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Consumer Acceptance of mHealth Services: A Comparison of Behavioral Intention Models

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Abstract

Recent appropriation of mobile devices to deliver health services is transforming the healthcare landscape, offering reduced costs and increased access for service providers and consumers. This paper examines factors influencing consumers' decisions to adopt mobile health (mHealth) services through a comparison of three behavioral intention models. A national web-based survey of 482 French adults indicates that the model of goal-directed behavior (MGB) more fully, though less parsimoniously, explains consumers' acceptance of mHealth services. This research provides insight into the usefulness of the MGB in improving understanding of the determinants of behavior situated at the intersection of health, service, and technology.

Keywords: mHealth, model of goal-directed behavior, acceptance, technology, model comparison

Consumer Acceptance of mHealth Services: A Comparison of Behavioral Intention Models

Health services are now partially or entirely delivered via mobile phone owing to the ubiquity and increasingly powerful capabilities of mobile devices such as smartphones (Klasnja & Pratt, 2012). Termed mHealth services, these services enable the delivery of personalized therapeutic and/or preventative services at the times most needed through a medium integrated into people's daily lives (Whittaker, Merry, Dorey, & Maddison, 2012). The mHealth services that support self-care in particular may offer benefits such as reduced costs and improved access (Collier & Kimes, 2013). Importantly, these benefits cannot be realized for either consumers or service providers without widespread consumer adoption of mHealth services.

Defined as "using wireless mobile communication to aid health services delivery" (Lester, van deer Kip, Taylor, Coleman, & Marra, 2011, p. 218), mHealth has become recognized as beneficial for health consumers in terms of increased control, more convenience, and improved health care quality and costs (PricewaterhouseCoopers, 2012). Past research indicates that key mHealth uses for consumers are: obtaining health advice, connection with health care providers, reminders for adherence to medical treatments, and personal health management (Rai, Chen, Pye, & Baird, 2013).

While much of the past research in mHealth has centered on implementation, a number of studies have focused on consumer mHealth usage intentions (e.g., Rai et al., 2013; Cocosila & Archer, 2010; Agarwal, Anderson, Zarate, & Ward, 2013). Findings from these studies suggest that predictors of mHealth uptake include health care availability and personal innovativeness towards mobile services (Rai et al., 2013), security, privacy and trust, personal information technology (IT) innovativeness, anxiety (Cocosila & Archer, 2012), perceived value, satisfaction with health provider, and communication tactics (Agarwal et al., 2013). A systematic review of 52 studies undertaken by Or and Karsh (2009) showed that human–technology interaction factors for uptake included perceived usefulness, perceived ease of use, Internet dependence, self-efficacy, anxiety, and intrinsic motivation.

While past mHealth research employs an array of different theoretical perspectives, it draws prominently from behavioral intention models (Yousafzai, Foxall, & Pallister, 2010), such as the theory of reasoned action (TRA) (Fishbein & Azjen, 1975) and the theory of planned behavior (TPB) (Ajzen, 1991), that are also well-established in the health domain (e.g., Cooke & French 2008; McEachan, Conner, Taylor, & Lawton, 2011) to predict and explain end-user uptake of health-related IT (Holden & Karsh, 2010). In their review of the use of the technology acceptance model (TAM) in health IT, Holden and Karsh (2010) analyzed 16 data sets and found that "although TAM did a fair job predicting and perhaps explaining clinical end-use acceptance and use of health IT, there is much room for improvement" (p. 169). A key shortcoming of these models, however, is that they do not take into account that most behavior is performed to achieve personal goals and, as such, neglect a significant motivational impetus of behavior (Perugini & Bagozzi, 2001).

Consumers' adoption of technology is proposed to be goal-directed (Bagozzi, 2007), as are health behaviors such as reducing smoking, coping with stress, and exercising (Taylor, Bagozzi, & Gaither, 2005). Goal-directed behavior is better predicted by models incorporating goal-focused antecedents (Perugini & Bagozzi 2001; Perugini & Conner 2000; Taylor et al., 2005). On this basis, the model of goal-directed behavior (MGB) has been proposed as a means to improve understanding of consumers' acceptance of mHealth services (Schuster, Drennan, & Lings, 2013). Although research indicates that the MGB explains more variance in health behavior than the TRA and TPB (e.g., Taylor et al., 2005), the model has not been extensively applied in technology-based self-service (TBSS) contexts or in marketing generally (Bagozzi & Dholakia 2006).

This research will thus compare the TRA and TPB (established models in the TBSS literature) and their extension, the MGB, in the under-researched domain of consumers' decisions to adopt mHealth services. In so doing the research will contribute in three key ways to extant literature. First, it will test the efficacy and value of TRA and TPB in comparison to MGB as theoretical underpinnings in the mHealth acceptance and use research area. Second it will augment understanding of the utility of the MGB as a theoretical framework for explaining consumers' adoption of the ever-expanding TBSSs in the health domain, specifically emerging mHealth services. Third, the research will further elucidate the explanatory boundaries of the MGB in line with the call for further investigation of the model's capacity to explain behavior across contexts (Fry, Drennan, Previte, White, & Tjondronegoro, 2014; Taylor, 2007).

Behavioral Intention Models

The TRA is a general model that successfully predicts actual behavior based on behavioral intention (Sheppard, Hartwick, & Warsaw, 1988). In turn, behavioral intention is jointly determined by a favorable attitude toward the behavior and subjective norms supportive of the behavior (Fishbein & Ajzen, 1975). Attitude is a tendency to evaluate or appraise a behavior favorably or unfavorably, while subjective norms are based on the individual's perception of whether important referents support or reject the behavior (Ajzen, 1991). A key limitation of the TRA, however, is that the focal behavior must be under the complete volitional control of the individual (Sheppard et al., 1988). Behaviors influenced by external factors, such as those that require resources, skills, or the cooperation of others, do not satisfy this requirement. Consumers' use of TBSSs, such as mHealth services, may thus not be sufficiently explained by the TRA, as these services demand consumers learn new knowledge and behaviors (Meuter, Bitner, Ostrom, & Brown, 2005).

The TPB extends the TRA by incorporating the effects of perceived behavioral control on behavior not under the complete volitional control of the individual (Ajzen, 1991). The TPB specifies that perceived behavioral control positively influences behavior and refers to individuals' "perception of the ease or difficulty of performing the behavior of interest" (Ajzen, 1991, p.183). It reflects individuals' beliefs regarding their access to skills, resources, and opportunities needed to perform a behavior. Nonetheless, the TPB treats behavior as a terminal outcome and fails to consider that many behaviors are undertaken for the purpose of personal goal achievement (Perugini & Bagozzi, 2001). Consumers adopt technologies in the pursuit of goals or outcomes such as improved efficiency (Bagozzi, 2007). Consumers' acceptance of mHealth services, such as those services supporting smoking cessation or improved mental health, is especially likely to be goal-directed. Coping with stress and reducing smoking, in addition to other health behaviors such as exercising and eating healthily, are exemplars of goal-directed behavior (Taylor et al., 2005).

The MGB extends the TPB by accounting for goal and affective influences on behavior (Perugini & Bagozzi, 2001). Positive and negative anticipated emotions stem from an individual's appraisal of how they would feel following goal attainment and failure respectively. On the basis that individuals are motivated to make behavioral choices that promote positive affect and avoid negative affect (Bagozzi & Dholakia, 2002) these anticipated emotions positively influence performance of behavior deemed instrumental to goal achievement. The MGB further specifies desire as the most proximal determinant of behavioral intention (Perugini & Bagozzi, 2001). Perugini and Bagozzi (2001) argue that although attitude, subjective norms, and perceived behavioral control provide reasons for acting they do not possess the explicit motivational content needed to induce an intention to act. This is contained within the "desire to act". Desire is thus "a personal motivation to perform an action" (Perugini & Bagozzi, 2001, p. 71) and stems from reasons that make a given end-state desirable, including negative and positive anticipated emotions, attitude, subjective norms, and perceived behavioral control (Leone, Perugini, & Ercolani, 2004).

Comparing Behavioral Intention Models

The TRA has been extensively applied to health behaviors (see Sheppard et al., 1988) and to technology adoption behaviors, particularly in its more specific form, the TAM (see Schepers & Wetzels, 2007; Holden & Karsh, 2010). The TPB has been also employed as a basis for examining a wide range of health behaviors (see Godin & Kok, 1996; McEachan et al., 2011) and consumers' adoption of technology (e.g. Curran & Meuter, 2005; Dabholkar & Bagozzi, 2002). There is also growing empirical support for the MGB in a variety of behavioral domains such as weight management (Perugini & Bagozzi, 2001), drinking responsibly (Fry et al., 2014), and self-regulation of hypertension (Taylor et al., 2005). The MGB has also been shown to provide a basis for explaining technology-related behaviors, specifically participation in virtual communities (Bagozzi & Dholakia, 2002) and software learning (Leone, Perugini, & Ercolani, 2004).

The literature further includes studies that provide insight into the relative utility of these behavioral intention theories. In health-related behaviors the TRA and TPB explain more variance than other models, such as the protection motivation theory and health belief model (Cooke & French, 2008). A recent meta-analysis shows that the TPB explains 44.3% of the variance in intentions and 19.3% in actual health behavior (McEachan et al., 2011). However, consistent with the meta-analysis by Godin and Kok (1996), behavior type was found to affect the utility of the model, with physical activity and diet behaviors better predicted by the TPB than behaviors such as safer sex. In terms of the relative importance of predictors McEachan et al.'s (2011) meta-analysis shows attitude exhibited the strongest effect on behavioral intention, followed by perceived behavioral control and subjective norms. This is consistent with a meta-analysis of the TRA and TPB in the context of attendance at health screening services, which shows the attitude–intention relationship is strong, while subjective norms and perceived behavioral control moderately impact behavioral intention (Cooke & French 2008).

Despite the undeniable utility of the TRA and TPB, several studies indicate that the MGB explains more variance in intention and behavior (Leone et al., 2004; Perugini & Bagozzi, 2001; Taylor et al., 2005). One study, for instance, compared the predictive power of the TRA, TPB, and MGB in the context of information search behavior, finding that the MGB explained 60% of the variance in behavioral intention compared to 41% for the TPB and 40% for the TRA (Taylor, 2007). Of note, however, is that while there is strong and consistent support for effect of desire some studies found that only positive anticipated (Fry et al., 2014; Leone et al., 2004; Taylor et al., 2005) or negative anticipated emotions (Perugini & Bagozzi, 2001) impacted on intention respectively. Nevertheless, overall, the literature suggests the MGB may more sufficiently explain consumers' acceptance of mHealth services, which is the behavioral context of the study.

Method

Context

Mental illness represents a foremost global public health concern (Harrison et al., 2011). In part, the impact of mental illness can be attributed to a failure to access professional mental health services (Harrison et al., 2011). This represents a significant problem given the higher risk of serious outcomes such as work disability and hospitalization (Kessler et al., 2003). Mobile phone technology has recently been appropriated to overcome some of the barriers to using professional mental health services. These barriers include discomfort with traditional therapy procedures, the stigma and embarrassment associated with therapeutic activities, privacy concerns, and the cost and inconvenience of accessing professional mental health services (Donker et al., 2013). Empirical support for the clinical efficacy of mHealth services for mental health is also emerging (e.g. Harrison et al., 2011; Proudfoot et al., 2013).

This paper concentrates specifically on the research context of mHealth services for mental health in France for the following reasons. In France, 12 million people suffer from a mental illness, with an associated cost of 5% of gross domestic product (GDP) (Fondation FondaMental & Institut Montaigne, 2014). According to a survey by the French National Institute of Prevention and Health Education, nearly 8% of French people aged between 15 and 75 experienced a major depressive episode in the 12 months preceding the survey—more than in Switzerland (7%), the United States of America (USA), Canada or Italy (3–5%) (Chan Chee, Beck, Sapinho, & Guibert, 2005). Further, the use of traditional interpersonal mental health services is limited in France (Alonso et al., 2007). Accordingly, mHealth services may represent a promising means to improve use of mental health services provided determinants of consumer acceptance and adoption of these services are adequately understood and leveraged.

Research Design

The study's focus on consumers' acceptance (as measured by intention to use) rather than adoption of mHealth services for mental health is appropriate practically and supported theoretically. In France mHealth services for mental health are only emerging, with no large-scale availability of these services; focusing on the adoption of the service would thus be impractical. Further, previous research reveals a strong and significant relationship between behavioral intention and targeted behavior (Sheppard et al., 1988), thereby providing support for the use of behavioral intention as a proxy for actual behavior.

Data were collected through a national, web-based survey from a quota sample of French adults. The models are thus tested in the same context, using respondents sampled from the same population, facing the same usage decision. Owing to this commonality, observed differences can be attributed with reasonable confidence to the models themselves (Mathieson, 1991). The services of a global market research firm were employed to collect the data from a pre-recruited consumer panel, where consumer panel members have pre-committed to respond to surveys for a financial or other reward.

Pre-validated scales from Perugini and Bagozzi's (2001) and Perugini and Conner's (2001) conceptualizations of the MGB were adapted for the survey. The same measures were employed for the shared constructs across the TRA, TPB, and MGB: attitude, subjective norms, perceived behavioral control, and behavioral intention. This provides a more solid basis for directly comparing these behavioral intention models (Mathieson, 1991). Items were first translated into French and the back-translated to check for accuracy.

Sample

Following data cleaning, the sample of 482 French adults comprised 50.8% male respondents. This is comparable to the general French population, where males comprised 48.4% of the population as of January 2015 (INSEE, 2015a). The largest portion (44.6%) of respondents were between the ages of 18–35 years old, followed by respondents aged 46–55 years old (28.6%) and 36–45 years old (26.8%). The mean age of the sample was 37.9 years old, similarly comparable to the mean age of the general French population of 40.6 years old (INSEE, 2015b). Finally, the majority of respondents classified themselves as an "employee" (32.8%) or a "mid-level manager/professional" (22%). The occupational profile of the sample appeared to approximate that of the population (INSEE, 2013), with a key exception being the rate of unemployment which is higher in the population.

Analysis

Structural equation modeling was employed to analyze the data. The chi-square statistic ($\chi2$), two additional global fit indices (SRMR and RMSEA), an incremental fit index (CFI) and a parsimony index (χ^2/df) were used to assess model fit in line with the argument that multiple fit indices should be employed to assess model tenability (Markland, 2007). Since the TRA and TPB are not entirely nested within the MGB, owing to the model's inclusion of behavioral desire, these models were compared descriptively rather than statistically. Non-nested models are generally compared only in a descriptive fashion (MacCallum, 2009).

Results

Descriptive Statistics

Respondents, on average, reported people important to them would be supportive of their use of an mHealth service for mental health ($\bar{x} = 5.74$). They perceived some control over using an mHealth service for mental health ($\bar{x} = 4.08$), and possessed a moderate attitude toward using these services ($\bar{x} = 4.20$). Respondents anticipated they would experience positive emotions if they were successful in achieving their mental health goal ($\bar{x} = 5.30$). On the other hand, respondents did not anticipate experiencing negative anticipated emotions in the event of failing to achieve their goal ($\bar{x} = 3.33$). On average, respondents' desires ($\bar{x} = 3.81$) and intentions ($\bar{x} = 3.43$) to adopt mHealth services for mental health were low.

Measurement Models

The TRA, TBA, and MGB measurement models demonstrated acceptable, but not good or close, fit to the data (Table 1). The fit indices suggest the covariance matrix was reproduced in the data well in parts, but that changes to improve model fit may be warranted. Modification indices (M.I. > 10) and standardized residuals (+/- 1.96) were used to identify areas of model strain. This resulted in the removal of an item from the Intention scale, an item from the Desire scale, and two items from the Attitude scale. The re-specified measurement models demonstrated improved fit to the data. While the χ^2 was large and significant for all the re-specified measurement models (Bollen-Stine $p < .05$) since χ^2 is highly sensitive to sample size and deviations from normality (Byrne, 2001) it was not used to reject the models given this study's large sample size (n = 482) and significantly multivariate non-normal data. The χ^2/df for all models were close to 3, indicating acceptable, but not parsimonious, fit. Again for all models, the RMSEA was < .07 and the 90% confidence intervals ranged between 0 and .08, indicating acceptable fit. The SRMR coefficients were < .05, indicating good fit, and the CFI coefficients exceeded .95, indicating good model fit given model complexity and sample size.

Insert Table 1 here.

The path estimates ($\Lambda > .70$, $p < .05$) and squared multiple correlations ($R^2 > .50$, $p < .05$) for all observed variables were acceptable and the average variance extracted (AVE) values for each factor exceeded .50, indicating convergent validity. The maximum shared squared variances (MSV) were less than the AVE values, indicating discriminant validity. Moreover, since cross-loadings are not represented by the measurement models and the models demonstrate acceptable fit with the data this provides additional evidence that the latent factors are adequately differentiated. To examine the internal consistency reliability of the measures Cronbach's Alpha (ά) coefficients were calculated. All Cronbach's Alpha coefficients exceeded .70.

Structural Models

The TRA and TPB both explained approximately 71% of the variation in respondents' intentions to use an mHealth service for mental health (Table 2). In comparison, the MGB explained approximately 84% of the variation in respondents' intentions. Consistently across the three models, subjective norms had the strongest positive relationship with intention. Attitude had a weaker positive relationship with intention. Perceived behavior control was not found to have a significant effect on intention. Similarly, neither positive anticipated emotions nor negative anticipated emotions significantly impacted respondents' intentions to use an mHealth service for mental health. Notwithstanding the TRA determinants, behavioral desire from the MGB was the only other significant predictor of intention.

Insert Table 2 here.

Discussion

The MGB explained the most variance in behavioral intention (84%)—more than the TPB (72%) or the TRA (71%). This result suggests that the MGB more fully explains consumers' intentions to use mHealth services for mental health and corresponds with other research in health behavior contexts, where the MGB has been shown to possess superior explanatory power relative to the other behavioral intention models (Perugini & Bagozzi, 2001; Taylor, 2007; Taylor et al., 2005). Notably, the additional variance explained by the MGB appears to stem from the inclusion of behavioral desire rather than anticipated emotions. This result is consistent with Perugini and Bagozzi's (2001) finding that the MGB explains significantly more variance in intentions and behavior than a TPB variation that included anticipated emotions.

In contrast, the non-significant effect of both negative and positive anticipated emotions on behavioral desire raises questions as to the utility of these predictors, particularly given previous reports of significant variation in their performance (Taylor, 2007); that is, some studies show that only positive anticipated emotions (Fry et al., 2014; Leone et al., 2004; Taylor et al., 2005, Schuster et al., 2015) or negative anticipated emotions (Perugini & Bagozzi, 2001) respectively influence behavioral intentions significantly in the manner delineated by the MGB. However, a non-significant result for both types of anticipated affect is unexpected given the role of goals and emotions is purported to be underestimated in research examining consumers' use of technologies (Bagozzi, 2007). Further, recent research has shown anticipated affective reactions significantly impact intentions to perform a health behavior (Conner, Godin, Sheeran, & Germain, 2013). Schuster et al. (2013) suggest that in abstract goal contexts, such as mental health, consumers may have difficulty envisioning goal achievement or failure, negating the formation and influence of positive and negative anticipated emotions.

In addition, perceived behavioral control did not have a significant effect on behavioral desire. This result contradicts findings of previous meta-analyses showing that attitude exhibited the strongest effect on behavioral intentional, followed by perceived behavioral control and subjective norms (Cooke & French 2008; McEachan et al., 2011). The descriptive statistics suggest that perceived behavioral control may be moderately high for the majority of consumers, limiting variability and prediction of behavioral intention. This is in line with Ajzen’s (1991) argument that perceived behavioral control becomes less important with higher volitional control over the behavior. It may be that service delivery through mobile phone removes some of the key external barriers to accessing the mental health service, such as cost and accessibility, resulting in relative high and consistent consumer perceptions of perceived behavioral control. In fact, greater consumer control over the service delivery process and improved accessibility are cited as key consumer benefits of self-service technology (Meuter et al., 2005).

Last, the results also show that subjective norms were a stronger predictor of behavioral desire than attitude. Attitude has generally been found to be the strongest influence on intentions to perform health behaviors (Cooke & French 2008; McEachan et al., 2011). The saliency of subjective norms may be attributable to the social stigma surrounding mental health. However, subjective norms strongly influenced consumers’ intention to use a smoking cessation service delivered via mobile device (Andrews, Cacho-Elizondo, Drennan, & Tossan, 2013)—an arguably less stigmatized service category. This suggests using an mHealth service in general may be perceived as more socially risky owing to its deviation from established interpersonal means of accessing health services.

Implications

Overall, the results provide further support for research showing that behavior type moderates the utility of the behavioral intention models (Godin & Kok, 1996; McEachan et al., 2011). Although the MGB explained the most variance in behavioral intention—notwithstanding behavioral desire—attitude and subjective norms were the only two significant predictors in the model. This result suggests consumers' acceptance of mHealth services may be more parsimoniously explained by the TRA or TPB. This reflects Bagozzi and Dholakia's (2002) study on another technology-related behavior, consumers' participation in virtual communities, where only attitudes and positive anticipated emotions influenced behavioral desire.

The results also suggest that general models of behavior, such as the TRA, TPB, and MGB, traditionally employed with substantial success to understand health behavior may not provide as comprehensive an understanding of consumers' decisions to adopt mHealth services as models more specific to technology-related behaviors, such as the TAM (Davis, 1989). Some studies that have compared the TPB and TAM, for example, have found that the TAM explains more variance in consumers' intentions to use technologies (Chau & Hu, 2001). However, it is important to note that a review of studies employing the TAM to explain consumers' reactions to health technologies identified the need to incorporate several additions and modifications to the model, concluding that an important future direction is to adapt the model specifically to the health care context (Holden & Karsh, 2010). Together our findings and those of previous research highlight the complexity of this behavioral domain. Specifically, consumer adoption of self-care mHealth services is multi-layered in that functionally it is both a health behavior and a technology adoption behavior and, thus, neither technology adoption or health behavior models appear to provide in-depth insight into this behavior. This highlights the need for the development of more targeted models and provides an important direction for future research.

The findings are moreover useful for policy- and decision-makers considering investment in mHealth, particularly in France. In the study, consumers' desires and intentions to use mHealth services for mental health were relatively low. In line with the call for caution in scaling up mHealth services (Tomlinson, Rotheram-Borus, Swatrz, & Tsai, 2013), the results of our study suggest that efforts should be made to increase consumers' acceptance of this type of technology-enabled health care prior to significant investment in mHealth services. The results also highlight the social acceptability of using mHealth services for mental health. Given that subjective norms were the strongest predictor of desire to use mHealth services, however, further promotion of the social acceptability of using this type of health service would be beneficial. Additionally, the findings underline the fact that consumers held a moderate attitude toward using mHealth services for mental health. As such, greater focus on promoting the benefits of mHealth services is necessary.

Limitations

While this study has provided insights into the utility of the MGB for explaining consumers' acceptance of mHealth services it has limitations. First, this research focused on only one country and utilized a consumer panel, thus limiting the generalizability of the results. Differences in the social acceptability of mHealth services, for example, may exist across cultures, as highlighted by previous research on consumers' acceptance of information technologies. In the case of mHealth services for mental health specifically, variation in the levels of stigmatization surrounding mental health may also influence social acceptability of these services. Future research should thus replicate this study in other countries, consistent with the call for further assessments of behavioral intention models across cultures (Michaelidou & Hassan, 2014), particularly with non-panel samples to minimize potential response bias. A second key limitation is that the study focused on behavioral intentions and does not include the actual behavior. The results of this study should be considered in light of research showing a gap between individuals' intentions and behavior (Sheeran, 2002). As mentioned previously, however, there is no large-scale availability of mHealth services for mental health in France. Consequently, this research focused on consumers' decisions to adopt these emerging TBSSs in line with other research showing a strong and significant relationship between behavioral intention and targeted behavior (Sheppard et al., 1988).

Conclusion

Improved understanding of consumer responses to the rapid and broad technological developments in health services is necessary to ensure that their consumer and provider benefits can be realized. This research sought to contribute some clarity regarding the most suitable models to explain consumers' decisions to adopt promising and increasingly widespread mHealth services and, in this way, provide insights for both policy-makers and researchers in the field. This study compared models shown to explain technology-related and health behavior, specifically the TRA, TPB, and MGB. Results indicate that although the MGB most sufficiently explained consumers' acceptance of mHealth services, the TRA may explain this behavior most parsimoniously. The study, however, also suggests that additional research is required to provide improved understanding of this complex behavioral domain situated at the intersection of health, service, and technology.

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Table 1

Comparisons of Measurement Model Fit

Model	χ^2	χ^2/df	*p*	SRMR	RMSEA	CFI
TRA						
Specified Model	515.924	5.108	*p*=.001	.0293	.092 LL: .085 UL: .100	.961
Re-specified Model	192.448	3.104	*p*=.001	0.211	.066 LL: .056 UL: .077	.984
TPB						
Specified Model	537.580	4.167	*p*=.001	.0273	.081 LL: .074 UL: .088	.964
Re-specified Model	208.925	2.487	*p*=.001	.0195	.056 LL: .046 UL: .065	.986
MGB						
Specified Model	2278.999	3.748	*p*=.001	.0423	.076 LL: .072 UL: .079	.933
Re-specified Model	1467.707	3.096	*p*=.001	.0421	.066 LL: .062 UL: .070	.953

Table 2

Standardized Regression Weights and Squared Multiple Correlations for Structural Models

Model	β	R^2
Theory of reasoned action		
ATT	0.207*	
SN	0.687*	
INTENT		0.717*
Theory of planned behavior		
ATT	0.202*	
SN	0.673*	
PBC	0.035	
INTENT		0.718*
Model of goal-directed behavior		
ATT	0.147*	
SN	0.768*	
PBC	0.055	
PAE	0.003	
NAE	0.014	
DESIRE	0.918*	0.838*
INTENT		0.842*

Note. * p<.05, two-tailed.