DEVELOPMENT AND VALIDATION OF THE TECHNOLOGY ADOPTION PROPENSITY (TAP) INDEX

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ABSTRACT

The present study develops and empirically tests a parsimonious new multiple-item scale to measure consumers' propensities to adopt new technologies. We show that a consumer's likelihood to embrace new technologies can reliably be measured by a 14-item index that combines assessments of consumers' positive and negative attitudes towards technology. Consistent with prior work on technology readiness, we show four distinct dimensions of consumers' technology adoption propensity: two inhibiting factors, dependence and vulnerability, and two contributing factors, optimism and proficiency. We develop the index on a cross-sectional dataset of U.S. consumers then establish the validity of each of the four component scales on two dissimilar validation sets. The resulting index shows sound psychometric properties and may be used by researchers interested in the antecedents or effects of each of the independent sub-scales.

Keywords: high technology, scale development, technology readiness, information technology, innovation adoption, technology adoption.

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1. Introduction

Businesses are increasingly introducing new technological products to the market, as well as a broad array of new technologies to interface with customers and deliver services (Meuter, Ostrom, Roundtree, & Bitner, 2000; Parasuraman, 2000). Firms devote considerable resources to developing these innovations (Burke, 2002). Given the rapid rate of technological obsolescence in most markets, the ability to accurately forecast demand for and user acceptance of high-tech products and services is essential for firms (e.g., Hoeffler, 2003; Norton & Bass, 1987).

Many consumers readily embrace newly introduced technologies. For example, online purchasing is growing at a rate of more than 25% year over year (*Ipsos Insight*, 2009) and in 2008, 25% of consumers reported using automated store checkouts during more than half of their shopping occasions (Dean, 2008). However, some high-tech products have shown disappointingly slow adoption rates despite optimistic forecasts (*Financial Times*, March 20, 2002). A well-known example is the Segway Scooter, unveiled in 2001, which sold fewer than 10,000 units by mid-2004 (Alexander, Lynch, & Wang, 2008). In addition, many consumers report a decrease in their use of some technology-based service delivery systems. For instance, 30% of consumers surveyed in 2008 reported that they had reduced their overall Internet usage, and 25% said that they had stopped buying online (Consumer Reports National Research Center 2008). Furthermore, consumers may never fully utilize products they purchase. Consumers return 11-20% of all electronic goods, resulting in restocking and reselling expenditures that cost companies $13.8 billion in 2007 alone (*Wall Street Journal*, May 2008).

Effectively segmenting and targeting customers based on their likelihood to purchase and use new technologies could help firms better capitalize on their high-tech investments by maximizing the effectiveness of marketing spending and minimizing losses due to returned merchandise and underutilized service delivery systems. Prior work predicting technology acceptance has tended to focus on individual design features (e.g., Thompson, Hamilton, & Rust, 2005; Zhu, Nakata, Sivakumar, & Grewal, 2007) or attitudes toward specific technologies (e.g., Bruner II & Kumar, 2005; Davis, Bagozzi, & Warshaw, 1989; Gurran & Meuter, 2005). Less attention has been given to a third factor, consumers' chronic predispositions towards adopting new technologies. To the extent that individuals possess differing tendencies to adopt new technologies, measuring these tendencies is critical for accurate forecasting and effective targeting of high-tech products and services. Extant work in this domain has largely been directed toward service-based technologies (Parasuraman, 2000). Viewing technology through a wider lens, the current study develops and validates a new psychometric scale designed to measure consumers' propensities to adopt a broad range of new technological products and services.

2. Consumers' Complex Relationships with New Technology

For over two decades, researchers have attempted to understand consumers' adoption of, and ongoing relationships with, new technologies. Davis (1986) proposed the Technology Acceptance Model (TAM), an adaptation of the Theory of Reasoned Action (Ajzen & Fishbein, 1980), which identifies consumer beliefs about *perceived usefulness* and *ease of use* as the primary drivers of consumers' attitudes toward new technologies. Davis, Bagozzi, and Warshaw (1989) later used the TAM to explore user acceptance of and resistance to computer systems.

Subsequent research has applied the TAM to a host of other technologies such as email, word processors, and the Internet (e.g., Karahanna & Straub, 1999; Lee, Kozar, & Larsen, 2003). As the TAM developed as a widely applied theoretical model, additional variables such as anxiety, complexity, self-efficacy, and social influence emerged as explanatory drivers of technological acceptance, the particular driver(s) dependent on the specific technology studied (Lee, et al., 2003; Venkatesh, Morris, Davis, & Davis, 2003).

A second stream of technology-related research has attempted to profile *early trier* segments for innovative services such as interactive in-home video shopping (Darian, 1987; Greco & Fields, 1991), multi-channel shopping (Konuş, Verhoef, & Neslin, 2008) and self-service technologies (Gurran & Meuter, 2005; Meuter, Bitner, Ostrom, & Brown, 2005). As with the TAM, most early adopter segmentation studies have focused on specific technologies rather than a broad range of product and service categories.

Research has also explored the intricacy of consumers' relationships with technological innovation, identifying several paradoxes consumers confront when dealing with new technologies. Mick and Fournier (1998) identified eight paradoxes, which include: control/chaos, freedom/enslavement, new/obsolete, competence/incompetence, efficiency/inefficiency, fulfills/creates needs, assimilation/isolation, and engaging/disengaging. They observed a number of coping strategies that consumers use in dealing with these paradoxes, suggesting that technology adoption may be linked to how well consumers cope with technological paradoxes. Subsequently, Meuter et al. (2000) derived a list of satisfying (e.g., "solved intensified need", "better than the alternative," "did its job") and dissatisfying (e.g., "technology failure," "process failure," "poor design," "customer-driven failure") incidents with self-service technologies. As with the findings of Mick and Fournier, their work suggests a complex and paradoxical consumer relationship with new technologies.

Drawing on the aforementioned paradoxes as a conceptual underpinning, and approaching technology primarily from the perspective of firms using technology-based means of marketing to and serving customers, Parasuraman (2000) developed the Technology Readiness Index (TRI) to measure consumers' enduring propensities to embrace new technologies. As a second-order formative index (i.e. it is assumed the sub-scales measure independent constructs which in combination *cause* the latent TRI construct), the TRI combines measures of four constructs which are not highly correlated to provide an overall assessment of a consumer's conflicting attitudes towards and beliefs about technology. Parasuraman identified consumers' degree of *innovativeness* and *optimism* as contributors to technology readiness and their degree of *discomfort* and *insecurity* as inhibitors of readiness. The TRI's focus on service delivery and online technologies effectively addressed the technological explosion in marketing at the time: e-commerce and Internet-based delivery systems.

In the decade since the TRI was published, researchers have discovered additional important components of consumers' relationships with new technologies, including fatigue from the increased number of features (Thompson, et al., 2005), anxiety when considering using technology (Meuter, Ostrom, Bitner, & Roundtree, 2003), anticipation of enjoyment or fun derived from new technologies (Bruner II & Kumar, 2005; Childers, Carr, Peckc, & Carson, 2001; Pagani, 2004), frustration with the complexity of new technologies (Strebel, O'Donnell, & Myers, 2004; Wood & Moreau, 2006), perceived risk of using a technology (Lam, Chiang, & Parasuraman, 2008) and confusion and a sense of being overwhelmed by technology (*Business Week*, January 1, 2009).

3. Measuring a Consumer's Propensity to Adopt Technology

While the TRI continues to serve as a useful tool for measuring consumers' propensity to embrace online and other automated services, in the last decade what constitutes a "new" technology has changed. An analysis of the individual TRI items shows many are specific to technologies or situations that were new at the scale's inception but are no longer so. For example, contributing items such as "you like the idea of doing business via computers…," and "you like computer programs that allow you to tailor things to fit your own needs" appear specific to computers, a commonplace technology for many consumers today. In addition, the insecurity inhibiting factor of the TRI has items specific to the Internet (e.g., "you do not feel confident doing business with a place that can only be reached online," and "you do not consider it safe to do any kind of financial business online"). References to specific technologies such as these ground the TRI in a particular technological era and limit its usefulness as a measure of overall technology readiness. Hence, a new scale that measures consumers' attitudes toward a varied and flexible concept of technology that seamlessly incorporates the specific technologies of each new era would be useful to researchers and marketers.

An additional concern with the TRI is its length (36 items), which may make it difficult to administer in practice (e.g., Stanton, Sinar, Balzer, & Smith, 2002). Shorter questionnaires tend to elicit more truthful answers and avert response fatigue when compared to longer ones (e.g., Narayana, 1977). Indeed, respondent fatigue and/or acquiescence bias due to questionnaire length may prohibit the use of the TRI by researchers wanting to use the scale in combination with other multi-item measures.

The current research utilizes survey data collected both online and via pencil and paper to develop a new 14-item index which measures consumers' beliefs about and attitudes towards new technology. The aim of this study is to provide researchers and firms with a parsimonious scale which reliably predicts consumers' propensity to adopt a wide range of new technologies, even as what constitutes new technology continually changes. We call our scale the "Technology Adoption Propensity" (TAP) index, and show that this measurement instrument effectively predicts consumers' likelihood of adopting a wide variety of new high tech products and services.

4. Conceptual Framework and Item Development

We began item development with a broad definition of technology as "the application of science, especially to industrial or commercial objectives." This definition incorporates both technological products and methods of service delivery, and is broad enough to include the wide range of technologies previously studied in the literature as well as future technological innovations. With this definition in mind, we started with the TAM model (Davis, 1986) as a baseline for generating a conceptual model of technology adoption propensity (TAP). The TAM's constructs of *usefulness* and *ease of use* reflect two fundamental questions that consumers may ask themselves in order to formulate a belief about a given technology:

(1) How beneficial will this new technology be once I start using it?

(2) How difficult will it be for me to learn to use it properly?

Anticipating that the benefits will outweigh the time and effort should serve as positive information of adoption of the new technology. However, answering these two questions may be complicated by a variety of factors.

In considering the first question, consumers may recognize that technology use results in both positive and negative outcomes. Positive outcomes that consumers may experience and expect include increased control, freedom, and efficiency in life, increased adaptability and flexibility, and greater social assimilation (Lee, et al., 2003; Mick & Fournier, 1998; Parasuraman, 2000). Negative outcomes include high perceived usage risk (Lam, et al., 2008), loss of control as one becomes more dependent on technology, and social isolation (Lee, et al., 2003; Mick & Fournier, 1998). Any of these positive and negative factors may influence consumers' expectations of how much benefit (if any) they will gain from technology use, and thus to their propensity to adopt new technologies.

In order to answer the second question, consumers must consider two relevant factors: the new technology and themselves as consumers of technology. With regard to the technology itself, consumers form complexity expectations (Wood & Moreau, 2006) of how challenging technologies will be to learn. Complexity expectations may be amplified as the number of new technologies and the number of technological features increase, which can lead to consumer fatigue (Meuter, et al., 2003; Thompson, et al., 2005) and confusion (*BusinessWeek*, 2009). The difficulty of learning a new technology also depends on characteristics of the individual as a consumer of technology. One's desire to learn how to use new technologies and the belief in one's ability to do so influence a consumer's expectation of the time, cognitive effort, and emotional energy she will expend learning a new technology. A positive assessment of one's aptitude for learning new technology should decrease expectations of the time and effort required to learn to use new technologies. Moreover, self-efficacy (Lee, et al., 2003) and a sense of oneself as a technology leader (Parasuraman, 2000) have both also been found to influence adoption.

Based on the aforementioned factors, we developed a battery of 47 items related to expected outcomes of use, complexity expectations, and the consumers' assessment of their eagerness and aptitude for learning new technologies. We adapted 17 of the items from Parasuraman's (2000) TRI and generated 30 new items to cover the breadth of insights identified in other research. To the extent possible, we followed the well-established multi-item marketing scale development procedures outlined by Churchill (1979). To ensure that the scale measures consumers' personal disposition towards technology rather than their understanding of technology's place in society as a whole, most items were written in the first person. For example, an item referring to technology's ability to enhance one's sense of control over daily life was written as "Technology gives *me* more control over my daily life" rather than as "Technology gives *people* more control over their daily lives." In addition, we were careful to avoid references to specific technologies, such as "online," so that the scale could apply to future new technologies, whatever they may be.

5. Quantitative scale development

Data were collected via two different methods. To develop the initial scale, an opt-in nationwide survey was administered to 567 adult United States residents via the Vanderbilt eLab online consumer panel (dataset 1, DS1 henceforth). Data from an additional 356 United States residents were collected approximately one month later by the same method as a hold-out sample for scale validation purposes (dataset 2, DS2 henceforth). Respondents in DS1 and DS2 were offered a chance to win $100 in exchange for their participation in the survey. One out of each 100 respondents was randomly selected for the $100 prize. As an added validation sample, 504 pencil and paper surveys were collected from a convenience sample of undergraduate students at a University in the Northwestern United States (dataset 3, DS3 henceforth) in exchange for course credit.

Respondents were instructed to answer each of the 47 initial TAP items, as well as an additional 30 items designed to explore past technology adoption behaviors across a range of technology domains[1]. In addition, demographic information was captured: age, gender, education level, ethnicity, country of birth, country of residence, English language proficiency. Respondents were included in the final analysis only if they answered all 47 of the TAP items. Consequently, 529, 335, and 499 respondents were retained in the three respective datasets. The average age of respondents was 46.7 in DS1 (range=18-86; median=48; SD=13.8), 45.6 in DS2 (range=18-84; median=47; SD=14.1), and 21.4 in DS3 (range=18-44; median=21; SD=3.0). In DS1, 65.8% of respondents were female, 34.9% were female in DS2, and 39.3% were female in DS3. The median respondent in DS1 completed at least some college; the median respondent in DS2 completed at least an Associate's degree; all respondents in DS3 were current Bachelor's degree students. Thus, not only the method of data collection, but also the properties of the respondent pools varied across the two validation samples.

5.1. Scale construction: Exploratory factor analysis

We employed exploratory factor analysis (EFA) on DS1 for scale development followed by confirmatory analysis (CFA) on DS2 and DS3 to determine model fit. We chose to first perform an EFA since CFA does not show how well items load on non-hypothesized factors and because misspecification of the number of factors will typically not be detected by CFA (Kelloway, 1995). Because one potential limitation of the TRI scale is high factor cross-loadings,

[1] The full survey is available upon request from the authors.

the present research is particularly concerned with creating a parsimonious scale that exhibits relatively low cross-loadings.

We conducted EFA in SPSS 19. Measures of sampling adequacy were strong (KMO = .952; Bartlett's Test of Sphericity sig. = .000). We used principal components extraction with a PROMAX (oblique) rotation, utilizing both a latent root criterion (Eigenvalues > 1) and analysis of the scree plot to assess the initial factor structure. These criteria strongly suggested either four or five factors. Separate EFAs were conducted extracting 3-6 factor structures. It was determined that the three factor structure omitted an important inhibiting technology adoption factor, while the six factor solution contained a factor specific to automated systems. Our primary consideration, therefore, was whether to include four or five factors. In analyzing the five factor solutions, two factors were rather highly negatively correlated ($ø = -.69$) and the items on these factors at face value appeared to be negatively related versions of one another. Furthermore, a four factor solution explained 71% of variance, while adding a fifth factor explained only an additional 0.1% of variance. Thus we determined that a four factor solution best fit our data. A four factor solution is also consistent with prior work on technology readiness (Parasuraman, 2000).

As parsimony was our goal, we employed stringent decision rules for item selection. First, we used an iterative process to eliminate items with lower than .6 loadings on any factor, consistently eliminating the item with the single lowest loading. Next, we removed items that loaded highly onto two factors, eliminating those which loaded at a level of .3 or greater on a non-primary factor (Hair, Anderson, Tatham, & Black, 1998). Items exhibiting low communalities (<.55) were also eliminated. Finally, some remaining items were eliminated based on high correlations with another item in the same sub-scale (>.70), as we surmised that these items were essentially measuring the same thing. Four items loaded onto the first factor, four onto a second factor, three onto a third factor, and three onto a fourth factor. The final EFA pattern matrix, along with Cronbach's alpha for each of the four factors is show in Table 1. Descriptive statistics for the final scale items are shown in Table 2.

[Table 1 here]

[Table 2 here]

5.2. Scale validation: Confirmatory factor analysis

Next, we attempted to validate the resulting 14 items and factor structure on the initial scale development sample (DS1), as well as two additional samples (DS2 and DS3) using CFA in AMOS 19. All items loaded significantly on their respective factors across each of the three samples, as shown in Table 3. In addition, the overall model fit was good in each of the three datasets according to the standard fit indices (Hu & Bentler, 1998):

(1) DS1: SRMR=.049; RMSEA=.061; CFI=.96; TLI=.95; χ^2 (71)=208.85, p=.000; χ^2/df=2.94.

(2) DS2: SRMR=.057; RMSEA=.059; CFI=.96; TLI=.95; χ^2 (71)=152.23, p=.000; χ^2/df=2.14.

(3) DS3: SRMR=.056; RMSEA=.052; CFI=.94; TLI=.92; χ^2 (71)=168.65, p=.000; χ^2/df=2.38.

The significant χ^2 for each of the three datasets is likely due to large sample sizes as χ^2 is almost always significant for $n > 200$. Notably, although the two validation samples were collected via different methods (DS2 collected electronically and DS3 collected via pencil and paper) and the average age of the two samples are quite different, our scale still provides a good fit in each sample, thus providing support for its veracity.

[Table 3 here]

Like the TRI, the TAP index includes two contributing factors and two inhibitors. For the TAP index, *optimism* and *proficiency* are contributors and *dependence* and *vulnerability* are inhibitors. A consumer's TAP score is equal to the sum of her average scores on each of the four factors, with inhibiting factors reverse coded. Only the TAP optimism factor is conceptually similar to a factor put forth in the TRI. The four TAP factors are described as follows:

Optimism is a belief that technology provides increased control and flexibility in life. This factor incorporates aspects of the perceived usefulness of technology to make life easier and allow us to do the things we want to do at convenient times. The optimism factor is similar to the factor of the same name identified in the TRI. However, the TAP optimism construct is distinct in that it is specific to beliefs about control and flexibility and does not include beliefs about increased efficiency as does the optimism construct in the TRI. In addition, the optimism items in the TAP index refer to how technology enhances the respondent's life rather than how it enhances the lives of generalized others.

Proficiency refers to confidence in one's ability to quickly and easily learn to use new technologies, as well as a sense of being technologically competent. Proficiency is identified as the second contributor rather than "innovativeness," as put forth in the TRI. This is perhaps not surprising given that new technologies have become more sophisticated over the last decade, and consumers' complexity expectations (Wood & Moreau, 2006) and degree of frustration (Strebel, et al., 2004) with these new technologies has likely increased in response. Given the ubiquity of technology in contemporary society, it stands to reason that consumers' confidence in their ability to effectively learn and use new technologies has now become more critical to their adoption propensity than their sense of being a technology pioneer (as per the TRI).

Dependence is a sense of being overly dependent on, and a feeling of being enslaved by, technology. Previously brought forth by Mick and Fournier (1998), this factor was not identified by the TRI. We conjecture that a heightened sense of dependence on technology by contemporary consumers is likely a response to technology's increased pervasiveness over the last decade. Indeed, many consumers now report an addiction to laptop computers, cell phones and wireless devices (e.g., *Success*, March 26, 2008; *CNN* July 1, 2007) and spending too much time on laptop computers and cell phones has even been identified as a leading cause of divorce in the United States (*Wall Street Journal*, January 11, 2011)!

Vulnerability refers to a belief that technology increases one's chances of being taken advantage of by criminals or firms. Unlike the "insecurity" factor identified in the TRI, which was defined as "distrust of technology and skepticism about its ability to work properly," vulnerability in the TAP index reflects a concern that technology will work *too* well for anyone using it for nefarious purposes. Thus, vulnerability measures the degree to which respondents believe that their odds of being victimized are increased by new technologies because the technologies facilitate exploitative practices. For example, a single unwise click on a spam email can lead to computer infection, stolen passwords, or even identity theft (*Economist*, November 20, 2010). We conjecture that as consumers become aware of potential malicious activities that technology gives rise to, their sense of vulnerability increases.

For each of the three datasets, inter-correlations among the TAP dimensions are shown in Table 4.

[Table 4 here]

As expected, the two contributing factors, optimism and proficiency, are positively correlated. The two inhibiting factors, dependence and vulnerability, are also positively correlated with one another. Both optimism and proficiency are negatively correlated with vulnerability, whereas each contributing factor is not strongly correlated with dependence. This finding is conceptually sound; there is no compelling reason to believe that feelings of enslavement or hyper-dependence on technology should necessarily be related to one's optimism about or feelings of proficiency in using technology.

To assess discriminant validity, we followed the technique recommended by Fornell and Larcker (1981). It was found that the correlation between pairs of sub-scales was less than the square root of the average variance extracted of the two constructs in all cases except for between dependence and vulnerability in DS2 (see diagonal of Table 4). Given the moderately high correlation between optimism and proficiency, as well as between dependence and vulnerability, we conducted additional tests of discriminant validity by collapsing the correlated dimensions to see if the model fit improved. In each case, the model fit did not improve by dropping to three dimensions from four, thus supporting our four factor structure. For example, collapsing optimism and proficiency into a single factor on DS1 produced worse SRMR (.072) and RMSEA (.118) fit scores, as did reducing dependence and vulnerability into a single factor (SRMR=.117, RMSEA=.108). Thus there is strong evidence that the contributing and inhibiting factors are related but not redundant.

6. Test of Overall Construct Validity: TAP Index

For a scale to exhibit construct validity, the measure must empirically demonstrate findings that are consistent with conceptual expectations (Cronbach & Meehl, 1955). Hence, the TAP index would exhibit construct validity if individuals with low total scores on the TAP (sum of average score on each of the four subscales, with inhibiting factors reverse coded) generally avoid technology relative to people with high scores. Consequently, we sought to show that, in accordance with empirical evaluations conducted during the development of the TAP index, an individual's score on the TAP would predict her usage and ownership of technology products and services. Our survey dataset included answers to a series of 21 yes/no items regarding respondents' use of technology-based services and ownership of high-tech products (smart phones, electronic books, robotic cleaning devices, etc.). To determine if mean TAP scores reliably predicted responses to each yes/no item, a series of logistic regressions were conducted. As shown in Table 5, significant support was found for the predictive ability and construct validity of the TAP index such that those who answered "yes" to usage behavior questions tended to have significantly higher TAP scores than did those who answered "no." Mean TAP scores of each group for each item are shown in Table 5.

[Table 5 here]

Our survey dataset also includes answers to seven items designed to gauge respondents' frequency of use of select technology-based offerings. Responses to these seven items were based on a 5-point scale anchored at 1 = never use and 5 = use more than once a month. For each of these items, frequency of use was regressed on the respondents' average scores on each of the four TAP factors using OLS regression. As shown in Table 6, we again find support for the predictive ability and construct validity of the TAP index such that it significantly predicts frequency of use behavior in accordance with conceptual expectations. In addition, in the majority of cases the subscales were independently predictive of frequency of use behavior. The positive coefficients for inhibiting factor dependence are conceptually sound as frequency of use and feelings of technological dependence are likely to be positively related.

[Table 6 here]

7. Conclusion

The objective of this research was to develop a parsimonious yet predictive measure of consumers' attitudes toward a varied and flexible concept of technology. Specifically we aimed to devise a measure of consumer's propensities to adopt technology that could adapt with the rapidly evolving array of high technology products and services. The results of our investigation suggest that a consumer's technology adoption propensity (TAP) can reliably be measured using a 14-item index consisting of two contributing (optimism and proficiency) and two inhibiting (dependence and vulnerability) factors. We show that the TAP index can predict consumers' technology usage behaviors across a range of high-tech products and services. We expect that as a more succinct and timeless measurement tool than prior scales designed for a similar purpose, the TAP index will prove to be a robust and useful scale for academics and practitioners alike.

From a theoretical standpoint, this research provides new insights into contemporary dispositional drivers and inhibitors of technology adoption. A belief that technology provides increased control and flexibility in life (optimism) and a sense of one's proficiency in learning and using technology both contribute to consumers' technology adoption. However, consumers concerns about technology also play a substantial role in technology adoption. Feeling overly dependent on technology and feeling vulnerable to malicious activities facilitated by technology each inhibit technology adoption. Clearly these dispositional factors interact with situational and offering-specific factors in determining whether and to what degree a consumer ultimately adopts a new technology.

A potential limitation of our scale development procedure is two of the three datasets used in the construction of the index were collected via a Web-based sample. One could argue that these individuals are inherently more technologically savvy than the average U.S. consumer and thus are relatively more likely to adopt new technologies than the general population, perhaps biasing the quantitative scale development results. However, recent estimates indicate that over ¾ of all Americans now use the Internet (*Internet World Stats*, January 2011, from http://www.internetworldstats.com/top25.htm). Moreover, individuals who have not yet adopted the Internet would likely simply score lower on the TAP index than other groups. This is perhaps one interesting avenue for future research.

Because of the pervasiveness of technology in contemporary consumers' lives, there are many applications for future research using the TAP index. One avenue would be to compare and contrast TAP scores across different cultures, countries, or world regions. Practitioners could use the TAP index to more readily identify potential slow or rapid adoption regions and alter sales forecasts or marketing mixes accordingly. Another potential avenue of research is to more fully explore the behavioral consequences of the inhibiting factors identified in this work. We conjecture that as the sophistication of technological products and services continues to increase, a heightened feeling of dependence on technology or an increased feeling of vulnerability may have lasting consequences on consumer well-being. For example, it would be interesting to investigate how consumers' well-being is impacted by their feelings of dependence on smart phones and other high-speed wireless devices.

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References

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Englewood Cliffs, N.J.: Prentice-Hall.

Alexander, D. L., Lynch, J. G., & Wang, Q. (2008). As time goes by: Do cold feet follow warm intentions for really new versus incrementally new products? *Journal of Marketing Research, 45* (3), 307-319.

Bruner II, G. C., & Kumar, A. (2005). Explaining consumer acceptance of handheld internet devices. *Journal of Business Research, 58* (5), 553-558.

Burke, R. R. (2002). Technology and the customer interface: What consumers want in the physical and virtual store. *Journal of the Academy of Marketing Science, 30* (4), 411-432.

Childers, T. L., Carr, C. L., Peckc, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of Retailing, 77* (4), 511-535.

Churchill, G. A., Jr. (1979). A paradigm for developing better measures of marketing constructs. *Journal of Marketing Research, 16* (1), 64-73.

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin, 52* (4), 281-302.

Darian, J. C. (1987). In-home shopping: Are there consumer segments? *Journal of Retailing, 63* (2), 163-186.

Davis, F. D. (1986). *A technology acceptance model for empirically testing new enduser information systems: Theory and results.* Massachusetts Institute of Technology, Cambridge, MA.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35* (8), 982-1003.

Dean, D. H. (2008). Shopper age and the use of self-service technologies. *Managing Service Quality, 18* (3), 225-238.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18* (1), 39-50.

Greco, A. J., & Fields, D. M. (1991). Profiling early triers of service innovations: A look at interactive home video ordering services. *Journal of Services Marketing, 5* (3), 19-26.

Gurran, J. M., & Meuter, M. L. (2005). Self-service technology adoption: Comparing three technologies. *Journal of Services Marketing, 19* (2), 103-113.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate data analysis* (Fifth Edition ed.). Upper Saddle River, N.J.: Prentice Hall.

Hoeffler, S. (2003). Measuring preferences for really new products. *Journal of Marketing Research, 40* (4), 406-420.

Hu, L.-t., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods, 3* (4), 424-453.

Karahanna, E., & Straub, D. W. (1999). The psychological origins of perceived usefulness and ease-of-use. *Information & Management, 35* (4), 237-250.

Kelloway, E. K. (1995). Structural equation modelling in perspective. *Journal of Organizational Behavior, 16* (3), 215-224.

Konuş, U., Verhoef, P. C., & Neslin, S. A. (2008). Multichannel shopper segments and their covariates. *Journal of Retailing, 84* (4), 398-413.

Lam, S. Y., Chiang, J., & Parasuraman, A. (2008). The effects of the dimensions of technology readiness on technology acceptance: An empirical analysis. *Journal of Interactive Marketing, 22* (4), 19-39.

Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003). The technology acceptance model: Past, present, and future. *Communications of AIS, 2003* (12), 752-780.

Meuter, M. L., Bitner, M. J., Ostrom, A. L., & Brown, S. W. (2005). Choosing among alternative service delivery modes: An investigation of customer trial of self-service technologies. *Journal of Marketing, 69* (2), 61-83.

Meuter, M. L., Ostrom, A. L., Bitner, M. J., & Roundtree, R. (2003). The influence of technology anxiety on consumer use and experiences with self-service technologies. *Journal of Business Research, 56* (11), 899-906.

Meuter, M. L., Ostrom, A. L., Roundtree, R. I., & Bitner, M. J. (2000). Self-service technologies: Understanding customer satisfaction with technology-based service encounters. *Journal of Marketing, 64* (3), 50-64.

Mick, D. G., & Fournier, S. (1998). Paradoxes of technology: Consumer cognizance, emotions, and coping strategies. *Journal of Consumer Research, 25* (2), 123-143.

Narayana, C. L. (1977). Graphic positioning scale: An economical instrument for surveys. *Journal of Marketing Research, 14* (1), 118-122.

Norton, J. A., & Bass, F. M. (1987). A diffusion theory model of adoption and substitution for successive generations of high-technology products. *Management Science, 33* (9), 1069-1086.

Pagani, M. (2004). Determinants of adoption of third generation mobile multimedia services. *Journal of Interactive Marketing, 18* (3), 46-59.

Parasuraman, A. (2000). Technology readiness index (tri): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2* (4), 307-320.

Stanton, J. M., Sinar, E. F., Balzer, W. K., & Smith, P. C. (2002). Issues and strategies for reducing the length of self-report scales. *Personnel Psychology, 55* (1), 167-194.

Strebel, J., O'Donnell, K., & Myers, J. G. (2004). Exploring the connection between frustration and consumer choice behavior in a dynamic decision environment. *Psychology & Marketing, 21* (12), 1059-1076.

Thompson, D. V., Hamilton, R. W., & Rust, R. T. (2005). Feature fatigue: When product capabilities become too much of a good thing. *Journal of Marketing Research, 42* (4), 431-442.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27* (3), 425-478.

Wood, S. L., & Moreau, C. P. (2006). From fear to loathing? How emotion influences the evaluation and early use of innovations. *Journal of Marketing, 70* (3), 44-57.

Zhu, Z., Nakata, C., Sivakumar, K., & Grewal, D. (2007). Self-service technology effectiveness: The role of design features and individual traits. *Journal of the Academy of Marketing Science, 35* (4), 492-506.

Table 1

EFA Pattern Matrix

Item	Component			
	1	2	3	4
1. Technology gives me more control over my daily life.	.85			
2. Technology helps me make necessary changes in my life.	.85			
3. Technology allows me to more easily do the things I want to do at times when I want to do them.	.84			
4. New technologies make my life easier.	.81			
5. I can figure out new high-tech products and services without help from others.		.94		
6. I seem to have fewer problems than other people in making technology work.		.84		
7. Other people come to me for advice on new technologies.		.79		
8. I enjoy figuring out how to use new technologies.		.77		
9. Technology controls my life more than I control technology.			.85	
10. I feel like I am overly dependent on technology.			.84	
11. The more I use a new technology, the more I become a slave to it.			.78	
12. I must be careful when using technologies because criminals may use the technology to target me.				.86
13. New technology makes it too easy for companies and other people to invade my privacy.				.83
14. I think high-tech companies convince us that we need things that we don't really need.				.69
Cronbach's α	.87	.87	.78	.73

Note: all loadings less than .30 are not shown.

Table 2

Descriptive Statistics for TAP Index Items

	Minimum	Maximum	Mean	Std. Dev.	Skewness	Kurtosis
1…gives me control…	1	5	4.03	.93	-.95	.95
2…helps me make...changes …	1	5	3.67	.98	-.60	.24
3...more easily do…things …	1	5	4.17	.84	-1.04	1.42
4…make my life easier.	1	5	3.92	.94	-.73	.28
5. I can figure out…	1	5	3.47	1.14	-.44	-.49
6…fewer problems..making [it] work.	1	5	3.64	1.07	-.52	-.31
7…people come to me for advice…	1	5	3.04	1.30	-.10	-1.07
8. I enjoy figuring out how to use…	1	5	3.67	1.15	-.64	-.26
9…controls my life…	1	5	2.43	1.08	.41	-.50
10…I am overly dependent…	1	5	2.77	1.15	.13	-.81
11…I become a slave to it.	1	5	2.89	1.14	.00	-.76
12…criminals may...target me.	1	5	3.30	1.14	-.30	-.66
13…invade my privacy.	1	5	3.44	1.11	-.42	-.38
14…things that we don't really need.	1	5	3.48	1.16	-.44	-.57

Table 3

Confirmatory Factor Loadings: DS1, DS2, DS3

Item	Factor 1 (Optimism)	Factor 2 (Proficiency)	Factor 3 (Dependence)	Factor 4 (Vulnerability)
1…gives me control…	.78, .80, .65			
2…helps me make...changes …	.73, .77, .49			
3...more easily do…things …	.80, .82, .59			
4…make my life easier.	.85, .84, .64			
5. I can figure out…		.79, .75, .81		
6…fewer problems..making [it] work.		.81, .86, .78		
7…people come to me for advice…		.78, .77, .71		
8. I enjoy figuring out how to use…		.81, .77, .73		
9…controls my life…			.73, .65, .55	
10…I am overly dependent…			.70, .70, .52	
11…I become a slave to it.			.78, .72, .75	
12…criminals may...target me.				.61, .41, .38
13…invade my privacy.				.77, .61, .53
14…things that we don't really need.				.70, .67, .51

Note: DS1 loadings appear first in each cell, D2 loading second, DS3 loadings third.

Table 4

Correlations among Dimensions: DS1, DS2, DS3

	Factor 1 (Optimism)	Factor 2 (Proficiency)	Factor 3 (Dependence)	Factor 4 (Vulnerability)
Factor 1 (Optimism)	.79, .81, .59			
Factor 2 (Proficiency)	.67, .58, .36	.80, .79, .76		
Factor 3 (Dependence)	-.02, .00, .15	-.02, .06, -.12	.73, .69, .61	
Factor 4 (Vulnerability)	-.42, -.40, -.28	-.42, -.24, -.24	.44, .67, .44	.70, .57, .48

Note: DS1 loadings appear first in each cell, D2 loading second, DS3 loadings third.
Note: The square roots of the average variance explained appear on the diagonal of this table

Table 5

TAP Score Mean Comparison (all datasets)

Have you ever done the following:	% Answering Yes	TAP Score		χ^2
		YES	NO	
1. Booked travel arrangements online	78.6	1.41	0.77	19.76[a]
2. Purchased an item costing over $100 online	88.4	1.42	0.19	45.14[a]
3. Checked information on your bank account online	91.4	1.36	0.43	19.65[a]
4. Moved money between bank accounts online	78.0	1.47	0.58	39.58[a]
5. Applied for a credit card online	43.9	1.74	0.91	48.51[a]
6. Signed up for any type of insurance online	29.9	1.85	1.03	40.08[a]
7. Signed up for telephone or cable service online	39.0	1.86	0.90	62.91[a]
8. Signed up for any household utility, such as gas, electric, or cable services online	36.9	1.81	0.96	47.95[a]
9. Paid a bill online	86.0	1.40	0.51	27.44[a]
10. Owned a Kindle or similar electronic book device	14.5	1.98	1.16	23.51[a]
11. Owned access to an electronic book to read on your computer	33.9	1.86	0.98	49.18[a]
12. Owned audio files such as music or audio books online	68.6	1.58	0.61	59.09[a]
13. Owned or rented video media such as a movie or TV show online	60.2	1.66	0.70	65.27[a]
14. Owned a cell phone with a digital camera	83.2	1.42	0.57	29.24[a]
15. Owned a "smart phone" with Internet access	49.0	1.74	0.84	58.46[a]
16. Owned a robotic cleaning device such as a Roomba	9.9	1.64	1.24	4.02[b]
17. Owned an iPad	8.5	1.94	1.22	11.30[a]
18. Filed your taxes online	53.7	1.55	0.96	24.90[a]
19. Used an online bank that **did not** have a brick and mortar location	23.2	1.87	1.11	29.11[a]
21. Does your current vehicle include voice activation technology for cell phone use or interfacing with the stereo or comfort control systems?	12.6	1.84	1.20	12.78[a]
22. If no, is this a feature you hope to have on your next vehicle?	50.3	1.70	0.85	49.08[a]

[a] difference significant at p<.01; [b] difference significant at p<.05

Table 6

Frequency Items Regressed on Factor Scores (all datasets)

Please indicate how frequently you use/do each of the things below:	Optimism Coefficient	Proficiency Coefficient	Dependence Coefficient	Vulnerability Coefficient	Model F (df=4)
1. Use a GPS system:	.12[c]	.30[a]	.19[a]	-.21[a]	27.38[a]
2. Use "self check-out" at stores:	.06	.16[a]	.07	-.14[a]	10.36[a]
3. Deposit over $100 at an ATM:	.20[a]	.20[a]	.18[a]	-.09[c]	17.90[a]
4. Video calling such as Skype:	.01	.26[a]	.24[a]	-.24[a]	21.70[a]
5. Voice over IP calling:	.07	.40[a]	.10[b]	-.07	39.02[a]
6. Online data backup services:	.18[a]	.27[a]	.13[a]	-.15[a]	30.92[a]
7. Buy an item at a vending machine or pay a parking meter using your cell phone:	.09[b]	.04	.15[a]	-.01	10.55[a]

[a] significant at p<.01; [b] significant at p<.05; [c] significant at p<.10