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2009

Incorporating Choice into Models of Technology Adoption

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ABSTRACT

Research investigating technology adoption has assumed that the individual accepting the technology has only one technology in mind when making their adoption decision. Models such as the UTAUT, TAM, PCI assume that the decision whether or not to adopt the technology occurs within a bubble – there is no explicit understanding in these models that no other technologies exist outside of the one technology under study and that a user has no other acceptance perceptions towards any other comparable technologies. Drawing upon prior work from the marketing literature on choice, we suggest three theoretical approaches to conceptualizing choice and three mathematical approaches to measuring the choice comparison. We report upon a study of technology choice among 60 MBA students, who were given an open source and online spreadsheet application to use for one-month. We conclude by discussing the implications of our findings and suggest new avenues of research on technology choice.

KEYWORDS

Adoption, technology choice

INTRODUCTION

Research investigating technology adoption has assumed that the individual accepting the technology has only one technology in mind when making their adoption decision. Models such as the Unified Theory of Acceptance and Use of Technology (UTAUT), Technology Acceptance Model (TAM), and the Perceived Characteristics of Innovations (PCI) assume that the decision whether or not to adopt the technology occurs within a bubble – that no other technologies exist outside of the one technology under study and that a user has no other acceptance perceptions towards any other comparable technologies. Yet, practical experience suggests that all individuals, while going through the process of deciding which technology to utilize are either implicitly or explicitly comparing the candidate technology to others.

Consider a scenario where a salesperson carries a laptop, wi-fi enabled Personal Digital Assistant (PDA), cell phone with web surfing capabilities, and a Blackberry device. Given these choices, which device will the user select to check e-mail if the airport offers free wi-fi access? Which device is used to access the web? And what motivates the salesperson to select a particular device over another that is selected? *If we assume* that all of the technologies are similar in the fit of the technology to the task at hand, then what is the basis of the choice?

From a research perspective, traditional approaches to understanding the technology adoption decision are technology-centric rather than human-centric – that is, the focus is on understanding perceptions towards one technology rather than how a human selects that technology within a portfolio. In other words, our current approaches to understanding technology adoption neglect the choice that a user makes and only focuses on ipso facto acceptance perceptions that are a result of that choice and therefore could not answer the questions posed in the above scenario. These limitations are exemplified in the model that will be used in this paper – the Perceived Characteristics of Innovations (PCI) (Moore et al. 1991) and (Rogers 1995), which argues that perceptions of a target system determine usage behavior. Nonetheless, whether the focus is on perceptions of one technology, there is no comparison explicitly made within any of these models to assess if one technology better services the individual better than the others.

In contrast, this paper will focus on choice, arguing that a user decides which technology to use based upon a comparison of alternatives. We are not making a decision on the appropriateness of the task to the technology (or a Task-Technology Fit perspective), rather, we are assuming that all of the technologies fit the task at hand and that there are competing alternatives. We are therefore specifically interested in the decision of whether or not to adopt (or *use*) a technology. Thus, the objective of this paper is to incorporate choice into the PCI model of technology acceptance. The remainder of this paper will proceed as follows. First, previous work in the area of acceptance using the PCI model will be discussed. A theoretical framework of choice will then be presented and integrated into PCI model of technology acceptance. The results from an empirical study will then be presented. Finally, conclusions will be offered and the implications of the study will be discussed.

LITERATURE REVIEW

The diffusion of innovation approach (based upon diffusion research (Rogers 1995) claims that there are fundamental characteristics of a new technology that promote its usage and "adoption." This approach argues that there are eight characteristics of innovations that influences acceptance: the *relative advantage* of the system over its precursor, the *compatibility* of the innovation with the users' work patterns, the ability to *try out* an innovation, the *ease of use* of the innovation, the *visibility* of the innovation, the *demonstrated results* from using the innovation, the *image* associated with using the innovation, and the *voluntariness* of use. Moore & Benbasat (1991) argued that took the characteristics of innovations and argued that these are not absolute, but perceptional, thus, originating the Perceived Characteristics of Innovations. The diffusion view specifies "that adopters should have more positive perceptions of using the (innovation) than non-adopters and thus score higher on the scales developed" (Moore et al. 1991).

While the TAM and its' constructs have been widely used in the past, the Moore and Benbasat PCI scales have been widely neglected in their actual implementation. "Despite its' theoretically rich development and fairly rigorous initial testing, the full set of PCI belief constructs has received relatively little empirical attention" (Plouffe et al. 2001). Further, while the original study attempted to uncover the differences between adopters and nonadopters without using deterministic models of human behavior, subsequent research has studied the phenomenon by relying upon studies that use causal models, determining the ability of the PCI scales to predict user acceptance. In subsequent work on the development of the PCI scales, Moore and Benbasat tested the ability of the constructs to predict usage behavior of individuals (Moore et al. 1996). They concluded that the most significant perceptions that had an effect on degree of use were ease of use, relative advantage, and compatibility (a finding also confirmed by (Gagliardi et al. 1995)). Relative advantage and compatibility were also found to be significant predictors of intention to adopt a group support system (Chin et al. 1995).

While early research validated the predictiveness of the characteristics in isolated studies, research has sought to compare the TAM to the PCI. Recent research has found (Plouffe et al. 2001) that the PCI belief constructs explain more variance in adoption intent than the TAM suggests, but also suggest that ease of use is not as significant as the TAM suggests.

PCI research has recently begun looking at the acceptance process longitudinally. Agarwal and Prasad found that initial use is shaped by the characteristics of compatibility, visibility, trialability, and voluntariness and that this initial use allows for the development of feelings of relative advantage and result demonstrability, which helps to build long-term usage (Agarwal et al. 1997). Karahanna and colleagues suggests that the initial use is shaped by social factors (such as visibility), while subsequent usage is dependent more upon attitude (Karahanna et al. 1999).

The original model of the PCI constructs assumes that each perception independently contributes to towards intention. This view has recently been updated to account for the emergence of perceptions (Compeau et al. 2007) and, in the current paper, we will adopt the modified PCI model to understand technology choice. While the proposed model outlined how each of the PCI constructs is inter-related, we have instead opted for a reduced set of PCI factors. Specifically, for the sake of parsimony, we have selected to focus only on the direct impacts and those perceptions that directly influence the direct impacts. While we acknowledge this as a potential limitation (which we will expand upon later), we suggest that the

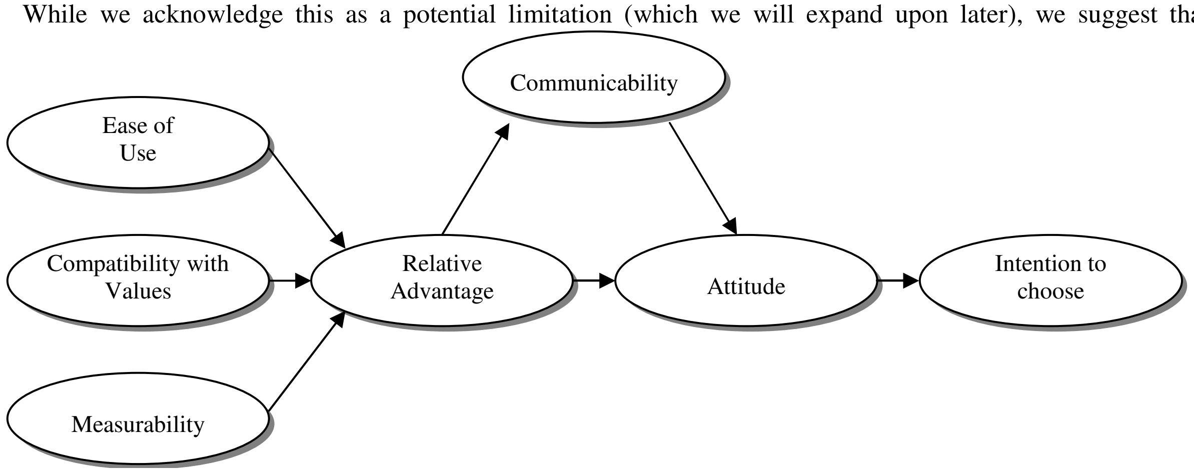

Figure 1. Research Model

variables outlined below are the *most* likely to impact our dependent variable due to their theoretical proximity to the behavior that we are seeking to understand – choice. We have outlined our proposed research model above in Figure 1. Next, we will turn to a discussion of how we will integrate choice into our nomological network.

Integrating Comparisons in to the PCI

Given the limitations within the current views of technology adoption in understanding individual choice of the technology, a framework is needed to guide the development of the new approach. To aid in the understanding of comparisons, we draw from the marketing literature, specifically the Mental Comparison Model (Dabholkar 1994) as a backdrop for the integration. According to the Mental Comparison Model, an individual attempting to choose between alternative products (or services) engages in a comparison of the products vis-à-vis one another, in terms of the beliefs, expectancy, attitudes, and intentions towards using the product. However, using the Mental Comparison Model requires a researcher to understand the product and the context of choice and that, depending upon the comparison, the researcher must choose whether a belief, expectancy, attitude, or intention comparison model would be most appropriate. In other words, these are four independent, non-integrated models of choice.

For the purpose of this research, we are not focused upon selecting one of these four particular comparison models, but to draw upon the theoretical rationale and justification for choice and to integrate this approach into the PCI model. The central tenant for the Mental Comparison Model is that an individual, when deciding upon a product will compare the products within the portfolio of choice along a variety of dimensions. In our case, an individual, when deciding which technology to engage within a given context, will compare the attributes of the technologies vis-à-vis one another, in addition to the direct perceptions of the individual technologies themselves. It is the salience of the perceptions that will dictate the selection of the individual technology. We have depicted this graphically in Figure 2 below. We posit that an individual makes a two-step assessment. In step 1, the individual assesses their perceptions of the individual technology for each of the attributes within the PCI inventory. In step 2, the individual assesses the perceptions for each technology relative to one another for each of the attributes.

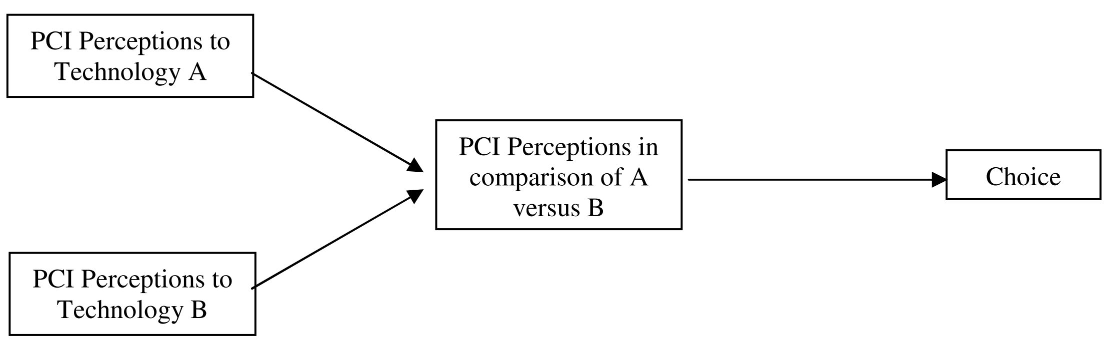

Figure 2. Framework of Technology Choice

Theoretically, the aforementioned approach to choice assumes an information-processing view of the human cognition – that an individual will simplify their decision-making by making comparisons on dimensions that are deemed salient to that individual and that an individual will seek the comparison that will mitigate the cognitive load. Taking the perceptions of the individual technologies along each of the dimensions enumerated in the PCI approach as *input*, the individual then *processes* these perceptions relative to one another to produce the choice as *output*. But, theoretically, how do we interpret and measure the comparison? We will explore this next.

Theorizing the Comparison

Based upon the previous discussion, we posit that an individual, when given a choice between alternative technologies, compares their perceptions of technology A versus technology B along the dimensions of the PCI. As an exploratory study, we are interested in understanding whether the salience of the comparison factors is consistent with those of the direct intention-based perceptions;, nonetheless, we must explore how to theorize the comparison. To theorize this comparison, we will draw upon and extend the work of Dabholkar's Mental Comparison Model. Dabholkar (1994) highlighted four potential models of choice. We we will utilize two of these four (namely the belief comparison model and the expectancy comparison model) and outline our own contribution – the attitude comparison model.

The difference between the two has to do with when the individual makes the comparison. Does a user first evaluate the perceptions towards each technology without reference to the other or does a user compare the perceptions relative to one another? How do these either separate or joint perceptions influence attitude? And, is attitude a function of a comparison or separate beliefs? How and when an individual assesses the technology separates our three models of choice. We – we will review each of these models next.

Attitude Comparison Model

According to the attitude comparison model of choice, users first assess perceptions towards each technology separately. These independent assessments lead to the creation of attitudes - with– separate attitudes towards each technology alternative. Based upon each of these separate attitudes, the user formulates an intention to select one technology over another.

Expectancy Comparison Model

According to the expectancy comparison model of choice, users first assess perceptions towards each technology separately. Based upon these two separate perceptions, the users then compare the options and develop a comparison attitude. This joint attitude then shapes the intention to select one technology over the other. In contrast to the attitude comparison model, the user holds separate perceptions of the technologies, but they possess a single comparison attitude of the technologies.

Belief Comparison Model

According to the belief comparison model of choice, users do not hold separate perceptions; instead, – everything is a comparison of one technology versus another. First, the user compares perceptions for each of the options to one another. Then, having formulated these perceptions of one technology over another, the next step is that the user forms an attitude towards one technology over another and, then outlines an intention to select the technology corresponding to this attitude.

Comparing the Three Approaches

The three approaches to technology choice are outlined in Table 1 below. Each approach differs on when the user makes the choice decision – is it during the perception stage? The attitude stage? Or only when the intention is formed. These three competing approaches offer us three lenses through which to understand the formulation of technology choice.

Approach	Perceptions	Attitude	Intention
Attitude Comparison Model	$\text{Perceptions}_{\text{TECH A}}$ $\text{Perceptions}_{\text{TECH B}}$	$\text{Attitude}_{\text{TECH A}}$ $\text{Attitude}_{\text{TECH B}}$	$\text{Intention}_{\text{CHOICE}}$
Expectancy Comparison Model	$\text{Perceptions}_{\text{TECH A}}$ $\text{Perceptions}_{\text{TECH B}}$	$\text{Attitude}_{\text{COMPARISON}}$	$\text{Intention}_{\text{CHOICE}}$
Belief Comparison Model	$\text{Perceptions}_{\text{COMPARISON}}$	$\text{Attitude}_{\text{COMPARISON}}$	$\text{Intention}_{\text{CHOICE}}$

Table 1. Approaches to Technology Choice

RESEARCH CONTEXT

In Fall 2008, 75 MBA students who were enrolled in an Introduction to IS course at a university in the Southeastern United States were required as part of the course to participate in a research study designed to understand technology choice. The first author was the instructor for two sections (38 students in one section and 37 in another) of the course and required the students to complete the research requirements as part of their grade. The research context that we selected to utilize was the choice of which spreadsheet application that the student would use for future spreadsheet needs.

Two spreadsheet solutions were used by each student for a period of one month. For the first month, half of the students used Zoho (www.zoho.com); Zoho is an online provider of a spreadsheet application (Zoho Sheets). Simultaneously, the other half of the students were required to download, install, and use Open Office Calc (http://www.openoffice.org/), an open source spreadsheet application. After a month, the students switched and used the other application, thus giving experience with both applications.

At the beginning of the month, the instructor provided training onin the application that the student was required to use – 30 minutes of in-class time was devoted to training students about the software. The training allowed the instructor to provide the student with the relevant functionality of the technology needed to complete the assignments (detailed next) using the application. Following the training, each student completed an "initial impressions" survey of each technology.

The students were given a weekly assignment to complete using the spreadsheet application, with – each student completed a total of eight assignments (4 using Zoho and 4 using Open Office Calc). Each assignment asked the student to complete a business analysis on data and required the student to use the application for approximately one hour. After completing the weekly assignments, the students completed a "final impressions" survey for each technology. In addition, after using both applications, the students completed a "comparison" survey, where they were asked to assess the differences between the two technologies. To receive full credit for completing the class assignment, the student was required to: (a) complete the "initial impressions" survey for each technology; (b) complete the "final impressions" survey for each technology; (c) complete the "comparison" survey; and (d) complete all eight assignments. Sixty students fulfilled these criteria and were included in our data set.

Measurement

With the proposed research model in mind (Figure 1), our next step was to clarify the measurement of the constructs. To measure the constructs, we generated items that corresponded to the proposed theoretical model (items were based on Compeau, et al, 2007). For each construct, we selected items previously validated within the literature, only changing the wording to reflect our research context. Regardless of the three approaches to understanding choice, our dependent variable (intention to choose) remained the same. To measure intention, we selected a Likert scale where we asked an individual to assess their intention to select Zoho over Open Office Calc. In all questions of choice (which we will detail next), Zoho was always the option that was used as the basis of comparison.[1]

Measuring the Comparisons

Previous work on understanding comparisons between perceptions has proposed competing approaches to modeling these differences, namely: (1) Direct perceptions; (2) Subtraction; and (3) Ratios. These three approaches were previously employed by Dabholkar (1994) and we utilized these three as well for the purpose of our investigation. Each approach differs theoretically and mathematically, thus giving us additional insight into our understanding of user choice.

The direct perception approach theorizes that, if the user makes their own comparison, then the best approach is to directly ask about this comparison. From a measurement perspective, this calls on a user to compare one technology over another. To model this approach, in all of our perceptions and attitude questions, we asked users about their views of Zoho over Open Office Calc.

The subtraction approach theorizes that individuals look at each option as "not being as good as" another or, that individuals are mentally subtracting a set of features when they compare between various options. Mathematically, this would call on a researcher to understand the perception towards technology A and the perception towards technology B and then subtract one from another to arrive at a difference score. To model this approach, we subtracted the perception of each item for Open Office Calc from the Zoho score to arrive at individual perception subtraction items.

The ratio approach theorizes that individuals examine options based on a comparison of a difference – e.g. technology A has "twice as many" features as technology B or technology A is "half as good" as technology B. Mathematically, this would require on a researcher to understand each independent perception towards the technologies and then create a ratio of one over another. To model this approach, we calculated the ratio of the perception of Zoho to the perception of Open Office Cal for each perception and attitude item.

With the three choice models and the three difference approaches, we formulated 9 models to analyze. Each of the three choice approaches was modeled under the condition for each of the three difference approaches, thus providing us insight on to how a user makes a choice. We will next turn to a discussion of our data analysis.

[1] Due to space limitations, specific items were not included. Items are available upon request.

Data Analysis

We analyzed the data using structural equation modeling. Given our small sample size, we were unable to use a covariance-based approach (MacCallum et al. 1993) and thus selected the partial least squares (PLS) approach, specifically PLS-Graph (version 3.00, build 1126) software. This approach allowed us to understand each of the nine models of technology choice.[2]

Measurement Model

The first step in a PLS analysis is the analysis of the measurement (or outer) model. The analysis was completed by first examining the adequacy of the measures to ensure that the items measured the constructs as they were designed. As a guideline, Chin (1998, p. 325) states, "Standardized loadings should be greater than 0.707....But it should also be noted that this rule of thumb should not be as rigid at early stages of scale development. Loadings of 0.5 or 0.6 may still be acceptable if there are additional indicators in the block for comparison basis." (Chin 1998) Using this criterion as an assessment, eleven items were eliminated from the Attitude and Expectancy Comparison Model (2 from Relative Advantage; 1 from Compatibility with Values; 3 from Ease of Use; 2 from Communicability; 1 from Measurability; and 1 from Attitude) and twelve from the Belief Comparison Model (the above 11 with the addition of 1 from compatibility with values).

Second, to determine whether the items loaded on other constructs, as well as on their theorized construct, we computed cross-loadings. For cross-validated items to be included in the finalized data set, the loading must be greater on the intended construct than on any other constructs. Consequently, on determining that none of the items loaded higher on any construct other than the intended construct, we included all the items. [3]

Using the loadings from the constructs in the model, we created composite reliabilities for the constructs in the model. Table 2 below shows the composite reliabilities for each construct, as well as. We also computed the average variance extracted and the correlations between the constructs. A comparison of and compared the square root of the average variance extracted with the correlations among constructs to ensure that, on average, each construct was more highly related to its own measures than to other constructs (Chin, 1998, p. 327). [4]

Direct Perceptions	Zoho	Calc
Attitude	0.973	0.978
Communicability	0.92	0.911
Compatibility	0.952	0.935
Ease of Use	0.96	0.957
Measurability	0.923	0.963
Relative Advantage	0.975	0.974

Comparisons	Direct	Subtract	Ratio
Intention	0.98	0.99	0.978
Attitude	0.962	0.966	0.953
Relative Advantage	0.981	0.965	0.962
Compatibility	0.968	0.845	0.894
Ease of use	0.964	0.942	0.916
Communicability	0.876	0.838	0.874
Measurability	0.913	0.928	0.952

Table 2. Composite Reliabilities

[2] The largest number of items on one construct is six and, using the "rule of 10" approach to PLS, with 60 respondents, there is adequate sample size to test for significance
[3] Due to space restrictions, we have not included the loadings or cross-loadings in the text
[4] Due to space restrictions, we have not included this table in the text

Structural model

Table 3 presents the results of the data analysis using PLS-Graph. To determine the statistical significance of the paths, the bootstrapping procedure with 100 samples was used – all results are significant at $p < 0.005$. To understand the nature of technology choice, we will first analyze the results within choice approach (comparing the comparisons) and within comparisons (comparing the choices); as well as across choice and across comparison.

	Expectancy Comparison	Expectancy Comparison Subtraction	Expectancy Comparison Ratio	Belief Comparison	Belief Comparison Subtraction	Belief Comparison Ratio	Attitude Comparison	Attitude Comparison Subtract	Attitude Comparison Ratio
EOU → RA	Calc 0.677 Zoho 0.684	Calc 0.676 Zoho 0.684	Calc 0.676 Zoho 0.684	0.824	0.628	0.668	Calc 0.677 Zoho 0.684	Calc 0.677 Zoho 0.684	Calc 0.677 Zoho 0.684
Value Compatibility → RA	Calc 0.183 Zoho ns	Calc 0.182 Zoho ns	Calc 0.182 Zoho ns	ns	ns	ns	Calc 0.182 Zoho ns	Calc 0.182 Zoho ns	Calc 0.182 Zoho ns
Measurability → RA	Calc -0.305 Zoho ns	Calc -0.305 Zoho ns	Calc -0.305 Zoho ns	ns	ns	ns	Calc -0.304 Zoho ns	Calc -0.304 Zoho ns	Calc -0.304 Zoho ns
RA r^2	Calc 0.695 Zoho 0.485	Calc 0.695 Zoho 0.485	Calc 0.694 Zoho 0.485	0.724	0.441	0.479	Calc 0.694 Zoho 0.485	Calc 0.694 Zoho 0.485	Calc 0.694 Zoho 0.485
RA → Communicability	Calc ns Zoho 0.563	Calc ns Zoho 0.262	Calc ns Zoho 0.259	ns	ns	0.223	Calc ns Zoho 0.260	Calc ns Zoho 0.260	Calc ns Zoho 0.260
Communicability r^2	Calc 0.011 Zoho 0.066	Calc 0.008 Zoho 0.069	Calc 0.009 Zoho 0.067	0.023	0.013	0.050	Calc 0.012 Zoho 0.068	Calc 0.012 Zoho 0.068	Calc 0.012 Zoho 0.068
RA → Attitude	Calc -0.365 Zoho 0.563	Calc -0.672 Zoho 0.738	Calc -0.569 Zoho 0.728	0.794	0.798	0.807	Calc 0.824 Zoho 0.751	Calc 0.824 Zoho 0.751	Calc 0.825 Zoho 0.751
Communicability → Attitude	Calc ns Zoho 0.268	Calc ns Zoho 0.192	Calc ns Zoho 0.240	0.123	ns	0.105	Calc 0.123 Zoho 0.181	Calc ns Zoho 0.181	Calc ns Zoho 0.181
Attitude r^2	0.415	0.729	0.656	0.675	0.677	0.699	Calc 0.716 Zoho 0.668	Calc 0.716 Zoho 0.668	Calc 0.716 Zoho 0.667
Attitude → Intention	0.871	0.657	0.607	0.875	0.657	0.607	Calc -0.430 Zoho 0.634	Calc -0.663 Zoho 0.528	Calc -0.586 Zoho 0.667
Intention r^2	0.758	0.432	0.368	0.765	0.431	0.368	0.385	0.459	0.425

Table 3. Research Results

First, within expectancy comparison approach, we see that the highest r-squared is for the direct comparison (0.758), followed by subtraction (0.432) and then ratio (0.368). The attitude – intention relationship followed a similar pattern, with the highest being the direct comparison (0.871); subtraction (0.657); and ratio (0.607). This pattern was not consistent, however, across all of the relationships in the model – the highest attitude r-squared was for subtraction (0.729); followed by ratio (0.656); and then direct comparison (0.415). We attribute this finding to the antecedent findings, with both relative advantage and communicability having differential impacts on attitude depending upon the approach. Further analysis of the antecedents reveals a pattern of differences between Calc and Zoho with the relationships between value compatibility and relative advantage; measurability and relative advantage; relative advantage and communicability; and relative advantage and attitude. The only similar relationship between the two was ease of use to relative advantage.

Similar to expectancy comparison approach, within the belief comparison approach, we also observed that the highest r-squared was for the direct comparison (0.765), followed by subtraction (0.431), and then ratio 0.368). The attitude – intention relationship was similar to the expectancy comparison, however the attitude r-squared were not significantly different across the three comparison options. The relative advantage to attitude relationship was inverse from the other analysis within the belief comparison approach – the highest relationship was found in ratio (0.807); then subtraction (0.798); and direct perceptions (0.794), yet these were not statistically significant differences. The non-significance of the various perceptions for both Zoho and Calc influenced the belief comparison approach, causing non-significant relationships for a number of paths, including value compatibility to relative advantage; measurability to relative advantage; and relative advantage to communicability (with the exception of the ratio approach).

Next, the attitude comparison approaches yielded a different pattern from the other two choice approaches – the highest r-squared was from subtraction (0.459); followed by ratio (0.425); and direct comparison (0.385). While the intention r-squared was different across the different comparisons, the attitude r-squared results were similar (Calc: 0.716 and Zoho: 0.715). The difference between the different choices was the attitude – intention relationship.

Analyzing both choice and comparison approaches simultaneously, the highest intention r-squared was for the belief comparison, direct perception approach (0.765), followed by the expectancy comparison, direct perception approach (0.758). Following these two models, there was a gap until the following: attitude comparison subtract (0.459); expectancy comparison subtract (0.432); belief comparison subtract (0.431); and attitude comparison ratio (0.425). The last set of models also grouped together: attitude comparison, direct perceptions (0.385); expectancy comparison ratio and belief comparison ratio (0.368).

DISCUSSION

Given the lack of statistical significant difference between the top two models (namely the belief and expectancy comparison approaches), our findings are not conclusive on the point in which an individual makes the choice selection. However, if we analyze the trend across all nine approaches, the expectancy approach tends to be higher than the belief comparison. This trend allows us to conclude that the best predictor of choice derives from the belief comparison approach. Our conclusion is strengthened by the finding that the direct perception measurement was the most significant predictor of intention across all of the choice approaches. Asking an individual directly about the comparison was more significant than mathematically calculating either the subtraction or the ratio from the independent technology perceptions. Taken together, we therefore conclude that understanding technology choice is a relative process for an individual from the beginning of the perception formulation through the intention to choose.

Nonetheless, while we have found that our best models were able to predict a great deal of variation in the intention to select one technology over another, the number of non-significant path loadings suggests that more research is needed to understand the factors that individuals use as the basis of comparison. While we have integrated choice in to the PCI approach, we suggest that additional research should investigate whether our current set of technology perception factors are germane in the context of choice.

We suggest that additional factors that are significant in the context of understanding technology adoption for a single technology may lack the power to explain choice. We posit that the lack of statistically significant paths is not a function of low sample size, but rather that the choice comparison is a more complex decision than a singular adoption and that additional work is needed to better understand this process. We highlight the need to delve deeper in to this process to understand additional factors that may be considered.

Beyond additional factors, we also suggest that additional work should investigate the role of task in technology selection. While we have assumed (as articulated in the introduction) that all of the candidate technologies are appropriate for the task, what if this assumption is removed? Additional work should investigate how varying tasks alter the choice decision.

Next, we have selected a specific model with which to integrate choice (namely the PCI approach) and, while have not fully investigated the full PCI model suggested by Compeau, et al (2007), we recognize that adoption decisions do not occur in a vacuum, but rather within a socio-technical context. We therefore highlight the need to broaden our simple approach to understand facilitating conditions and other organizational factors that shape the choice decision. We suggest that additional work should help to understand the broader factors that shape technology choice.

Finally, we have limited our choice decision to two technologies. We suggest that most technology choice decisions occur with more than two options and therefore suggest the need to better understand the choice process when more than two options are available. In the case of a portfolio, how are decisions made? Does the nature of the choice decision change when there are more options available? While our work is a beginning towards understanding the choice decision, we encourage other researchers to draw upon our findings to begin investigating the complexity of technology choice.

CONCLUDING THOUGHTS

Research investigating technology adoption has assumed that the individual accepting the technology has only one technology in mind when making their adoption decision. We have sought to overcome this limitation by providing three choice approaches and three comparison approaches to understand how an individual makes this selection. Based upon our findings, we have suggested a series of unanswered questions that will continue to provide us with insights in to the technology adoption process.

REFERENCES

1. Agarwal, R., and Prasad, J. "The Role of Innovation Characteristics and Perceived Voluntariness in the Acceptance of Information Technologies," *Decision Sciences* (28:3) 1997, pp 557-582.
2. Chin, W. "Issues and Opinion on Structural Equation Modeling," *Management Information Systems Quarterly* (22:1) 1998, pp 7-16.
3. Chin, W., and Gopal, A. "Adoption Intention in GSS: Relative Importance of Beliefs," *DATA BASE* (26:2&3) 1995, pp 42-64.
4. Compeau, D., Meister, D., and Higgins, C. "From Prediction to Explanation: Reconceptualizing and Extending the Perceived Characteristics of Innovating," *Journal of the AIS* (8) 2007, pp 409-439.
5. Dabholkar, P. "Incorporating Choice into an Attitudinal Framework: Analyzing Models of Mental Comparison Processes," *Journal of Consumer Research* (21:1) 1994, pp 100-118.
6. Gagliardi, P., and Compeau, D. "The Effects of Group Presentations on Intentions to Adopt Smart Card Technology: A Diffusion of Innovations Approach," ASAC, 1995, pp. 20-32.
7. Karahanna, E., Straub, D., and Chervany, N. "Information Technology Adoption Across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs," *MANAGEMENT INFORMATION SYSTEMS QUARTERLY* (23:1) 1999, p 14.
8. MacCallum, R., and Browne, M. "The Use of Causal Indicators in Covariance Structure Models: Some Practical Issues," *Psychological Bulletin* (114) 1993, pp 533-533.
9. Moore, G., and Benbasat, I. "Development of an instrument to measure the perceptions of adopting an information technology innovation," *Information Systems Research* (2:3) 1991, pp 192-222.
10. Moore, G., and Benbasat, I. "Integrating diffusion of innovations and theory of reasoned action models to predict utilization of information technology by end-users," *Diffusion and Adoption of Information Technology*) 1996, pp 132-146.
11. Plouffe, C., Hulland, J., and Vandenbosch, M. "Research Report: Richness Versus Parsimony in Modeling Technology Adoption Decisions--Understanding Merchant Adoption of a Smart Card-Based Payment System," *INFORMATION SYSTEMS RESEARCH* (12:2) 2001, p 208.
12. Rogers, E. *Diffusion of Innovations* Free Press, 1995.