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Apps and Autonomy: Perceived Interactivity and Autonomous Regulation in mHealth Applications

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Thousands of smartphone apps geared toward monitoring health behaviors are released regularly. Even as developers flood the market with mHealth apps, consumers seem overwhelmed with choices and report lack of sustained use, which raises questions about their efficacy. An online survey (N = 513) found that perceived interactivity not only has a direct effect but also exerts an indirect effect via greater autonomous regulation on users' attitudes and behavioral intentions toward mHealth apps. Frequency of tracking and updating personal data showed significant effects on behavioral intentions. Theoretical and practical suggestions for the design and evaluation of mHealth apps are discussed.

Keywords: *Autonomy; E/M-Health; Interactivity; mHealth Apps; Self-Monitoring*

Investments in the mobile health applications (mHealth apps) market are growing, with the wearables market estimated to be about $19 billion by 2018 (PharmaVoice, 2018). Globally, nearly 133 million units of wearables were sold, with fitness and health tracking apps being the most popular among millennials (Beaver, 2018). With nearly 325,000 health apps already available (Research2Guidance, 2017) and more being developed, it is important to understand if and how these apps are effective. In 2015, less than a quarter (24%) of health apps surpassed a 50,000-downloads mark (Berthene, 2016). Associated with these low downloads, other reports suggest lack of long-term engagement, suggesting that the sheer availability of apps does not always result in actual use. Research attributes this to a lack of understanding of theory and motivational techniques in the design of these apps (Conroy, Yang, & Maher, 2014; Shute, 2014). For instance, the motivational technology model (Sundar, Bellur, & Jia, 2012) proposes that technological affordances, such as interactivity, can positively influence individuals' intrinsic motivation and subsequently promote better health attitudes and behavior. The extant research on interactivity has focused mainly on Web-based platforms (Yang & Shen, 2018), with limited studies in mobile contexts (Gao, Rau, & Salvendy, 2010). Thus, we examine whether perceptions of interactivity in mHealth apps affect users' motivation, attitudes, and intentions.

Interactivity and Perceived Interactivity

Interactivity has been a widely studied concept. While some scholars have argued that interactivity is a technological attribute, calling it "actual" or objective interactivity (Liu & Shrum, 2002; McMillan, 2002; Sundar, 2004, 2007; Williams, Rice, & Rogers, 1988), others have recognized the importance of subjective evaluations, also called perceived interactivity (Bucy, 2004; Bucy & Tao, 2007; Liu & Shrum, 2002; Wu, 2005). Several studies have shown that the mere presence (or addition) of actual interactivity does not guarantee correspondingly higher *perceptions* (i.e., greater subjective evaluations) of interactivity in the minds of users (Bucy & Tao, 2007; Chu & Yuan, 2013; Song & Zinkhan, 2008; van Noort, Voorveld, & van Reijmersdal, 2012; Voorveld, Neijens, & Smit, 2011). Further, a recent meta-analysis (Yang & Shen, 2018) showed that the effect sizes of perceived interactivity tend to be much larger than that of objective interactivity.

In the realm of health technologies, McMillan (2002) found that a perception-based model was a better predictor of attitudes and relevance than a feature-based one. Perceived interactivity mediated the effects of regulatory fit on brand satisfaction (Jin & Lee, 2010) and led to greater user satisfaction and repeat use (Willoughby & L'Engle, 2015). Gustafson et al. (2014) found that users of an interactive app designed to offer continuing care for alcohol use disorders reported fewer risky drinking days due to enhanced patient-counselor interaction via the app. Lu, Kim, Dou, and Kumar (2014) reported greater behavioral intentions (visiting and recommending a fitness center) due to heightened interactivity and media richness. Hence, prior empirical research shows that interactivity can influence users' attitudinal and behavioral outcomes, leading to the following hypothesis:

> H1: Greater perceived interactivity will lead to more positive attitudes (H1a) and behavioral intentions (H1b) toward mHealth apps.

Self-Monitoring, Self-Determination, and Interactivity

Trying to learn more about daily behaviors, our patterns, and ourselves is an innate human drive (Fogg, 2003). Hence, interactive technologies that tap into this drive for constant self-monitoring (e.g., keeping track of calories consumed, steps taken, heart rate, etc.) are said to enhance perceptions of autonomy (Sundar et al., 2012). An advantage offered by mHealth applications is that they encourage constant self-monitoring or tracking of personal data (Consolvo, McDonald, & Landay, 2009; Heffernan et al., 2016). Autonomy is also a central construct in self-determination theory (SDT), which distinguishes between autonomous and controlled regulation of individual behavior (Deci & Ryan, 2000). Behaviors that are autonomy driven are said to be inherently rewarding, allowing for maximum personal growth and development. In contrast, behaviors that are determined by external factors (e.g., doctor's recommendations) are not self-driven. Hence, controlled regulation motives are likely to be inversely related to self-monitoring and autonomy-enhancing activities afforded by interactive interfaces (Dennison, Morrison, Conway, & Yardley, 2013; Heffernan et al., 2016). Given interactivity's potential to boost autonomy (Fogg, 2003; Sundar et al., 2012), we believe that greater perceived interactivity will be positively associated with autonomous regulation and negatively related to controlled regulation. Several studies on chronic illness and disease management have provided empirical support for the effectiveness of self-regulation in meeting health goals (Maes & Karoly, 2005). However, we do not know if these findings extend to newer forms of health regulation via mobile apps; thus, we examine how users' evaluations of interactivity in mHealth apps contribute toward autonomous and controlled regulation:

> H2: Greater perceived interactivity in mHealth apps will be positively associated with autonomous regulation (H2a) and negatively associated with controlled regulation (H2b) motives.

The motivational technology model (Sundar et al., 2012) proposes that effects of interactivity on preventive health attitudes and behaviors are mediated by one's intrinsic motivation. Based on this, we explore whether perceived interactivity has an indirect effect on attitudes and intentions via more autonomous (i.e., more intrinsic) versus controlled regulation:

> RQ1: Does autonomous regulation positively mediate the effects of perceived interactivity on attitudes (RQ1a) and behavioral intentions (RQ1b) toward mHealth apps?

> RQ2: Does controlled regulation negatively mediate the effects of perceived interactivity on attitudes (RQ2a) and behavioral intentions (RQ2b) toward mHealth apps?

Self-Monitoring Features in mHealth Applications

Even though automatic tracking of health information is one of the most desired features (Rabin & Bock, 2011), very few mobile apps include one (Breton, Fuemmeler, & Abroms, 2011). When a self-monitoring feature is present and used regularly, it encourages individuals to engage in desirable health behaviors (Klasnja & Pratt, 2012) such as more intentional physical activity (Consolvo et al., 2008; Turner-McGrievy et al., 2013) and weight reduction (Mattila et al., 2008). When users deliberately monitor their everyday activities, these applications foster greater self-awareness and provide novel insights (Dennison et al., 2013). However, it is unclear what specific technological features of mHealth apps are integral to this self-monitoring process. Conceptually, this study looked at two types of self-monitoring: *tracking* (generalized monitoring of health behaviors via mobile apps) and *updating* (specific activities, such as editing and customizing personal health information). Self-monitoring is active and user driven. In contrast, automatic, sensor-based tracking is more passive, with minimal user involvement. Thus, we examine the effects of two unique features of self-monitoring in mobile media—*tracking* and *updating* personal health information:

> RQ3: Does frequent tracking lead to more positive attitudes and behavioral intentions toward mHealth apps?
>
> RQ4: Does frequent updating lead to more positive attitudes and behavioral intentions toward mHealth apps?

Method

Participants

We conducted an online survey on Amazon's Mechanical Turk (MTurk) platform. Participants had to be 18 years old or older, users of mHealth apps, and residents of the United States to participate. Participants received $1.00 for participating. The sample consisted of 513 individuals (47.5% were female), and the mean age was 30.3 years (SD = 8.3).

Measures

Perceived interactivity

Users' perception of interactivity toward mHealth apps was measured via 12 items. The items were adapted from prior studies that tapped into various dimensions of interactivity, such as active control, responsiveness, two-way communication, etc. (Leiner & Quiring, 2008; Liu, 2003; Liu & Shrum, 2002; McMillan & Hwang, 2002; Wu, 2005). An exploratory factor analysis (EFA) with principal axis factoring and oblique rotation was used to explore underlying factors among the observed variables, since it examines both common and unique variance (Park, Dailey, & Lemus, 2002). The results of this analysis show a unidimensional factor for perceived interactivity, with one factor explaining 49.39% of the variance. The factor matrix showed two items with poor factor loadings (less than 0.5), which were excluded (Tabachnick & Fidell, 2012). This resulted in a 10-item, unidimensional scale of perceived interactivity.

Autonomous and controlled regulations

Autonomous regulation (six items) examined the extent to which participants used mHealth apps for their intrinsic value and enjoyment. The *controlled regulation* (six items) tapped into extrinsic factors that drove mHealth apps use. These items were adapted from Ryan and Connell (1989).

Attitude and behavioral intentions

An overall *attitude* measure was created using a scale of 15 items, which assessed users' evaluations on how well a set of adjectives described mHealth apps. A *behavioral intention* measure (five items) captured users' intention to continue their engagement with mHealth applications. These measures were adapted from Sundar, Bellur, Oh, Xu, and Jia (2014).

Self-monitoring measures

Frequency of tracking was measured by asking participants how often they keep track of changes in their health using an app on a scale from 1 (*never*) to 5 (*very frequently*). *Frequency of updating* tapped into how often they update their information on apps, measured from 1 (*several times a day*) to 5 (*once or twice a month*), reverse coded. Users' perceived competence in using cell phones, prior app downloads, and demographics were used as covariates.

Results

Findings from multiple regression analyses (Table 1) indicated that perceived interactivity positively predicted attitudes (H1a: $\beta = .50$, $p < .001$) and behavioral intentions (H1b: $\beta = .40$, $p < .001$). As proposed in H2a and H2b, perceived interactivity was positively correlated with autonomous regulation and negatively correlated with controlled regulation (Table 2).

Further, supplemental mediation analyses (Hayes, 2013, PROCESS model 4, with 5,000 bootstrap samples and 95% confidence intervals) showed that *autonomous regulation* did lead to positive indirect effects, mediating the effect of perceived interactivity on attitudes ($ab = .05$; LLCI = .02, ULCI = .09) and behavioral intentions ($ab = .11$; LLCI = .06, ULCI = .16; RQ1a and RQ1b). Given cross-sectional data, we tested an alternative mediation model and found that perceived interactivity mediated the effects of autonomous regulation on attitudes ($ab = .14$; LLCI = .10, ULCI = .19) and behavioral intentions ($ab = .12$; LLCI = .08, ULCI = .17).

Additionally, attitudes also significantly mediated the effects of perceived interactivity ($ab = .29$; LLCI = .22, UCLI = .37), frequency of tracking ($ab = .06$; LLCI = .03, ULCI = .10), and frequency of updating ($ab = .04$; LLCI = .01, UCLI = .07) on behavioral intentions. *Controlled regulation* did not lead to any significant indirect effects (RQ2a and RQ2b). Frequency of *tracking* (RQ3: $\beta = .09$, $p = .04$) and frequency of *updating* (RQ4: $\beta = .09$, $p = .04$) had a positive influence on behavioral intentions but not on attitudes.

Table 1 Linear Regression Models on Attitudes and Behavioral Intentions.

	β	*B* (Std. Error)	*t*	sig.
DV: Attitudes				
Age	.10*	.01 (.00)	2.75	.01
Gender	−.01	−.02 (.05)	−.34	.73
Ethnicity	.07	.04 (.02)	1.88	.06
Education	−.11**	−.11 (.03)	−3.03	.00
Income	−.02	−.01 (.02)	−.60	.55
Prior app download	.13**	.10 (.03)	3.22	.00
Cell phone competence	.11*	.13 (.05)	2.80	.01
Perceived interactivity	.50**	.54 (.04)	12.81	.00
Frequency of tracking	−.01	.00 (.03)	−.15	.88
Frequency of updating	.05	.03 (.02)	1.30	.19
Adj. R^2	.38			
DV: Behavioral Intentions				
Age	.08*	.01 (.00)	2.02	.04
Gender	−.05	−.08 (.06)	−1.39	.17
Ethnicity	−.01	−.01 (.03)	−.38	.71
Education	.05	.05 (.04)	1.28	.20
Income	−.05	−.04 (.03)	−1.28	.20
Prior app download	.11*	.10 (.04)	2.63	.01
Cell phone competence	.13**	.18 (.06)	3.10	.00
Perceived interactivity	.40**	.49 (.05)	9.64	.00
Frequency of tracking	.09*	.07 (.03)	2.10	.04
Frequency of updating	.09*	.05 (.03)	2.07	.04
Adj. R^2	.33			

Note. The VIF scores range from 1.05 to 1.50, suggesting that multicollinearity is not an issue. *$p < .05$, **$p < .001$

Discussion

The key contributions from this study can be summarized as follows: (a) it is important to account for users' subjective experience of interactivity when evaluating mHealth apps; (b) apps that encourage greater autonomous regulation among users lead to favorable outcomes; and (c) designs of future mHealth apps need to be based on theoretical considerations of what features work and why.

Our findings are consistent with the literature on the importance of perceived interactivity, which significantly impacted both attitudes and behavioral intentions. This study not only replicates the positive effects of perceived interactivity, typically studied in Web-based domains (Yang & Shen, 2018), but also extends it to mHealth apps. Further, the mediation analyses showed that perceived interactivity promoted a greater sense of autonomous regulation, which subsequently influenced attitudes and behavioral intentions. This is consistent with prior findings, which have shown that

Table 2 Descriptive Statistics, Correlations, and Reliability for Study Measures.

	1	2	3	4	5	6	7	8	9
1. Prior app download	1								
2. Cell phone competence	.41**	1							
3. Perceived interactivity	.32**	.16**	1						
4. Freq. of tracking	.37**	.18**	.40**	1					
5. Freq. of updating	.28**	.19**	.20**	.44**	1				
6. Attitudes (apps)	.35**	.24**	.58**	.28**	.20**	1			
7. Behavioral intentions (apps)	.35**	.26**	.51**	.36**	.26**	.62**	1		
8. Autonomous regulation	.30**	.20**	.44**	.35**	.20**	.39**	.45**	1	
9. Controlled regulation	.05	.14**	−.13**	.10* (p = .03)	.11*(p = .02)	−.02	.02	.28**	1
Mean	*3.69*	*4.36*	*4.09*	*3.50*	*3.00*	*3.84*	*4.01*	*3.49*	*1.91*
Std. Deviation	*.88*	*.56*	*.63*	*1.14*	*1.29*	*.68*	*.79*	*.82*	*.87*
Cronbach's alpha	NA	.82	.91	NA	NA	.95	.85	.78	.86

Note. NA = Not applicable.
**$p < .001$.

intuitive, user choice drives app-selection decisions (Dogruel, Joeckel, & Bowman, 2015). Supplemental analyses also showed that attitudes significantly mediated the effects of perceived interactivity, tracking, and updating on behavioral intentions. This could be understood via the theory of planned behavior (Ajzen, 1991), which posits attitudes as an important antecedent to behavior. Tests of these theoretically driven variables and paths add more nuance to our understanding of mHealth apps.

The two self-monitoring features explored in this study (frequency of tracking and updating) positively predicted behavioral intentions and were also positively correlated with autonomous regulation. Based on these results, creating incentives for frequent "check-ins" via text notifications, reward points, and building other active user engagement metrics into these apps are some recommendations to app designers. Several users rely on automatic updates, which are convenient. Nevertheless, our findings indicate that those who report frequently (more actively) monitoring their everyday health activities show greater autonomous regulation, which in turn predicts greater attitudes and intentions. These self-monitoring features inform both future app design and research intervention (outcome measures) strategies.

With survey design, this study explored direct and indirect associations among variables. Future research should investigate causal mechanisms that can systematically rule out alternative explanations. Examining specific types of mHealth apps and experimentally varying the levels of self-monitoring and interactivity are fruitful areas for future research. We need studies comparing perceived interactivity in mobile-based versus Web-based platforms, with more items that tap into other factors (e.g., active control) of this multidimensional construct. While frequency of tracking and updating gave preliminary insight into users' behavioral intentions, we need additional measures that can capture the concept of self-monitoring more comprehensively. Beyond autonomy, future research should also explore the role of competence and relatedness on mHealth app evaluations.

Disclosure statement

No potential conflict of interest was reported by the authors.

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