelihood of type I error (27-29). A conservative threshold value of alpha is recommended particularly for studies with large size wherein even minuscule differences are likely to reach statistical significance at alpha 0.05 (27-29).

Next, a bivariate correlation analysis was used to assess potential collinearity between the six MPAS subscales. Correlation values ranged from to 0.39 to 0.68 (30). A series of multivariate analysis of variance (MANOVA) models evaluated potential interactions between PD variables for each of the six MPAS subscales. These models did not reach statistical significance (P values >0.05). Four separate MANOVAs were conducted for each of the four PD variables and the linear combinations of MPAS subscales while adjusting for any significant differences in SocD factors.

Table 1 Age group and gender differences by marital status, education, income, and employment and living arraignment with children (n=1,055)

Variables	Race, n [%]		Ethnicity, n [%]		Gender, n [%]		Age group, n [%]	
	White	Non-white	Hispanic	Non-hispanic	Men	Women	18–29	30+
Education								
≤High school	98 [11]	17 [12]	19 [18]	96 [10]	62 [12]	53 [10]	63 [12]	52 [15]
Some college	261 [29]	38 [26]	30 [29]	269 [28]	151 [29]	148 [28]	162 [31]	137 [39]
Associate's degree	111 [12]	17 [12]	21 [20]	107 [11]	63 [12]	57 [11]	62 [11]	71 [20]
Bachelor's degree	330 [36]	57 [39]	29 [28]	358 [38]	189 [36]	198 [37]	192 [36]	19 [5]
Graduate or advanced degree	110 [12]	16 [11]	6 [6]	120 [13]	60 [11]	66 [13]	55 [10]	71 [20]
Employment								
Full-time	517 [57]	87 [60]	55 [52]	549 [58]	335 [64]	269 [51]	285 [54]	319 [61]
Part-time	179 [20]	35 [24]	22 [21]	192 [20]	88 [17]	125 [24]	125 [24]	89 [17]
Unemployed/disabled/retired	214 [24]	23 [16]	28 [27]	209 [22]	102 [19]	135 [26]	119 [22]	118 [22]
Income								
≤$32,000	212 [33]	37 [33]	38 [50]	211 [31]	129 [34]	120 [32]	132 [38]	117 [29]
$33,000–$60,000	222 [35]	42 [38]	21 [28]	243 [36]	130 [35]	134 [36]	121 [35]	143 [36]
≥$61,000	201 [32]	33 [29]	17 [22]	217 [32]	117 [31]	117 [32]	97 [28]	137 [35]
Marital status								
Single/separated/divorced/widowed	532 [58]	101 [70]	65 [62]	568 [60]	332 [63]	301 [57]	374 [71]	259 [49]
Married	378 [42]	44 [30]	40 [38]	382 [40]	193 [37]	229 [43]	155 [29]	267 [51]
Living w/t children								
Yes	271 [30]	25 [17]	26 [25]	270 [28]	111 [21]	185 [35]	87 [16]	209 [40]
No	639 [70]	120 [83]	79 [75]	680 [72]	414 [79]	345 [65]	442 [84]	317 [60]

Results

PD

Most participants in this study were white (86.3%, 910/1,055), non-Hispanic (90%, 950/1,055), and nearly half of all participants were men (49.8%, 525/1,055). Half of all participants (50.1%, 526/1,055) were between age 18 and 29, while 49.9% (529/1,055) were age 30 and older. Participant aged 18–87 years old (mean=32.5, SD=10.3). See *Table 1* for the distribution of participant SocD characteristics.

Differences in SocD variables between PD categories

Race

A significantly higher proportion of whites compared to non-whites were married (χ^2_1=6.53, P=0.01), and whites were more likely to report living with children than non-whites (χ^2_1=9.74, P=0.002). Racial differences were not found for the other SocD variables (all P>0.01).-

Ethnicity

A statistically significant association was observed for ethnicity and income (χ^2_4=10.64, P=0.005). Follow-up tests indicated that more non-Hispanics than Hispanics reported an annual income of ≤US $32,000 ($\chi^2_1$=10.56, P=0.0001). Overall, ethnicity was differentially associated with educational attainment (χ^2_4=17.89, P=0.001), however, follow-up tests including a Bonforonni adjusted alpha (P≤0.005) yielded no statistical significance in proportions between Hispanics and non-Hispanics for the five levels of education. No other significant differences were detected for ethnicity and other SocD variables (all P>0.01).

Gender

Women were more likely to report living with children than men, (χ^2_2=24.75, P<0.0001). Differences in employment status were also noted between genders (χ^2_1=18.53, P<0.001). Post hoc tests indicated that more men than women reported full time employment (P<0.0001), while women were likely to report part-time employment (P=0.004). There were no significant gender differences for other SocD variables (P values >0.01).

Age

An examination of the data by participant age group showed that participants ages 18–29 were more likely to be single compared to older participants (χ^2_1=50.61, P<0.0001), and individuals aged 30 or older were more likely to report living with children (χ^2_1=76.86, P<0.0001). Age differences for the other SocD variables did not reach statistical significance (P values >0.01).

Multivariate results

Table 2 presents the means and standard deviations for the PD and SocD variables and each of the MPAS subscales.

The first model assessed the role of race, marital status and living with children as they relate to scores on the MPAS. A significant main effect was noted only for the race variable [$F_{6, 1042}$=3.58; Wilks Lambda (λ) =0.98; *P*=0.002]. Univariate results showed that non-white participants had significantly higher mean scores on connectedness ($F_{1, 1047}$=6.70, P=0.01), Productivity ($F_{1, 1047}$=6.27, P=0.01), and Continuous Use, ($F_{1, 1047}$=15.99, P<0.0001) compared to white participants.

The second model assessed the relationship between ethnicity, income and the MPAS. A trend toward differences for each the variables was noted for the linear combination of the subscales; however, these associations did not reach statistical significance (P values >0.01).

The third model assessed the relationship between gender, employment, and living with children and the MPAS. A significant effect was found only for gender and the overall MPAS ($F_{6, 1038}$=7.11; λ=0.96; P<0.0001). Univariate statistics showed that women had higher mean scores than men on four subscales, connectedness ($F_{1, 1043}$=15.56, P<0.001), empowerment/safety ($F_{1, 1043}$=32.02, P<0.001), continuous use ($F_{1, 1043}$=7.31, P=0.007), and anxious attachment ($F_{1, 1043}$=19.09, P<0.0001). No significant gender differences were found for other MPAS subscales (P values >0.01).

Employment status was significantly associated with MPAS scores overall ($F_{12, 2038}$=9.04, λ=0.90; P<0.001). Participants with full time employment scored higher on productivity ($F_{2, 1043}$=40.36, P=0.001), continuous use ($F_{2, 1023}$=14.17, P<0.0001), and addiction ($F_{2, 143}$=6.61, P<001). Living with children did not contribute to the model (P=0.08).

A fourth model assessed the relationship between age, living with children, and marital status and the MPAS. A significant multivariate effect was found for age [$F_{6, 1042}$=7.33, Wilks Lambda (λ) =0.95, P<0.0001] and living with children ($F_{6, 1042}$=4.46, λ=0.97, P<0.0001) on the overall MPAS. Univariate analyses showed that participants under age 30 had higher mean scores than their older counterparts on connectedness ($F_{1, 1047}$=22.70, P<0.0001), productivity ($F_{1, 1047}$=6.38, P=0.01) and addiction ($F_{1, 1047}$=20.49, P<0.0001). Individuals living with children at home scored higher on four MPAS subscales: connectedness ($F_{1, 1042}$=9.65, P=0.002), anxious attachment ($F_{1, 1042}$=12.07, P<0.0001), addiction ($F_{1, 1042}$=16.46, P<0.0001), and continuous use ($F_{1,1042}$=11.01, P=0.001). Marital status was not significantly associated with MPAS constructs (P>0.01).

Discussion

This study examined the role of race, ethnicity, gender and age in shaping the nature of the relationship that individuals have with their mobile phone, in a national sample of American adults. The study findings provide insights into mHealth interventions approaches that may be particularly appealing to different demographic subgroups.

Our data indicate that non-white participants were more likely than whites to rely on their mobile phone to stay connected with friends and family, to organize or complete work/school tasks and tended to use this device continuously throughout the day. These patterns of mobile use suggest that mHealth intervention approaches that incorporate the involvement of a close family member or a friend to provide social support and model positive behaviors may address an important social need for non-whites. In addition, the use of this device by non-whites to organize and/or monitor work and school activities indicates that mobile phone application features that facilitate behavioral monitoring (e.g., goal-setting and self-monitoring) may have stronger appeal

Table 2 Estimated means and standard errors for the four multivariate models

Variables	Productivity	Connectedness	Empowerment	Continuous use	Anxious attachment	Addiction
First model						
Race						
White	13.47 (0.45)	12.01 (0.19)	14.44 (0.17)	11.75 (0.17)	12.17 (0.18)	10.09 (0.17)
Non-white	14.47 (0.16)	13.56 (0.53)	15.17 (0.48)	13.82 (0.49)	13.07 (0.53)	10.83 (0.50)
Marital status						
Single/separated/ divorced/widowed	14.22 (0.37)	12.90 (0.44)	14.99 (0.39)	13.20 (0.40)	12.82 (0.43)	10.58 (0.40)
Married	13.96 (0.31)	12.75 (0.36)	14.62 (0.33)	12.36 (0.33)	12.42 (0.36)	10.34 (0.34)
Living w/t children						
Yes	14.52 (0.42)	12.87 (0.50)	15.20 (0.45)	13.46 (0.46)	13.12 (0.50)	10.90 (0.47)
No	13.66 (0.22)	12.78 (0.26)	14.41 (0.24)	12.11 (0.24)	12.13 (0.26)	10.01 (0.24)
Second model						
Ethnicity						
Hispanic	14.24 (0.46)	12.65 (0.54)	15.22 (0.49)	11.62 (0.16)	12.23 (0.54)	10.91 (0.49)
Non-hispanic	13.35 (0.15)	12.12 (0.17)	14.17 (0.16)	12.81 (0.50)	12.00 (0.17)	9.86 (0.16)
Income						
≤$32,000	13.24 (0.33)	11.38 (0.39)	14.26 (0.35)	11.32 (0.36)	11.60 (0.39)	10.16 (0.36)
$33,000–$60,000	13.84 (0.43)	12.61 (0.50)	15.01 (0.46)	13.07 (0.47)	12.25 (0.50)	11.02 (0.46)
≥$61,000	14.26 (0.48)	13.17 (0.56)	14.82 (0.51)	12.25 (0.52)	12.50 (0.56)	9.98 (0.51)
Third model						
Gender						
Men	12.69 (0.32)	11.68 (0.37)	13.11(0.34)	10.98 (0.35)	11.01 (0.38)	9.61 (0.36)
Women	14.14 (0.18)	11.92 (0.21)	15.31 (0.19)	12.07 (0.19)	12.88 (0.21)	10.43 (0.20)
Employment						
Full-time	13.78 (0.17)	13.22 (0.19)	14.49 (0.18)	12.54 (0.18)	12.53 (0.19)	10.64 (0.18)
Part-time	13.60 (0.43)	12.55 (0.50)	14.23 (0.45)	11.49 (0.47)	11.70 (0.50)	10.18 (0.48)
Unemployed or disabled	12.87(0.30)	9.63 (0.35)	13.91 (0.32)	10.57 (0.33)	11.60 (0.35)	9.25 (0.34)
Living w/t children						
Yes	13.51 (0.34)	11.65 (0.39)	14.36 (0.16)	11.83 (0.37)	12.23 (0.39)	10.30 (0.38)
No	13.32(0.15)	11.95 (0.17)	14.06 (0.36)	11.22 (0.16)	11.66 (0.17)	9.74 (0.17)
Fourth model						
Age group						
18–29	14.42 (0.25)	12.69 (0.30)	14.81 (0.27)	12.39 (0.27)	12.52 (0.30)	11.01 (0.27)
30+	12.96 (0.18)	11.75 (0.22)	14.21 (0.20)	11.59 (0.20)	12.07 (0.22)	9.48 (0.20)
Marital status						
Single/separated/ divorced/widowed	13.90 (0.24)	12.21 (0.29)	14.70 (0.27)	12.06 (0.27)	12.43 (0.29)	10.25 (0.27)
Married	13.48 (0.19)	12.23 (0.23)	14.31 (0.20)	11.92 (0.21)	12.16 (0.23)	10.24 (0.21)
Living w/t children						
Yes	14.17 (0.27)	12.22 (0.32)	14.82 (0.29)	12.56 (0.30)	11.66 (0.18)	9.56 (0.17)

among this population consistent with their continuous use of this device. Healthy People 2020 indicates that information technologies that people use on a daily basis provide substantial opportunities to leverage health communication strategies that promote health-related behaviors and outcomes (31,32). For example, a mHealth physical activity intervention that uses activity trackers (e.g., via mobile phone accelerometer) might be expected to have strong appeal to this group.

However, non-whites' reported continuous use of their mobile phone may also indicate excessive use of this device, which may have important implications for the efficacy of mHealth approaches. It has been noted in previous studies that excessive mobile phone use is associated with poor physical health and overall well-being; it interferes with other aspects of functioning, including prioritizing engagement in health-related behaviors (e.g., physical activity and other self-care behaviors (33,34). A potential solution to overcoming this barrier might be to include sensory technology components to track users' behaviors as they occur in real time and provide automatic tailored feedback to alter their attention to the target health behavior.

The results from this study also showed that women reported using their phone as a source of connection to family and friends and viewed the phone as a source of empowerment more so than men. Moreover, in comparison to men, women were more likely to report using this device continuously throughout their day and were more likely to be anxious about the availability of their phone and to be nervous when without it. In regards to connectedness, social support is a central facilitator to health behavior promotion that women in particular often report lacking (33,34). Thus, interventions that leverage social influence through the medium of a social networking platform (e.g., peer support chatroom) that women can easily access addresses the socialization aspect that allow women feel connected with others. mHealth intervention content messages that address psychological and social barriers that influence the prioritization of the needs of others over one's personal health could empower this group to engage in various health behaviors and promote self-care. Similarly, mobile use patterns associated with continuous use and anxious attachment among women might be indicative of their preoccupation with daily and competing priorities that negate self-care. Intervention approaches that motivate women to set aside time to engage in health and mental health behaviors may help to decrease both the unremitting use and addictive relationship with their mobile phone. There is empirical evidence to suggest that physical activity engagement among women is associated with life satisfaction among women (35,36). Thus, mobile short text messages that address engagement in physical activity in the context of improved well-being may appeal to this group.

SocD results showed that employment status was tied to indicators of intense phone use. Specifically, individuals who were employed full time were more likely to use their phones for work productivity, but also to use it continuously throughout the day and showed addictive patterns of phone use. Mobile phone technologies provide users with the ease of accessing their work wherever they are and is related to work productivity in some groups (37,38). However, the availability of this technology may also facilitate obsessive working behaviors and conflicts between work and family life (e.g., spending time with family and friends (39,40). Over the past few years, clinical treatments have been developed to address the rise of mobile phone addiction, also called "nomophobia" (41-43). This pattern of mobile phone use may inform mHealth interventions that teach these individuals skills needed to eventually achieve a balanced work and personal life.

Age differences found in patterns of phone use showed that younger adults (those under age 30) were more likely than older adults to use their phones to connect with family and friends, to organize work/school, and were more likely to endorse addictive behaviors in mobile phone use. The high prevalence of mobile phone use among younger individuals is consistent with previous research (12,44-47). Moreover, persons aged 18–29 have been mobile phone owners during most of their lifetime, and thus are more likely to use this technology to complete many tasks compared to older adults. However, the prevalence of this technology and its long-term use may also predispose this group to developing abnormal/addictive relationships with their mobile phone (44-47). A recent report indicates that younger adults spend a significantly greater amount of time using various mobile applications compared to older adults (48). An increasing number of interventions aimed at decreasing mobile phone or internet addiction in young adults have been developed (49-51). While excessive use of mobile phone technology among this group indicates high level of acceptability to mHealth intervention, the nature of addiction to this device is a potential barrier for individuals to focus on the intervention messages and implementing recommended strategies.

Lastly, individuals who had children living at home noted using their phone more to stay connected to family and friends and tended to use their phones continuously throughout the day more than individuals not living with children. They also showed addictive behaviors towards their phones and endorsed feeling anxious about not having the phone continuously available. It may be that parents or guardians use their phone more frequently to communicate with their children because this form of communication is preferred among children (52-54). Moreover, parents or guardians may feel anxious without their mobile phone because it allows them to reach (and be reached by) their children in cases of emergencies. However, studies have shown mobile phone addiction among parents as an emerging problem, and that parents who were reportedly addicted to their mobile phone were also more likely to rate their children as having significant behavioral problems (55-57). Accordingly, parenting-skills based interventions or programs should assess the potential role of mobile use in parent-child relationships, children's behavioral issues and identify parenting skills that are necessary to address these issues.

Limitations

The following limitations are noted. This study did not directly assess whether individuals' relationship with their mobile phone would influence the likelihood of their participation in mobile-delivered interventions or programs. While individuals' mobile phone affinity may serve as an indicator of the potential acceptability of mHealth interventions, information from the MPAS alone is limited in predicting acceptance of mHealth approaches. The relevance of intervention content to the particular target group has been shown to be a strong factor in the acceptability and engagement in behavioral health interventions (1,2,58-61). This study also had a relatively small proportion of participants who identified as Hispanic, thus this study should be replicated with a larger sample of that population in order to make more firm conclusions about mobile phone affinity among Hispanics. It should also be noted that analyses included only demographic subgroups that were of adequate sample size. Adequate statistical power was not available to analyze results by individual racial groups other than white and our sample of Hispanics was relatively small. Therefore, it is unclear whether similar findings would be noted with other ethnic and racial subgroups (e.g., African American or Asian subgroups). Further research with these populations should consider investigating the aforementioned factors underlying individuals' acceptability of mHealth interventions and individuals' relationships with their mHealth across various demographic subgroups.

Nevertheless, these results extend current explanatory knowledge of race, ethnicity, gender and age on empirical psychosocial constructs for mobile phone use among adults. Additionally, the findings demonstrate the role of employment and living with children as contributory factors to the understanding of mobile use pattern among women and men, and among age subgroups. These findings emphasize the importance of a complete understanding of individuals' relationship with mobile technology in the assessment of acceptability and engagement of mHealth interventions among different adult subgroups.

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Footnote

Conflicts of Interest: The authors have no conflicts of interest to declare.

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