INFLUENCE OF ATTITUDE, ANXIETY AND SELF-EFFICACY TOWARD STATISTICS AND TECHNOLOGY ON STATISTICAL PACKAGE SOFTWARE USAGE BEHAVIOR

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Abstract

As practical skills in using statistical software could assist business professionals analyze data and make informed decisions, educators need to know how to motivate business students in learning and using the increasingly user-friendly statistical software. Using a sample of 207 online MBA students from an AACSB accredited university in the Midwest, a modified TAM model was examined using LISREL 8.80. The empirical results show that both *computer attitude* and *statistical software self-efficacy* have significant, positive effects on the *perceived usefulness*. In addition, it was found that both *perceived usefulness* and *perceived ease of use* positively influence learners' *intention to use statistical software*, whereas their *statistical anxiety* has a significant, negative impact on *perceived usefulness*, *perceived ease of use* and *behavior intentions*. Both theoretical and practical implications are discussed in this paper.

Introduction

As one of the more startling recent developments in postsecondary education in the United States (U.S.) is the unprecedented growth of online education, an extremely conservative estimate is that at least 3 million students are currently enrolled in an online class, and the field is growing at an annual rate of 41% (Primary Research Group, 2002; Shaer, 2007). For working adults, online courses have expanded educational opportunities to individuals who need to advance their career but might not otherwise have easy access to a traditional face-to-face college program. More than half of the U.S. institutions of higher learning offer courses through some forms of Internet-based technology (Evans and Haase, 2001; Lee et al., 2007; Shaer, 2007) and a recent survey shows that 43% of colleges that offer face-to-face business degree programs also offer online business programs (Allen and Seaman, 2005).

Following this e-learning trend, both technology-centered companies (e.g., Cisco, IBM, and Dell) and non-tech companies (e.g., MetLife) have added e-learning contents to solve the employee training puzzle (Bisoux, 2002). Likewise, business schools are offering more and more technology-enhanced or technology-based (online) courses for the working professionals. Among the increasingly popular e-learning programs is the online MBA program. Surprisingly, though many online MBA students appear to be more capable, savvy, and more demanding than the traditional MBA students (Bisoux 2002; p.45), little is known about online MBA students' attitudes toward learning a challenging course (e.g., statistics) through computer technology (e.g., statistics software program). Given that many of the online MBA students are full-time employees who plan to further climb the corporate ladder, it is important to understand how instructors can equip these business warriors with another handy tool to make better business decisions through the use of business statistics on a computer. The present study attempts to fill this void.

Overview of the Framework

Courses in statistics and business research are important to all business majors because these courses represent the only formal exposure to statistical analysis and research methods that many students may find useful later in their career. Analytical skills enhance students' ability to read, to interpret, to synthesize, and to use reported results. On the other hand, research production skills enable students to design and to initiate original research (Ravid & Leon, 1995). Students' experiences toward statistics, however, often are a source of anxiety that may lead learners to a negative perception, perhaps especially among those who have undergone 12 years of schooling without ever taking statistics as a subject.

While an increasing number of college students in the U.S. are required to enroll in at least one statistics course as a necessary part of their degree programs (Onwuegbuzie & Wilson, 2003), a large proportion of these students report experiencing high levels of statistics anxiety while enrolled in these classes. For instance, between two thirds and four fifths of graduate students have been found to experience unmanageable levels of statistics anxiety (Onwuegbuzie & Wilson, 2003). Besides, researchers have indicated that courses in statistics are among the most anxiety inducing among students taking non-mathematics-oriented disciplines (Schacht & Stewart, 1991; Zeidner, 1991). Unfortunately, high levels of statistics anxiety have been found to debilitate performance in statistics and quantitative-based courses (Onwuegbuzie, 1997). Further, statistics anxiety has been documented as affecting college students' ability to acquire the skills, knowledge, and strategies necessary to interpret and critique research reports. Also, this anxiety affects the ability to propose, to design, and to implement research studies (Onwuegbuzie, 1997).

It is intuitive that personal attitudes and opinions can influence the adoption of innovations (Rogers 1995). Zanakis and Valenze (1997; p. 10) note that "attitudes and perceptions about statistics influence … the extent to which students use statistics in their careers." Therefore, the preconceived notion about statistics is thought to have a sizable impact on online MBA students' willingness and desire to take advantage of the statistical software package in their job, even when they need to conduct some kind of statistical analysis.

To determine the extent for which external variables (computer attitude, statistical anxiety, and statistical software self-efficacy) influences user beliefs, and user beliefs influence their intentions about using statistical software, we propose that perceived usefulness and perceived ease of use are mediating variables and then assess the interconnection between three key external variables (computer attitude, statistical anxiety, and statistical software self-efficacy) and behavioral intention. Figure 1 represents a conceptual model that depicts the behavioral sequence of perceived usefulness, and perceived ease of use as intervening variables between external variables and behavioral intentions.

Literature Review

Among the required courses in most MBA programs, statistics is not necessarily a popular course and it is often considered a challenge by students. In the worst case scenario, students may be scared of the course and feel alienated. The result could be a lack of motivation and ability for students to apply statistical concepts/tests that may enhance their capability of making a better business decision in their job. Obviously, business statistics cannot enhance an individual's creative thinking skill nor improve her organization performance if not efficiently used. Being future-oriented, today's online MBA students need to be armed with the ability to make the best use of statistics or at least to understand research findings on their own since they are likely to be tomorrow's business leaders.

TAM

As noted earlier, the primary objective of this research is to investigate the influential factors on the adoption and continuous utilization of statistical software among online MBA students. In searching for the possible influential factors for the adoption of a commercial statistics software package (i.e., a continuous incremental innovation not only in classrooms but also in offices), we first turn to the conventional wisdom in the information technology literature --- the Technology Acceptance Model.

TAM was developed by Davis (1986) to explain the nature and determinants of computer usage. Two key components were found in Davis' (1986) TAM model: perceived usefulness and perceived ease of use. As articulated by Davis (1989), the former construct is referred to as "the degree to which a person believes that using a particular system would enhance his or her job performance," and the latter is referred to "the degree to which a person believes that using a particular system would be free of effort" (p. 320). It was postulated that actual system use is influenced by behavioral intention to use, attitudes toward using the system, perceived usefulness, perceived ease of use, and external variables such as documentation, system feature, training, and user support (Davis, Bagozzi, and Warshaw, 1989). Davis *et al*. (1989) tested this posited model and found support to this general TAM structure. In particular, their empirical results showed that both perceived usefulness and perceived ease of use exhibited significant influence on people's intentions, while the former had a stronger effect on promoting the use of computer technology.

TAM has been validated over a wide range of systems (Igbaria, et al., 1997; Karahanna and Limayem, 2000), has proven to have reliable and valid constructs (Doll, Hendrickson, and Deng, 1999; Chin and Todd, 1995), and routinely explains a considerable portion of usage intentions (Meister and Compeau, 2002; Lee et al., 2007; Rao and Troshani 2007; Turel and Yuan 2007; Yiu et al., 2007). Over the past two decades, TAM has been widely used to study the predictive power of technology users' attitude toward their intention in adopting a new innovation. Quite a number of research studies have identified major external variables of TAM as system characteristics, computer self-efficacy, individual differences, and enjoyment (Davis 1993; Hong *et al*. 2001-2002). Since perceived ease of use and perceived usefulness are two core variables in TAM, these two variables are employed to interpret online MBA students' intention to use a statistical software package in their job whenever appropriate.

External Variables

Though TAM has been identified as a useful model in a relatively wide range of applications, no research has used it to study the adoption behavior of increasingly user-friendly statistical software such as SPSS. Therefore, the following sections will discuss the role of external variables including computer attitude, statistical anxiety, and statistical software self-efficacy in the context of statistical package adoption.

Computer Attitude

Although not being examined within the original TAM model, several studies have examined the relationship between computer attitude and IT use. Based on the beliefs-attitudes-intentions paradigm, it has been hypothesized that computer attitudes affect users' behavioral intentions, which affect users' actual usage of computers (Rainer and Miller, 1996). Significant relationships have been found between computer attitudes and system usage in a number of empirical studies (Compeau and Higgins, 1995; Thompson et al., 1991; 1994).

Attitude toward computers is a "broad and general" concept (Chau 2001). Kay (1993) commented that with respect to measuring attitudes toward computers, it would be best to be as specific as possible about the content of the attitude object. Drawing from the results of prior TAM studies, it seems plausible to put perceived usefulness and perceived ease of use, the two key variables in TAM, as the mediating variables, between computer attitude and behavior intention to use a specific technology application. In other words, it is postulated that general computer attitudes affect the perceived usefulness and the perceived ease of use of a specific IIT, which, in turn, affect the behavioral intention of using that IT.

Statistical Software Self-Efficacy

In today's business environment, use of information technology by professionals in all functional areas of business organization is ubiquitous. As recent research has emphasized, understanding the differences among students in different academic disciplines is important (Chung *et al.*, 2002). Computer self-efficacy is a variable that has been proposed and examined as an additional explanatory variable of an individual's IS/IT usage (e.g., Compeau and Higgins, 1995; and Igbaria and Iivari, 1995). By recognizing relationships of statistical software self-efficacy among business professionals and students, prescriptive action may be taken by educators to provide proper statistical software usage supports or adequate training to future business professionals.

Self-efficacy is defined as "the belief that one has the capability to perform a particular behavior." (Compeau and Higgins, 1995). This concept ''refers to beliefs in one's capabilities to organize and execute the course of action required to produce given attainments'' (Bandura, 1997) and is thought to result from past accomplishments, vicarious experience, verbal persuasion, and emotional arousal (Bandura, 1977). Individuals' self-efficacy levels influence their ability to acquire skills, their choice of activities, and their willingness to continue in a course of action. Self-efficacy has been shown to significantly influence a user's attitude toward using computers, a user's anxiety towards using computers, and a user's actual computer use (Compeau and Higgins, 1995). It is our contention that identifying whether differences exist with regard to self-efficacy may help to explain successful statistical software usage.

Self-efficacy has been studied in psychology for decades (Bandura, 1986) and this construct was introduced to the MIS literature in the form of computer self-efficacy (Compeau and Higgins, 1995). Research has shown that it affects users' attitudes towards computers, actual computer usage, levels of anxiety toward computer use, and the outcomes of using computers (Compeau and Higgins, 1995). Recent studies show that self-efficacy is related to computer anxiety, training, learning performance, and computer literacy (Beckers and Schmidt, 2001; Chou, 2001). Computer self-efficacy has also been used as a proxy for an individual's internal control in the IT usage context (Venkatesh and Davis 1996; Lu and Hsiao 2007; Rao and Troshani 2007). Moreover, Chung et al. (2002) studied the differences in self-efficacy among students in the business, education, forest/wildlife, and liberal arts schools of a major university. They found that business students tend to have higher expectations from computer usage than students in other disciplines.

Given that individuals who have high statistical software self-efficacy are more likely to use statistical software (Igbaria and Iiravi, 1995; Marakas et al., 1998), we propose that individuals with high statistical software self-efficacy would feel higher levels of mastery over statistical software applications.

Statistical Anxiety

Statistics anxiety refers to the feelings of anxiety that are experienced by those taking a statistics course or undertaking statistical analyses, in terms of gathering, processing, and interpreting data (Cruise, Cash, & Bolton, 1985). sOnwuegbuzie, DaRos, and Ryan (1997) have defined statistics anxiety more broadly as worry and emotionality that occur when students encounter statistics in any form and at any level. Statistics anxiety has been conceptualized as being multidimensional (Cruise *et al*., 1985; Cruise and Wilkins, 1980; Onwuegbuzie et al., 1997). In particular, Cruise *et al*. identified the following six components of statistics anxiety: (a) Worth of Statistics, (b) Interpretation Anxiety, (c) Test and Class Anxiety, (d) Computational Self-Concept, (e) Fear of Asking for Help, and (f) Fear of Statistics Teachers.

Among the above six dimensions, the *Worth of Statistics* dimension refers to students' perceptions of the relevance and usefulness of statistics. It is thought that *Worth of Statistics* is a key source of statistics anxiety among students since a few students raised the question, "Why is Statistics a required course in the online MBA program?" It is hypothesized that students who hold a positive attitude toward statistics are likely to be more comfortable in using a statistical package in a class and later in their daily job.

Based on the above discussion, we posit the following hypotheses:

H1a: The higher the perceived level of statistical software self-efficacy, the more likely the higher the level of perceived usefulness toward the statistical software whenever appropriate in the job.

H1b: The higher the perceived level of statistical software self-efficacy, the more likely the higher the level of perceived ease of use toward the statistical software whenever appropriate in the job.

H2a: The higher the perceived level of computer attitude, the more likely the higher the level of perceived usefulness toward the statistical software whenever appropriate in the job.

H2b: The higher the perceived level of computer attitude, the more likely the higher the level of perceived ease of use toward the statistical software whenever appropriate in the job.

H3a: The lower the perceived level of statistical anxiety, the more likely the higher the level of perceived usefulness toward the statistical software whenever appropriate in the job.

H3b: The lower the perceived level of statistical anxiety, the more likely the higher the level of perceived ease of use toward the statistical software whenever appropriate in the job.

H3c: The lower the perceived level of statistical anxiety, the more likely the higher the level of behavioral intentions toward the statistical software whenever appropriate in the job.

H4: The higher the level of perceived ease of use toward the statistical software, the more likely the higher the level of perceived usefulness toward the statistical software whenever appropriate in the job.

H5: The higher the level of perceived usefulness toward the statistical software, the more likely one would continue to use the statistical software whenever appropriate in the job.

H6: The higher the level of perceived ease of use toward the statistical software, the more likely one would continue to use the statistical software whenever appropriate in the job.

The Sample

Questionnaires were administered to online MBA students enrolled in a graduate level advanced business statistics course in an AACSB accredited business school, located in the Midwest region of the U.S. The survey instrument was given to the students during the fifth and sixth weeks of the required fifteen-week-long online MBA classes. The prerequisite for the advanced statistics course was completion of an undergraduate business statistics course or an online MBA basic statistics course. In the beginning of a semester, students were informed of the upcoming survey and were asked to provide accurate information when answering the survey a few weeks later. Participating students can receive small credits toward their course grade and confidentiality is assured (Alpert, Alpert, and Maltz 2005).

Each individual respondent's answers were combined with all other survey participants' before the statistical analysis was performed. A total of 207 usable questionnaires were returned and used for the data analysis. Fifty-five percent of the respondents are male and the mean age is 31.9 years. Almost all respondents have a full-time job, with an average of 9.7 years working experience.

Measures

All constructs were measured from students' perspective using a self-report, online, Likert-type scale questionnaire. The proposed model consists of six constructs: (1) statistics anxiety, (2) computer attitude, (3) statistical software self-efficacy, (4) perceived usefulness, (5) perceived ease of use, and (6) behavioral intention. Items included in the questionnaire were adapted from prior research studies. Specifically, the measures for two of the three TAM variables (i.e., perceived usefulness, perceived ease of use) were adapted from Davis (1989). Among the four items used to measure behavior intentions, the first two items were adapted from Chau (1996) while the remaining two items were added by the authors.

As to the three external variables, computer attitude was operationalized with six items adapted from Harrison and Rainer (1992). The measure for statistical software self-efficacy was adapted from Compeau and Higgins (1995). The measure for statistical anxiety was adapted from Cruise *et al*. (1985), who used Factor Analysis to categorize eighty-nine question items into six dimensions: *Worth of Statistics*, *Interpretation Anxiety*, *Test and Class Anxiety*, *Computation Self-concept*, *Fear of Asking for Help*, and *Fear of Statistics Teachers*. In order to avoid the problem of data fatigue among the respondents, we consulted three experienced researchers in the field of MIS and Statistics, and then deliberately selected eight items from the first factor (i.e., *Worth of Statistics*) to represent the concept of statistics anxiety, which generally indicates "a negative attitude toward statistics" (Cruise *et al*. 1985; p. 93). Table 1 and Table 2 summarize the items related to each of the six studied constructs.

Data Analysis Method and Examination

In our data examination process, we first deleted cases incorporating missing values prior to data analysis. Second, we tested the assumptions underlying the use of structural equation modeling. With respect to sample size, it is generally accepted that the minimal sample size needed to ensure appropriate use of maximum likelihood estimation is 100–150 (Anderson and Gerbing, 1988). Notably, we tested for the existence of univariate and multivariate outliers and found no outliers.

Following Anderson and Gerbing's (1988) work, the proposed model was tested using a two-stage structural equation model. First, we performed confirmatory factor analysis (CFA) to evaluate construct validity regarding convergent and discriminate validity. In the second stage, we performed path analysis to test the research hypotheses empirically. The path-analytic procedure is becoming common in studies (Li and Calantone, 1998; Chaudhuri and Holbrook, 2001).

Overall Model Evaluation

The goodness of fit indices is summarized in Table 3. The Chi-square statistic is significant at the .05 level (Bollen, 1989), a finding not unusual with large sample sizes (Doney and Cannon, 1997). The values for CFI, NNFI, root mean square error of approximation (RMSEA), and standardized root mean residual (SRMR) are considered acceptable based on the standards suggested by Hu and Bentler (1995, 1999): 0.95 for CFI and NNFI, 0.06 for RMSEA, and 0.08 for SRMR. Given that these batteries of overall goodness-of-fit indices were acceptable and that the model was developed on theoretical bases, no re-specifications of the model were made. This enables us to proceed in evaluating the measurement and structural models.

Measurement Model Evaluation

We assessed the quality and adequacy of our measurement models by investigating unidimensionality, convergent validity, reliability, discriminant validity, and metric equivalence. First, unidimensionality was assessed on the basis of principal component analyses performed on all items. The fact that all items loaded 0.65 on the hypothesized factor and no significant cross-loading was found gives support to unidimensionality for each of the constructs. Second, convergent validity (i.e., the degree of association between measures of a construct) was assessed by reviewing the *t* tests for the factor loadings. The fact that all *t* statistics are statistically significant showed that all indicator variables provide good measures to their respective construct, which supported the convergent validity of the model (Hildebrandt, 1987; Steenkamp and Van Trijp, 1991). Third, reliability was supported as a result of the fact that all Cronbach alpha values exceeded 0.70, indicating acceptable reliability levels (Nunnally, 1978). Moreover, as can be derived from Table 3, all of the composite reliability measures are equal to or above 0.60, corresponding to Bagozzi and Yi's (1988) minimum values of 0.60. In sum, it is concluded that all studied constructs in the proposed model satisfy the reliability and validity requirements.

Next, CFAs were used to examine the adequacy of the measurement model. We used separate CFAs for external variables (statistical software self-efficacy, computer attitude, and statistical anxiety) and original TAM constructs (perceived ease of use, perceived usefulness, and behavioral intentions), and estimated the proposed measurement model using LISREL 8.80 (Joreskog and Sorborn, 1989, 1993). The results indicate reasonable overall fits between the model and the observed data. As is shown in Table 4, the value of GFI related to the external variables CFA model, original TAM construct CFA model, and even the full model fit of measurement models are all greater than 0.85 (Bagozzi and Yi, 1988). NNFI and CFI also far exceeded the recommended .90 threshold level (Bollen, 1989; Hoyle and Panter, 1995; Hu and Bentler, 1995). Overall, these indices demonstrated that the data reasonably fit the model well.

Empirical Results

Table 4 presents the assessment of overall model fit and the tests of research hypotheses of our model. The estimated coefficients are visualized in Figure 2, in which statistically significant path coefficients are represented by solid lines. Notably, all significant relationships between latent constructs are in the hypothesized direction. In our model, both statistical software self-efficacy and computer attitude consistently lead to perceived usefulness, which positively significantly affects behavioral intentions (support for hypotheses 1a, 2a, and 5). Nevertheless, both statistical software self-efficacy and computer attitude did not lead to perceived ease of use, which positively significantly affects perceived usefulness and behavioral intentions (not support for hypotheses 1b, 2b; but support for hypotheses 4 and 6). As to statistical anxiety, all the hypotheses with regard to original TAM constructs are negatively significant (support for hypotheses 3a, 3b, and 3c).

Discussions and Concluding Remark

Knowledge about statistical techniques can help marketing professionals to amplify the power of their customer database (Direct Marketing Association). As skills in using statistical software may assist marketers analyze data and make informed decisions, marketing educators need to motivate students in learning and using the increasingly user-friendly statistical software.

In an attempt to help marketing educators successfully design a course with quantitative materials (e.g., marketing research), this study examines the factors that may affect students' adoption of a commonly used statistical package such as SPSS. Specifically, the present study sheds light on the relationship between online MBA students' intention to use statistical software and a few important constructs, including perceived usefulness and the perceived ease of use toward a statistical software package, and respondents' anxiety level, self-efficacy about using statistical software, also, respondents' attitude toward computer. Our empirical results reveal that both perceived usefulness and perceived ease of use positively influence learners' behavioral intention to use statistical software, whereas their statistical anxiety has negative impact on all the three constructs. Furthermore, while both statistical software self-efficacy and computer attitude lead to positively significant influence on perceived usefulness, both the two external variables didn't have significant influence on perceived ease of use. This offers software producers the opportunity to increase systems usage by making systems more usable and useful, for example, through refined software selection or software introduction training. Our results also showed, however, that users' individual differences, such as computer attitude, statistical software self-efficacy, and statistical anxiety, can have a direct effect on perceived usefulness and perceived ease of use. Thus, both software producer and marketing educators cannot ignore user differences, but should tailor their selection and training methods to meet the needs of different users.

The significant effects of all three independent variables imply that researchers need to take into account both the factors explicated by the technology acceptance model (TAM) and other potentially important factors, such as the anxiety construct. In the current study, because we incorporated the main concepts from the TAM and the STARS models, our proposed model presents a more comprehensive picture of students' behavioral intention to adopt/use statistical software. Therefore, theory building in this area could benefit from examining the issues from multiple perspectives, as these perspectives may provide additional insights into those issues.

Both students and educators can benefit from the information presented by this study. Students should realize that, if they are reluctant in adopting new learning and decision making tools but this reluctance hampers their learning or job performance, they may ask themselves what the reasons might be. It could be that they do not feel these tools are useful, that they feel the tools are difficult to use, or that they hold a certain level of anxiety in the subject matter involved in these tools. If one or more of these are the underlying reasons, they may be in a better position to take corrective actions. Educators should also look into these factors if students do not actively engage in learning activities based on new learning software. For example, if an instructor finds out students are unwilling to use a new software package because they feel it is not useful on their job, the instructor should try to explain the reasons why the software will benefit them in the future in order to motivate students' learning. On the other hand, if the unwillingness is due to the fact that the students do not feel comfortable about the subject matter involved in the software, it would call for a different remedy.

There are some limitations of the study that could be addressed in future research in this area. Due to the exploratory nature of the study, only five factors deemed the most important in influencing respondents' behavioral intention are included. In particular, some constructs from the innovation adoption literature could also be used to explore students' behavioral intention to adopt new technology. Examples of these include compatibility, observability, relative advantage, triability, and complexity (Rogers 1995). They are widely discussed in the general innovation adoption literature but empirical studies about these constructs are only starting to emerge, and should also be utilized in future research in students' behavioral intention. Moreover, given that statistics play an important role in a graduate marketing research course, future research may want to validate the findings in a quantitative-oriented course in an online MBA program.

Endnotes:

1. In order to meet the length constraint (i.e., the length should not exceed 10-pages), most figures and tables are not presented here but they are available upon request.
2. Only major references are shown on the References section.

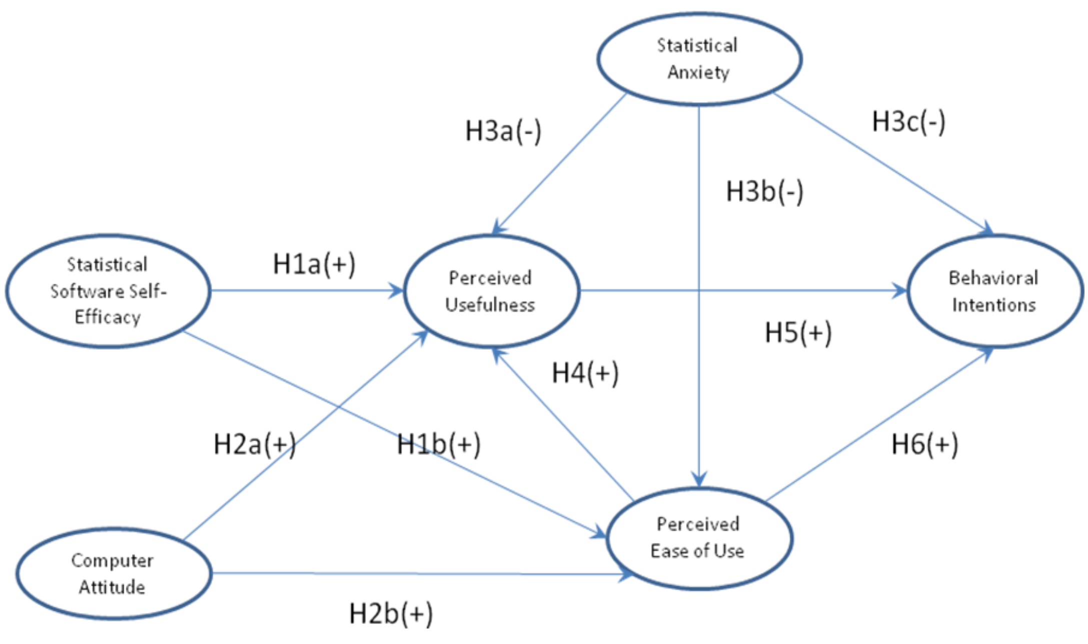

Figure 1. Conceptual Framework

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