Multifaceted Companion Devices: Applying the New Model of Media Attendance to Smartphone Usage

Karel Verbrugge

Isabelle Stevens, PhD

Lieven De Marez, PhD

iMinds-MICT-UGent

Ghent University

Department of Communication Sciences

Korte Meer 7-9-11, 9000 Gent, Belgium

Abstract

This study inspects the relationship between outcome expectations, habit strength, and smartphone usage by attempting to validate the new model of media attendance (NMMA) (LaRose and Eastin, 2004) , a social-cognitive theory of uses and gratifications. The fast adoption rate of smartphones, and their inherent characteristics as convergent, always-on, always-connected devices, warrant a closer look into user habitualization of this medium. Using a sample of 481 smartphone users selected from a larger panel, we were able to support the NMMA, although surprisingly no significant effect of habit strength on smartphone usage was found. While some uncertainties connected to the method are noted, this suggests a more complex reality, in which habitualization of a convergent media device does not necessarily implicate a significant rise in usage.

Keywords

model of media attendance, mobile communications technology, smartphone use, mobile internet, social cognitive theory, media use, habit strength, expected outcomes, deficient self-regulation, self-efficacy

Introduction

The manner in which a lot people use the internet has changed dramatically over the past few years. No longer is web browsing on a personal computer the dominant way of navigating the World Wide Web. The complex interplay between mobile internet connections improving in speed and availability, and the of user-friendly mobile devices has propelled the adoption of smartphones forward. In just a couple of years' time, smartphones account for half of all mobiels phones in the United states (Nielsen, 2012). Of specific relevance for this study, penetration of smartphones in Belgium is following closely, now at 38,5% (Schuurman, Veeckman, De Moor, & De Marez, 2012a).

The importance of these numbers cannot be understated. Smartphones are not just an extension of the existing internet, nor are they mere successors of mobile phones. These convergent devices do not only change the ways in which we interact with the internet. The use of smartphones must be put into a spatial and social context as well. The constant availability of an always-on, highly convergent, mobile internet device potentially has the ability to change the behavior of its user and the context in which it operates.

In order to get a broad understanding of how people deal with their newfound *companion device* in the context of daily life, getting a grasp of how the medium is being used is a first step. What can be said about the smartphone attendance, and how to best study it? The new model of media attendance (LaRose & Eastin, 2004) has proven to be more capable in explaining medium usage than classic U&G approaches, and the incorporation of habit strength is key (Oulasvirta, Rattenbury, Ma, & Raita, 2011; Peters, 2007b). Specific use patterns in which habitualization plays a big role (Oulasvirta et al., 2011; Tossell, Kortum, Rahmati, Shepard, & Zhong, 2012) have emerged and warrant a closer look into the interplay between smartphone usage based on outcome expectations and habits.

Theory & Literature

The new model of media attendance as proposed and tested by LaRose and Eastin (2004) is built upon two pillars. In essence, it embeds a classic uses and gratifications (U&G) approach within the larger framework of social cognitive theory (SCT), which is able to offer extended and additional explanatory constructs. Their main drive for doing so is the limited percentage of explained variance that typical uses and gratifications studies uncover, and the consistent raising of the variance explained by employing prospective measures: asking respondents what they expect from media use in the future, as opposed to what they have sought and obtained in the past (LaRose et al., 2004). This is consistent with Bandura's social cognitive theory (Bandura, 1986).

Social cognitive theory is a broad framework for explaining human behavior, which lays an important determination of behavior (in this case, media consumption or smartphone usage) in the expected outcomes of behavior. These expectations can be shaped by the users own experience or by observation. This defines media usage as overt behavior and allows expected outcomes to explain the behavior of both current and future users (LaRose et al., 2004, Lin, 1999).

The key connection between these SCT and U&G frameworks thus is the similarity between the gratifications sought-gratifications obtained structure used in U&G research and the enactive learning concept from SCT, which describes how humans learn from experience. This process of continuously adjusting expectations about the most likely outcome of behavior (i.e. media use) is basically indistinguishable from the U&G framework. The formulation of outcome expectations is then, according to LaRose et al. (2004), a way to connect gratifications sought and gratifications obtained.

Within the new model of media attendance, outcome expectations are organized through the basic types of human behavior described in SCT, adjusted contextually for internet gratifications (Larose, Mastro, & Eastin, 2001): novel sensory incentives (expanded to include information seeking behavior), social incentives (interaction with others), status incentives, monetary incentives, activity incentives (the desire to take part in enjoyable activities), and self-reactive incentives (pass time or relieve boredom).

In addition to these media use outcome expectations, SCT is also used to expand upon the understanding of uses and gratifications by adding two more mechanisms: self-efficacy and self-regulation.

Self-efficacy is the belief in one's capacity to organize and execute a certain course of action (Bandura, 1986). It is preceded by prior experience (Eastin and LaRose, 2000) and allows us to describe the way in which individuals who perceive themselves to be skilled in a certain task will invest increased effort into achieving successful outcomes.

Self-regulation, a construct defined within SCT (Bandura, 1991), defines how individuals monitor their own behavior, judge it in relation to personal and social standards, and then moderate their behavior if necessary by employing self-reactive incentives. When such self-regulation fails, an increase in media-use can be expected.

LaRose, Lin and Eastin (2003) conceptualize this issue in terms of habit strength and deficient self-regulation, concepts which are used directly in the new model of media attendance. Habit strength is defined as a failure of self-monitoring, which causes the recurring behavior pattern that make up the habitual behavior itself. In relation to expected outcomes, this is a forgetting of the initial active considerations we made the first times we performed a certain behavior. Expected outcomes thus logically precede habit strength in time. Habit strength should also be preceded by self-efficacy, as perceived mastery of a certain behavior is likely to reduce attentiveness. Deficient self-regulation is the specific state in which self-control fails and is related to problematic medium (specifically: internet) use. Although conceptually related, it precedes habitual behavior. LaRose and Eastin also posed a causation between self-reactive outcome expectancies and deficient self-regulation, with the internal focus of self-reactive behavior able to cause problematic medium use.

The New Model of Media attendance was thoroughly tested by Peters, Rickes, Jöckel, Von Criegern, & Van Deursen (2006). Firstly, they replicated the original study by Larose and Eastin (2004) on internet usage within a German context (instead of the original American one). They found the NMMA promising, especially concerning the integration of habit strength. Additionally, they applied the model to an examination of GPRS use in the Netherlands. Again, they found the model to display a much higher percentage of explained variance compared to previous U&G studies on mobile technology use (Peters, 2007a). This second study showed the applicability of the NMMA on other media contexts. Peters also states that in comparison to other models, the NMMA features the most detailed description of the underlying theoretical mechanisms that influence one's media usage and –adoption. This further motivates the use of this model.

Smartphone habits: attendance of an always-on medium

Smartphone attendance however is difficult to measure by means of self-reporting (such as in an online survey), due to the fragmented, ubiquitous and continuous usage. This medium specific usage also makes the difference between habit strength and expected outcomes a difficult one.

According to Peters et al. (2006), who found a surprising negative direct effect of expected outcomes on Internet habit strength in their replication study of LaRose et al.'s original test of the NMMA (2004), the relationship between expected outcomes is a complex one. This stems from the diminishing consciousness of expected outcomes as habitualization takes place, according to SCT (Bandura, 1986). Peters (2007) state that habitualization is an individual process, where the beginning of habitualization should lead to an increased awareness of the expected outcomes connected to the medium. As habitualization increases even further, this consciousness should decrease again. The correlation between expected outcomes and habit strength should thus be dependent on the stage of individual user habitualization. (Peters, 2007) This relationship, although a complex one, does imply a strong role for user experience and self-efficacy within the NMMA.

In the context of this study, it appears that habitual usage of smartphones plays an important role in understanding how people use their devices. A lot of this has to do with the specific characteristics of smartphone interfaces and the relation of these interfaces to the World Wide Web. The original web browser is not as fundamental as it appear to be on personal computers (Tossell et al., 2012). This coincides with a larger shift: the World Wide Web –the interlinked network of websites– is in decline and instead makes way for the rise of simple, sleek services that use the internet infrastructure (Anderson, 2010). Tossell et al. (2012) define these services as '*native internet applications*' (NIAs). In popular culture, they are called simply '*apps'*.

As studied in a small-scale qualitative study by Tossell et al. (2012), the use of these NIAs is closely connected to the experience of users and very habitual in nature. Browser use on smartphones gradually gave way to a more pronounced NIA activity. These NIA visits were short and concentrated to a fairly small and stable vocabulary of applications. This pattern was difficult to break into by new apps, and if the case did not cause the total NIA vocabulary to be grow.

However, differing use patterns did not necessarily coincide with an increased usage intensity. Instead, users could be placed at two ends of a behavioral continuum. *Pioneers* are an explorative kind and have longer use sessions with a larger variety of content. It could be argued that these users are more guided by a variety expected outcomes. *Natives* stuck more closely to their basic vocabulary of apps and were characterized in shorter use sessions. In essence, these users show a stronger level of habitualization. This could have important implications for the predictive power of both expected outcomes and habit strength, suggesting the strongest link between expected outcomes and smartphone use.

The complexity of the relationship between outcome expectations and habit strength is further illustrated by *'checking behavior'*. As defined by Oulasvirta et al. (2011), checking behavior consists of brief usage sessions repeating over time and is typical for smartphone use. They comprise a large part of smartphone usage and are stimulated by quick access to dynamic content. Oulasvirta et al. predict that checking behavior may lead to more use overall, calling these *'gateway habits'*. This supports the original relationship between outcome expectations and habit strength as defined by LaRose and Eastin (2004), with brief usage sessions based on expected outcomes leading to more habitual checking behavior. It also supports a relation between habit strength and smartphone use. Lastly, this study supports the connection between self-reactive outcome expectations and deficient self-regulation, as gateway habits stemming from self-reactive incentives could result in compulsive smartphone behavior.

Hypotheses

Our main goal is the validation of the new model of media attendance, as described by LaRose et al. (2004), within the new context of smartphone use. Keeping in mind the specific characteristics of this medium discussed above and their possible effects on the relationship between outcome expectations and habit strength, we are especially interested in the triadic relationship between outcome expectations, habit strength, and smartphone use. The main hypotheses of this study reflect this explorative focus, while keeping in mind the general relations within the original NMMA.

H1: Expected outcomes will be directly related to smartphone usage.

H2: Expected outcomes will be directly related to smartphone habit strength.

H3: Smartphone habit strength will be directly related to smartphone usage.

Method

Sample & Procedures

Data collection for this study was embedded within a larger interdisciplinary research project, funded by a non-profit research institute (iMinds) and several industry partners, among which a successful virtual mobile network operator. Specifically, a user panel of 4761 Dutch-speaking Belgian mobile internet users was created during the first half of 2012 and we performed extensive user profiling through multiple online survey waves in function of adoption estimates for novel mobile internet services and multi-method living-lab research spanning two years. Typical smartphone owners and mobile internet users in Flanders (Schuurman, Veeckman, De Moor, & De Marez, 2012b) are most likely male and younger than average. This is also strongly reflected in our user panel and an attempt to correct this was made by contacting a representative panel of the Flemish population (N=1560).

For this specific study, the smartphone owners in the above panel (N=4723) were contacted via email with an invitation to fill in the online survey. Of the 671 smartphone users who responded (14,20% response rate), we retained a data set of 481 cases after checking for missing data and deleting respondents who failed a control item within the survey (respondents were asked to answer 'completely agree' on item embedded within a set of regular Likert-scale items; 33 respondents failed this item). This sample size was found adequate for structural equation modeling.

Sample participants were 82% male, 18% female, while we would expect a 60% male, 40% female ratio according to the envisioned population (smartphone and mobile internet users in Flanders). 45% were aged 29 or younger (population: 25%), 28% were between the ages of 30-39 (population: 24,3%), 17% were aged 40-49 (population: 27,8%), 7% were between the ages of 50-59 (12,7%), and 3% were aged 60 and above (4,3%). The respondents were obviously biased towards a younger and dominantly male sample. This is an exaggeration of the existing gender and age distribution of smartphone users in Flanders (Schuurman et al., 2012b). Other sample demographics proved to be similar to the envisioned population.

In following with LaRose & Eastin (2004), we checked for significant relationships between demographic variables and the main explanatory variables. Similar connections were found (females had a lower self-efficacy, $r = .32$, and age was negatively related ($r = -.14$) to self-efficacy), yet we found no significant correlations between deficient self-regulation and gender. However, a negative correlation between age and smartphone usage was found ($r = -.25$), consistent with the dominant use of

Data Analysis

General statistical analyses were done using IBM SPSS Statistics version 19 (SPSS, Inc., 2010). We performed structural equation analysis using Amos 16.0.0 (Arbuckle, 2007) with maximum likelihood estimation to test the model of media attendance.

Measures

The original items of LaRose & Eastin (2004) were translated into Dutch and rephrased in order to be fitting within the context of modern smartphone use. We maintained a close resemblance to the original items and followed the same definitions of outcome expectations, adjusting within the boundaries of the original concepts defined by Bandura (1986). However, not all expected outcome factors were found to be of sufficient quality. In response, we adjusted the factors in a way that is consistent with previous theory. Social and status outcomes were found to correlate strongly, being inherently related and with items in the original model even being included in multiple factors. The resulting social outcomes factor was highly consistent ($\alpha = .86$). Due to the nature of the rephrased items moving away from a strict monetary focus, similar to those used by Peters (2009), we renamed the monetary outcomes gain outcomes ($\alpha = .73$). Self-Reactive outcomes ($\alpha = .83$) and novel outcomes ($\alpha = .73$) were consistent. Activity outcomes proved problematic ($\alpha = .58$) and were therefore excluded from the analysis. This inconsistency can possibly be attributed to the convergent nature of smartphones and the internet, providing a large variety of available entertainment applications. Thus, focusing activity items on music and games might no longer be relevant. In extension, this might also be the case when applying the items on contemporary internet use, as opposed to the internet environment studied by LaRose and Eastin in 2004. Confirmatory factor analysis proved the expected outcome factors to be of sufficient quality (χ^2 = 463.75, *df* = 221, *cmin/df* = 2.10, *RMSEA* = .057, *CFI* = .91).

In their work, LaRose & Eastin note on the difficulty of clearly making a distinction between habit strength and deficient self-regulation (2004). They subjected a pool of items to exploratory factor analysis in order to create seemingly meaningful factors reflecting both concepts. We experienced similar difficulty in delineating both concepts, with not all original items clearly belonging to one concept or the other. In order to shed light on these dubious items, we also performed a principal components factor analysis using varimax rotation. This uncovered two factors very similar to the proposed originals, maintaining the meaningful distinction between habit and deficient self-regulation, while showing good (deficient self-regulation: α = .75) to marginal (habit strength: α = .68) reliability. A confirmatory factor analysis proved these concepts of sufficient quality (χ^2 = 90,94, *df* = 33, *cmin/df* = 2,76, *RMSEA* = .91, *CFI* = .073)

In order to measure smartphone self-efficacy, we adapted and translated the Internet Self-Efficacy Scale (Eastin & LaRose, 2000) to smartphone use, as it was already replicated for the original. This rephrasing proved to be consistent (α = .92). We also replicated the Internet experience measure, asking for the amount of years and months the respondent had been using smartphones.

Measuring net smartphone usage through an online survey proved to be difficult. Due to the fragmented nature of smartphone usage, consisting of multiple short bursts of usage daily, it proved to be impossible to obtain reliable data by asking for the amount of minutes and hours a respondent spends using his smartphone. A much more promising and reliable method of measuring net smartphone usage would be through objective data-logging (as showed by Verkasalo et al. (2011), but this was not possible within the research context. In order to circumvent the difficulties of exact use measurement, respondents were asked to indicate how intensively they thought they used their smartphone on an average day, on an eleven-point scale ranging from 0 to 10. While this manner of self-reporting allows for a lot of subjectivity, it proved to be of good quality.

Results

The complete path model can be found in figure 2. Pearson correlation coefficients between the independent and dependent variables are shown in table 2. The model showed a good fit to the data (χ^2 = 51, 84 *df* = 19, *cmin/df* = 2,73, *RMSEA* = .085, *CFI* = .94). The structural model was able to explain 19% of smartphone usage variance. This is lower than the percentage of explained variance found in the original study (42%) (LaRose and Eastin, 2004), but is similar to the variance explained by the Peters et al. replication of the study, which was also 19%.

Most of the hypothesized relations were found to be significant. The standardized path coefficients in the model show a significant direct effect of expected outcomes on smartphone usage (β = .35) and this is the dominant effect on smartphone usage. Self-efficacy also has a significant effect on usage (β = .15), as does deficient self-regulation (β = .14). As expected, deficient self-regulation also has a significant effect on habit strength (β = .30), and so has smartphone self-efficacy (β = .21). Smartphone self-efficacy also has a direct effect on expected outcomes (β = .24).

Additionally, and as expected, smartphone experience proved to be a precedent of self-efficacy (β = .29). Self-Reactive outcomes also showed a direct effect on deficient self-regulation, as was predicted in the original model. Again similar to the original model, we found a suggested significant effect of self-efficacy on novel expected outcomes (β = .40).

Hypothesized by LaRose and Eastin (2004), yet without any significant effect in their study or in the replication studies by Peters (2007), we also did not find a significant effect from experience on habit strength. Thus, so far, this theoretical connection has not been validated.

Most surprisingly, and most importantly, we found no significant effect of habit strength on smartphone usage, despite the importance of this factor in previous applications of the new model of media attendance (LaRose et al., 2004, Peter et al., 2006).

Discussion

The initial findings of this study supports the relationship between expected outcomes, habit strength and smartphone usage as suggested by the new model of media attendance (LaRose & Eastin, 2004), and also underline the importance of user specific self-efficacy and experience. In total, a satisfactory percentage of variance in smartphone usage was explained (19%), which was very similar to previous model validations. Most importantly however, smartphone usage was predicted best by outcome expectations, while no significance direct effect of habit strength on smartphone usage was found.

First of all, these findings could be understood as to support the notion that as long as media use isn't completely habitualized, habit strength remains causally determined by outcome expectations. (LaRose et al., 2004, Peters, 2007). This is under the assumption that the habitualization process of smartphone usage in Belgium is still underway and that smartphone habits are not yet so pronounced as to become a relevant predictor for smartphone use. This explanation is unlikely, however. The characteristics of the sample used in this study and the general high levels of use of various internet applications on smartphones does not indicate the early stages of smartphone habitualization. Also, applying the path model to a split data file based on experience (as suggested by LaRose and Eastin, 2004), did not show any significant differences, nor did we find a significant correlation between experience and habit strength.

Secondly, our findings partially support the notion of 'checking behaviors' as proposed by Oulasvirta et al. (2011). Expected outcomes are a strong predictor of habit strength. However, we did not find any direct support for checking behaviors being strong enough 'gateway habits' to increase smartphone usage.

Still, we believe that both analyses belie the complexity of smartphones as a convergent and complex medium. The description of users along a continuum of 'pioneers' and 'natives' (Tossell et al., 2012), each with their own vocabulary of native internet applications, hints towards a more nuanced interpretation and a variation in smartphone usage on multiple levels, while still allowing for the direct effect of outcome expectations on habit strength.

On a primary level, we could postulate that habitualization of smartphones happens through the shaping of a vocabulary of applications tailored to the outcome expectations of the individual. The vast array of possible applications that can populate the highly convergent smartphone ranges from social applications (Facebook, Twitter, …), over multimedia (photo, audio, video, ...), games, and utility applications (calculator, flashlight, camera, …), to basic communications applications (telephone, sms, mail, …). The amount of habitualization will probably depend on the peculiarities of a user's personal vocabulary of apps and thus his outcome expectations. This also accounts for the effect of self-reactive outcome expectations on deficient self-regulation, and the correlations between respondents use profiles and the meaningful correlations between specific outcome expectations and respondent profiles found in the sample

On a second level, this specific vocabulary of apps possibly also dictates the direct effect of habit strength on smartphone usage. For example, a vocabulary of highly efficient apps used mostly for all types of electronic communication may elicit a high degree of habit strength, but may translate into limited use intensity. Differently, a vocabulary dominated by content aggregation apps consulted irregularly may not be cause for a strong habit, but may cause a lot of net smartphone usage.

In effect, this convergence of functions could make for an unpredictable relationship between habit strength and net smartphone usage, with expected outcomes instrumental in predicting both. This is in line with the findings in this study, but also raises questions concerning the applicability of the new model of media attendance on modern convergent media. This includes the internet on which LaRose and Eastin (…) first postulated the original model, which has since evolved to a much more multifaceted medium, allowing a more varied range of interactions. The modern smartphone is an extension of this multifaceted internet and a convergent medium in its own right, further increasing uncertainty.

Limitations

The first clear limitation of this study is its sample characteristics. Although we have been fortunate to have access to a large panel of smartphone and mobile internet users, this panel is skewed towards a younger, male, more technologically savvy group of users. This limits the generalization of these results. Furthermore, we believe that an online survey is not the most ideal method for measuring several key constructs of the NMMA within the context of smartphone usage. First, smartphone usage is inherently fragmented and consists of many short use sessions throughout the day. This most probably causes a large margin of error when registered through self-reporting. Though difficult to execute, we believe an objective registration of use sessions through data logging would be precise and more ideal. Secondly, the self-reporting of habit strength and deficient self-regulation might be problematic. As Oulasvirta et al. (2012) suggest, smartphone habits are not yet perceived as problematic. Additionally, we expect a possible social desirability bias. These biases might account to some extent to the lack of significant effect of habit strength on smartphone use.

Implications for further research

A primary point of concern is the difficulty of obtaining quality data on smartphone usage. Objective measurement of smartphone usage would be an immense opportunity to remove the significant uncertainty connected to the self-reported quantitative measurement of smartphone usage. Furthermore, the operationalization of habit strength and deficient self-regulation needs to be revised, with additional attention to the delineation between both related concepts. Finally, more research is needed on the relation between expected outcome incentives and habitual usage. This habitualization process is poorly understood in the context of mobile internet devices such as smartphones, and existing research hints towards a relationship much more complex than the relationship currently suggested by the new model of media attendance.

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Appendices

Figure 1

New Model of Media Attendance

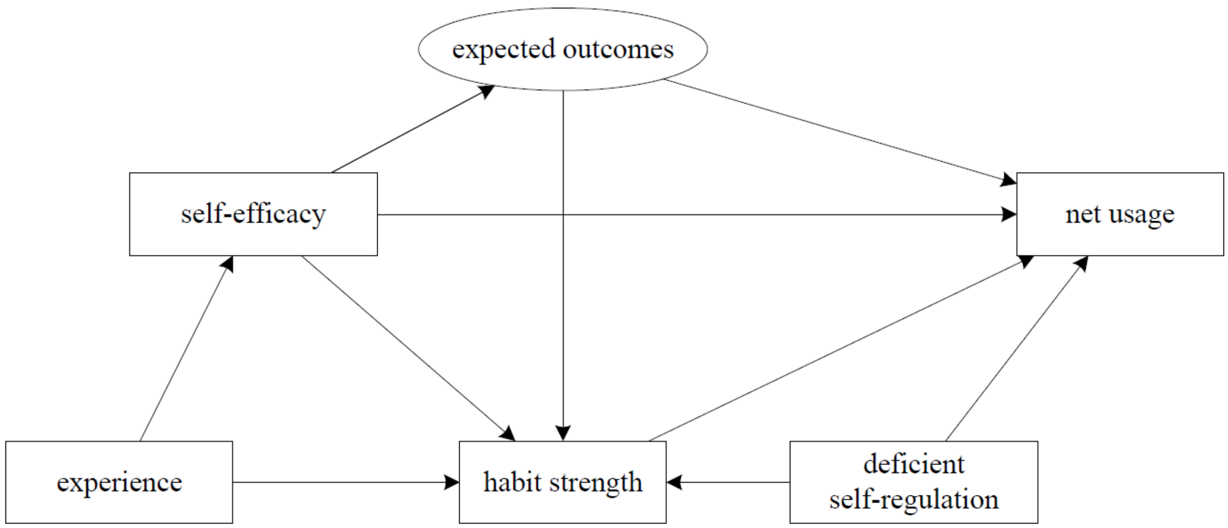
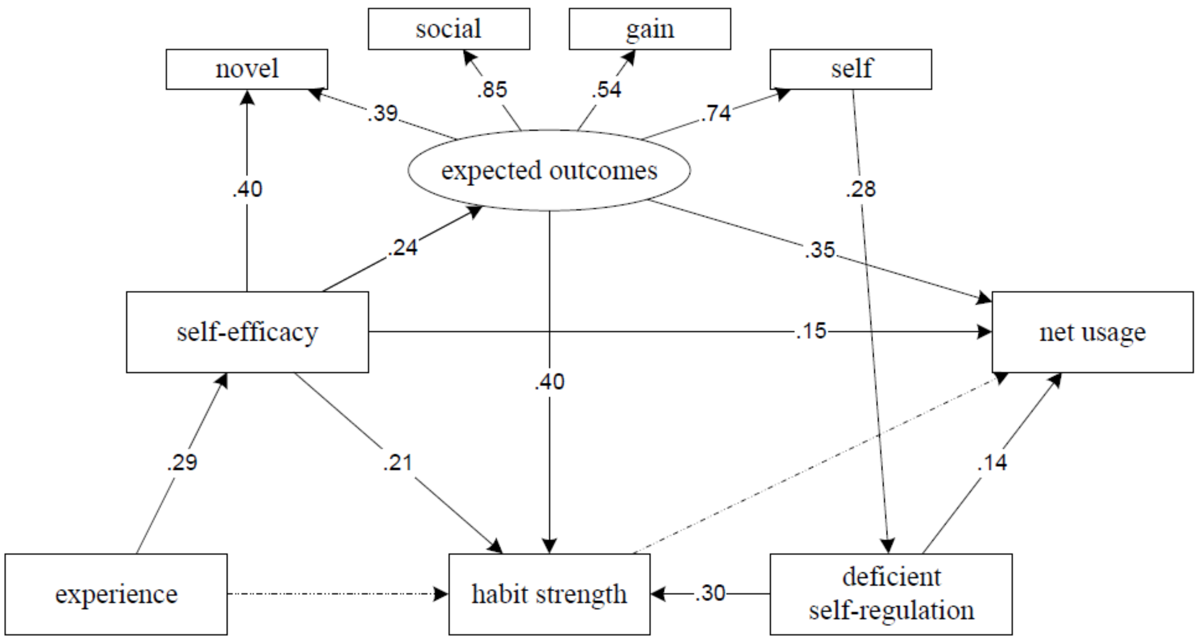


Figure 2

Path Analysis Model



Note: $\chi^2 = 51, 84$ $df = 19$, $cmin/df = 2{,}73$, $RMSEA = .085$, $CFI = .94$.

Only significant ($p < .05$) path coefficients are shown.

Table 1

Expected Outcomes, habit strength, deficient self-regulation, and self-efficacy items and scales: descriptive statistics, factor loadings, and Cronbach's α

Scale/Item	Mean	S.D.	β
Expected Outcomes (χ^2 = 463.75, df = 221, cmin/df = 2.10, RMSEA = .91, CFI = .057)			
Social Outcomes (α = .86)	**2,84**	**,80**	
find others who respect my views	3,01	1,07	0,63
find people like me	3,16	1,15	0,62
maintain a relationship i value	2,79	1,19	0,59
feel like i belong to a group	2,38	1,04	0,67
provide help to others	3,08	1,01	0,57
improve my future prospects in life	2,48	1,03	0,66
find something to talk about	2,99	1,10	0,68
Self-Reactive Outcomes (α = .83)	**3,10**	**,71**	
relieve boredom	3,57	1,07	0,51
find a way to pass the time	3,71	1,02	0,47
feel relaxed	3,30	,99	0,64
forget my problems	2,18	1,06	0,62
feel less lonely	2,39	1,11	0,62
cheer myself up	2,86	1,04	0,69
feel entertained	3,71	,86	0,51
Gain Outcomes (α = .74)	**2,67**	**,74**	

get products for free	2,28	1,04	0,54
find bargains on products and services	2,80	1,13	0,62
save time shopping	2,67	1,14	0,60
get free information that would otherwise cost me money	2,97	1,18	0,62
obtain information that I can't find elsewhere	2,79	1,16	0,50
get support from others	2,53	1,13	0,48
Novel Outcomes (α = .74)	**3,85**	**,78**	
get immediate knowledge of big news events	4,01	,92	0,69
find a wealth of information	3,90	,91	0,73
get up to date with new technology	3,66	1,06	0,66
Activity Outcomes (α = .58, excluded)	**3,25**	**,85**	
play a game I like	2,86	1,20	0,53
find new applications	3,52	,99	0,66
hear music I like	3,40	1,31	0,56
Habit Strength (α = .68)	**3,49**	**,61**	
My smartphone has become part of my daily routine	4,18	,75	0,65
I would miss my smartphone if I could no longer use it	4,04	,89	0,47
I would go out of my way to satisfy my need to use my smartphone	2,63	1,04	0,51
I find myself using my smartphone at the same moments every day	3,42	1,03	0,48
I use my smartphone more and more to have fun	3,18	,98	0,38
Deficient Self-Regulation (α = .75)	**1,84**	**,63**	
I feel my smartphone use is out of control	1,63	,76	0,73
I have a hard time keeping my smartphone use under control	1,86	,93	0,8

I sometimes try to conceal how often I use my smartphone	1,69	,86	0,57
I have tried unsuccessfully to reduce my smartphone use	1,78	,85	0,56
I get tense, moody, or irritable when I can't use my smartphone	2,22	1,09	0,51
Smartphone experience (months)	**35,40**	**23,60**	
Internet Self-Efficacy	**4,17**	**,68**	

Table 2

Pearson Correlation Coefficients of manifest variables

Variable	1	2	3	4	5	6	7	8
1. Usage	1,00							
2. Habit	,35**	1,00						
3. Def. Self-reg	,17**	,36**	1,00					
4. Social	,35**	,40**	,27**	1,00				
5. Self-Reactive	,30**	,46**	,38**	,62**	1,00			
6. Gain	,22**	,32**	,27**	,47**	,29**	1,00		
7. Novel	,30**	,43**	,19**	,45**	,32**	,51**	1,00	
8. Self-Efficacy	,23**	,34**	0,04	,21**	,13**	,27**	,46**	1,00
9. Experience	,095*	0,05	0,06	-0,02	-0,07	,116*	,132**	,264**

Note: *p < .05. **p < .01