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Computer attitude, statistics anxiety and self-efficacy on statistical software adoption behavior: An empirical study of online MBA learners

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A B S T R A C T

Educators need to know how to motivate business students (i.e., future business practitioners) to learn and use statistical software, which can provide the practical skills necessary for business professionals to analyze data and make informed decisions. 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 perceived usefulness. In addition, it was found that both perceived usefulness and perceived ease of use positively influence learners' intentions to use statistical software, whereas their anxiety with statistics has a significant, negative impact on perceived usefulness, perceived ease of use and behavioral intentions. Both theoretical and practical implications are discussed in this paper.

1. Introduction

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 three 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 (Saade, He, & Kira, 2008). More than half of the U.S. institutions of higher learning offer courses through some form of Internet-based technology (Evans & Haase, 2001; 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 & Seaman, 2005). Notably, Penn Foster (http://www.pennfoster.edu/index.html) which was known as an International Correspondence School (ICS), a correspondence school giant, has evolved into a global online education provider. Today one out of every 1410 Americans is actively enrolled in a Penn Foster program, and there are plans for more.

Following this e-learning trend, both technology-centered companies (e.g., Cisco, IBM, and Dell) and non-technical companies (e.g., MetLife) have added e-learning contents to solve the employee training puzzle (Bisoux, 2002). Likewise, business schools are offering increasingly more technology-enhanced (hybrid) or technology-based (online) courses for working professionals (Gibson, Harris, & Colaric, 2008). Among the increasingly popular e-learning programs is the online MBA program, which has turned out to be a buyer's market in today's competitive business education marketplace. Given that many of the online MBA learners are full-time employees with plans of climbing the corporate ladder, it is important for educators to equip these business warriors with tools for making better business decisions through the use of business statistics on a computer. Surprisingly, though many online MBA students appear to be more capable, savvy, and demanding than traditional MBA students (Bisoux, 2002), little is known about online MBA learners' attitudes toward learning a challenging course (e.g., statistics) through computer technology (e.g., statistics software) (Ma, Andersson, & Streith, 2005). Therefore, the present study attempts to fill this need by examining the influential factors that may facilitate or hamper the adoption of statistical software.

2. Overview of the framework

Courses in statistics are important to all business majors because they represent the only formal exposure to statistical analysis and research methods many students may find useful in their careers. Analytical skills enhance students' ability to read,

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interpret, synthesize, and use reported results. On the other hand, research production skills enable students to design and initiate original research (Ravid & Leon, 1995). Students' experiences toward statistics, however, are often a source of anxiety producing negative perceptions, perhaps especially among those with 12+ years of schooling without ever taking a course in statistics.

While an increasing number of college students in the U.S. are required to take at least one statistics course as a mandatory part of their degree programs (Onwuegbuzie & Wilson, 2003), a large proportion of these students report experiencing high levels of statistics anxiety with these classes. It is estimated that between two-thirds and four-fifths of graduate students experienced unmanageable levels of anxiety due to statistics (Onwuegbuzie & Wilson, 2003). Researchers have indicated that courses in statistics are among the most anxiety inducing, especially for students in 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, DaRos, & Ryan, 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. This anxiety also affects their ability to propose, design, and implement research studies (Onwuegbuzie et al., 1997).

Other than statistics anxiety, it is intuitive that personal attitudes and opinions can influence the adoption of innovations (Rogers, 1995). Echoing this notion, Zanakis and Valenzi (1997) noted that "attitudes and perceptions about statistics influence…the extent to which students use statistics in their careers" (p. 10). Therefore, the preconceived notion about statistics is thought to have a sizable impact on online MBA learners' willingness and desire to take advantage of statistical software in their jobs, even when statistical analysis needs to be conducted.

To determine the extent for which external variables (i.e., computer attitude, statistical software self-efficacy, and statistics anxiety) influence user beliefs, and user beliefs influence online MBA learners' intentions to utilize statistical software, the interconnection between three external variables and behavioral intentions are assessed. Fig. 1 represents a conceptual model depicting the behavioral sequence of perceived usefulness, and perceived ease of use as intervening variables between external variables and behavioral intentions.

3. Literature review

Among the required courses in most MBA programs, statistics is not necessarily a popular course, and it is often considered challenging by students. In the worst case scenario, learners may be afraid of the course or feel alienated. The result could be a lack of motivation and ability for learners to apply statistical concepts/tests that may enhance their capability of making a better business decision in their jobs. When inefficiently used, business statistics will not enhance one's creative thinking skills or improve performance within their organization. Being future-oriented, today's online MBA learners 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. The following section will briefly review the technology acceptance model (TAM), which is one of the most widely used conceptual models in explaining and predicting the adoption behavior of Information Technology (IT). Subsequently, the endogenous and exogenous constructs used in our extended TAM conceptual model will be discussed.

4. 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 learners. To find 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.

TAM was developed by Davis (1986) to explain the nature and determinants of computer usage. Two key components were found in the original TAM model: perceived usefulness and perceived ease of use (Davis, 1986). 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 intentions 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, & Warshaw, 1989). Davis et al. (1989)

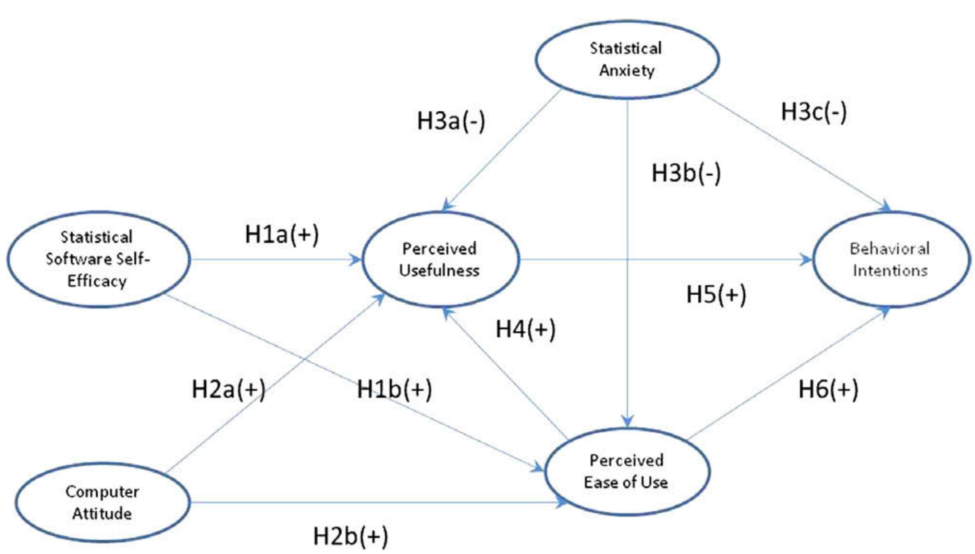

Fig. 1. Conceptual framework.

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 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 & Iiravi, 1995; Igbaria, Zinatelli, Cragg, & Cavaye, 1997; Karahanna & Limayem, 2000), has proven to have reliable and valid constructs (Chin & Todd, 1995; Doll, Hendrickson, & Deng, 1999), and routinely explains a considerable portion of usage intentions in various contexts (Jiang, Hsu, Klein, & Lin, 2000; Lee, Tseng, Liu, & Liu, 2007; Meister & Compeau, 2002; Rao & Troshani, 2007; Turel & Yuan, 2007; Yiu, Grant, & Edgar, 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, Thong, Wong, & Tam, 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 learners' intentions to use statistical software in their jobs whenever appropriate.

5. External variables

Though TAM has been identified as a useful model in a relatively wide range of applications over 20 years (Bagozzi & Richard, 2007), no research has employed it to study the adoption behavior of increasingly user-friendly statistical software such as SPSS. Further, Walczuch, Lemmink, and Streukens (2007) observed that "little effort has so far been made to combine personality-based and cognitive antecedents to technology use in one model" (p. 206). Accordingly, they hypothesized that personality traits (i.e., service employees' technology readiness) are antecedents to technology acceptance and their empirical findings show that "personality influences technology use" (p. 212). Thus, this study extends Walczuch et al.'s (2007) work by examining the role of three personality traits (i.e., computer attitude, statistics anxiety and statistical software self-efficacy) in the context of statistical software adoption.

6. Computer attitude

Although not being examined within the original TAM model, several studies have examined the relationship between computer attitude and IT use. Most theoretical models are based on Fishbein and Ajzen's (1975) theory of reasoned action, which suggests that an object leads to an attitude about it, and this attitude leads to the behavioral intentions regarding the object. Consequently, these intentions affect actual behaviors toward the object. Attitude is "an index of the degree to which a person likes or dislikes about the object" (Ajzen & Fishbein, 1980). Based on this beliefs-attitudes-intentions paradigm, it has been hypothesized that computer attitudes affect users' behavioral intentions, affecting their computer usage (Rainer & Miller, 1996). A number of empirical studies have found significant relationships between attitudes about computers and usage of them (Compeau & Higgins, 1995; Thompson, Higgins, & Howell, 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 intentions 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 IT, which, in turn, affects the intentions of using that IT.

7. Statistical software self-efficacy

In today's business environment, use of information technology by professionals in all functional areas of business organization is ubiquitous. In fact, colleges have recognized the need for computer training for business students (Shufeldt & Parmley, 1992). Recent research emphasized the importance of realizing that differences exist between academic disciplines (Chung, Schwager, & Turner, 2002). Computer self-efficacy is a variable that has been proposed and examined as an additional explanatory variable of an individual's IT usage (Compeau & Higgins, 1995; Igbaria & Iiravi, 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 support or adequate training to future business professionals (Bates & Khasawneh, 2007).

Self-efficacy is defined as "the belief that one has the capability to perform a particular behavior" (Compeau & 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, choice of activities, and willingness to continue in a course of action. Self-efficacy has been shown to significantly influence a user's anxiety toward using computers and their actual computer use (Compeau & Higgins, 1995). It is our contention that identifying whether differences exist with regard to self-efficacy can help explain successful statistical software usage.

Self-efficacy has been studied in psychology for decades (Bandura, 1997), and this construct was introduced to the MIS literature in the form of computer self-efficacy (Compeau & Higgins, 1995). Recent studies show that self-efficacy is related to computer anxiety, training, learning performance, and computer literacy (Beckers & Schmidt, 2001; Chou, 2001). Computer self-efficacy has also been used as a proxy for an individual's internal control in IT usage context (i.e., a user with a high level of self-efficacy tends to feel a stronger sense of control over the activities being performed) (Venkatesh & Davis, 1996). 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 suggested further research into understanding computer self-efficacy.

Given that individuals who have high statistical software self-efficacy are more likely to use statistical software (Marakas, Yi, & Johnson, 1998), we propose that individuals with high statistical software self-efficacy would feel higher levels of mastery over statistical software applications.

8. Statistics anxiety

Statistics anxiety refers to feelings of anxiety experienced by those taking a statistics course or undertaking statistical analyses in terms of gathering, processing, and interpreting data (Cruise, Cash, & Bolton, 1985). Onwuegbuzie et al. (1997) have defined statistics anxiety more broadly as worry and emotionality occurring when students encounter statistics in any form and at any level. Statistics anxiety is situation-specific because it comes to the forefront when students are learning statistical concepts, terminology and formula or applying statistics in a particular context (Benson & Bandalos, 1989). Statistics anxiety has been conceptualized as being multidimensional (Cruise & Wilkins, 1980; Cruise et al., 1985; Onwuegbuzie et al., 1997). In particular, Cruise et al. (1985) 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 learners' 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 online MBA learners raised the question, "Why is Statistics a required course in the online MBA program?" It is hypothesized that online MBA learners who hold a more positive attitude toward statistics are likely to be more comfortable in using a statistical package in a class and later in their daily jobs.

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

H1a: The higher the perceived level of statistical software self-efficacy, the higher the level of perceived usefulness of it.
H1b: The higher the perceived level of statistical software self-efficacy, the higher the level of perceived ease of use.
H2a: The higher the perceived level of computer attitude, the higher the level of perceived usefulness of the statistical software.
H2b: The higher the perceived level of computer attitude, the higher the level of perceived ease of using the statistical software.
H3a: The lower the perceived level of statistical anxiety, the higher the level of perceived usefulness of the statistical software.
H3b: The lower the perceived level of statistical anxiety, the higher the level of perceived ease of use of the statistical software.
H3c: The lower the perceived level of statistical anxiety, the higher the level of behavioral intentions to use the statistical software.
H4: The higher the level of perceived ease of use with the statistical software, the higher the level of perceived usefulness toward the statistical software.
H5: The higher the level of perceived usefulness of the statistical software, the more likely one would continue to use the statistical software.
H6: The higher the level of perceived ease of use, the more likely one would continue to use the statistical software.

9. 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 United States. Notably, the university's online MBA program has been quite successful, having roughly 600 students enrolled in this program, nearly ten times more than those enrolled in its traditional MBA program. Computer simulations, PowerPoint presentations (some are video-enhanced with the professor's "talking head" lectures), SPSS tutorials, questions/discussions via MSN instant messenger, self-assessment exercises (with the correct SPSS output and interpretations), graded group assignments, and a textbook with practical examples were used to involve students in more active learning. The survey instrument was given to the online MBA learners during the 5th and 6th weeks of the required 15-week-long online MBA course. The prerequisite for the advanced statistics course was completion of an undergraduate business statistics course or an online MBA basic statistics course. At the beginning of the semester, the learners were informed of the upcoming online survey and were asked to provide accurate information when answering the survey (posted on the university's online survey portal) a few weeks later in the semester. Participants received some credits toward their course grade and confidentiality was assured (Alpert, Alpert, & Maltz, 2005).

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

10. Measures

All constructs were measured from the respondents' perspective using a self-report, online, 7-point Likert type scale questionnaire, anchored by "strongly disagree" and "strongly agree." The proposed model consisted 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 intentions. Questions included in the questionnaire were adapted from prior research studies. Specifically, the measures for two typical TAM variables (i.e., perceived usefulness, perceived ease of use) were adapted from Davis (1989). Among the four items used to measure behavioral 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 statistics 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 issue of data fatigue among the respondents, we consulted three experienced researchers in the field of MIS and Statistics, deliberately selecting eight questions (out of the sixteen 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). Tables 1 and 2 summarize the items related to each of the six studied constructs.

11. 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. The minimal sample size needed to ensure appropriate use of maximum likelihood estimation is 100–150 (Anderson, 1987). Our sample size ($n = 207$) was considered to be reasonable and large enough to partially compensate for possible model misspecification and model complexity. Finally, we tested for the existence of univariate and multivariate outliers, which revealed no outliers.

Following Anderson and Gerbing (1988), 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 research studies (Chaudhuri & Morris, 2001; Li & Calantone, 1998).

Table 1
The survey instrument – endogenous constructs.

Items	Item-construct loading		Cronbach's alpha	Average variance extracted
	Standardized	*t*-statistic		
Perceived usefulness			0.96	0.84
Using a statistical package such as SPSS can improve my job performance	0.90	–		
Using a statistical package such as SPSS can make it easier to do my job	0.89	25.13		
Using a statistical package such as SPSS in my job can increase my productivity	0.93	21.40		
I find a statistical package such as SPSS useful in my job	0.93	20.30		
Using a statistical package such as SPSS would enable me to accomplish statistical analysis more quickly	0.93	18.93		
Perceived ease of use			0.93	0.79
I find it easy to get SPSS to do what I want it to do	0.79	–		
My interaction with SPSS is understandable and clear	0.94	12.49		
I find SPSS to be flexible to interact with	0.84	9.90		
It is easy for me to become skillful at using SPSS	0.97	9.56		
Behavioral intentions			0.92	0.83
I always try to use statistical software such as SPSS to conduct a task whenever it has a feature to help me perform it	0.89	–		
I always try to use statistical software such as SPSS in as many cases/occasions as possible	0.87	15.44		
Statistical software such as SPSS has lots of exciting functions that I intend to use	0.92	13.56		
I intend to increase my use of statistical software such as SPSS in the future	0.96	13.38		

Table 2
The survey instrument – exogenous constructs.

Items	Item-construct loading		Cronbach's alpha	Average variance extracted
	Standardized	*t*-Statistic		
Statistical software self-efficacy			0.86	0.59
I could complete a statistical analysis using statistical software such as SPSS				
if I had seen someone else using SPSS before trying it myself	0.68	10.73		
if I could call someone for help if I got stuck	0.87	13.17		
if someone else had helped me get started	0.70	10.91		
if someone showed me how to do it first	0.77	11.61		
if I had used similar software before this one to do the same job	0.80	12.14		
Computer attitude			0.89	0.63
Computers are bringing us into a bright new era	0.88	15.67		
The use of computers is enhancing our standard of living	0.91	16.32		
There are unlimited possibilities of computer applications that haven't even been thought of yet	0.75	12.33		
Computers are responsible for many of the good things we enjoy	0.69	10.83		
Working with computers is an enjoyable experience	0.70	11.17		
Statistics anxiety (attitudes toward statistics)			0.93	0.69
I wonder why I have to do all these things in statistics when in actual life I'll never use them	0.77	12.88		
Statistics is worthless to me since it's empirical and my area of specialization is philosophical	0.83	14.46		
I feel statistics is a waste	0.90	16.28		
I don't want to learn to like statistics	0.83	14.40		
I wish the statistics requirement would be removed from my academic program	0.78	13.21		
I don't understand why somebody in my field needs statistics	0.80	13.63		
I don't see why I have to clutter up my head with statistics. It has no significance to my life work	0.89	16.02		

12. Overall model evaluation

Separate CFAs were performed for external variables (statistical software self-efficacy, computer attitude, and statistics anxiety), typical TAM constructs (perceived ease of use, perceived usefulness, and behavioral intentions), and the full model which consists of all the constructs depicted in Fig. 1. The proposed measurement models were estimated using LISREL 8.80 (Joreskog & Sorborn, 1989, 1993). The goodness-of-fit indices is summarized in Table 3. Specifically, the Chi-square statistic is significant at the 0.05 level, not an unusual finding when large sample sizes are used (Doney & 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): .95 for CFI and NNFI, .06 for RMSEA, and .08 for SRMR. Given that the battery of overall goodness-of-fit indices was deemed acceptable and that the model was developed on a theoretical base, no re-specifications of the model were made. This enables us to proceed in evaluating the measurement and structural models.

Table 3
Goodness-of-fit indices.

Model/construct	χ^2/df	RMSEA	NNFI	SRMR	CFI
Exogenous	1.302	0.038	0.99	0.043	0.99
Endogenous	1.938	0.067	0.99	0.021	0.99
CFA-overall	1.477	0.048	0.98	0.051	0.99
Sequential path model	1.477	0.048	0.98	0.052	0.99
Suggested values	<3	<0.06	>0.90	<0.08	>0.95

13. Measurement model evaluation

We assessed the quality and adequacy of 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 .65 or higher on the hypothesized factor and no significant cross-loading was found gave support to unidimensionality for each of the studied constructs. Second, in a CFA setting, convergent validity (i.e., the degree of association between measures of a construct) was assessed by reviewing t statistics related to the factor loadings. The fact that all the t statistics are statistically significant at the 0.05 level showed that all indicator variables provide good measures to their respective construct, offering supportive evidence to convergent validity (Hoyle & Panter, 1995; Rao & Troshani, 2007). Moreover, Hair, Anderson, Tatham, and Black (1998) posited that the average variances extracted (AVE) values exceeding .50 offers supportive evidence for convergent validity (see Table 3). Discriminant validity was assessed using the procedure recommended by Anderson (1987) and Bagozzi and Phillips (1982). A series of Chi-square difference tests were performed on the nested models to assess whether the Chi-square values were significantly lower for the unconstrained models where the phi coefficient was constrained to unity (Anderson, 1987). The fact that all critical values related to the Chi-square difference at the .05 significance level are less than 3.84 in all possible pairs of constructs gave support to discriminant validity. With regard to construct reliability, evidence showed that all Cronbach alpha values exceeded the suggested 0.70 benchmark (Nunnally, 1978). Finally, as can be derived from Table 3, all of the composite reliability measures are equal to or above the commonly accepted minimum value of 0.60 (Bagozzi & Yi, 1988). In summary, a battery of tests gave support to the reliability and validity of the studied constructs in the proposed model.

14. Empirical results

Table 4 presents the assessment of overall model fit and the proposed research hypotheses tests. The estimated coefficients are visualized in Fig. 2, where statistically significant path coefficients are represented by solid lines. Notably, all significant relationships between latent constructs are in the hypothesized directions. In our model, both statistical software self-efficacy and computer attitude consistently lead to perceived usefulness, which positively and 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, but perceived ease of use does positively and significantly affect perceived usefulness and behavioral inten-

Table 4
Empirical results of the proposed model.

Causal path	Hypothesis	Expected sign	Path coefficient	t-Statistic	Assessment ($p \leqq .05$)
Statistical software self-efficacy → perceived usefulness	H1a	+	0.17	2.50	s.
Statistical software self-efficacy → perceived ease of use	H1b	+	0.07	1.10	n.s.
Computer attitude → perceived usefulness	H2a	+	0.25	3.43	s.
Computer attitude → perceived ease of use	H2b	+	−0.06	−0.83	n.s.
Statistics anxiety → perceived usefulness	H3a	–	−0.22	−3.33	s.
Statistics anxiety → perceived ease of use	H3b	–	−0.33	−4.87	s.
Statistics anxiety → behavioral intentions	H3c	–	−0.16	−3.47	s.
Perceived ease of use → perceived usefulness	H4	+	0.37	4.87	s.
Perceived usefulness → behavioral intentions	H5	+	0.60	9.81	s.
Perceived ease of use → behavioral intentions	H6	+	0.21	4.14	s.

Note. $\chi^2_{(369)}$ = 545.20, RMSEA = 0.048 (with a 90% confidence interval from 0.039 to 0.057); CFI = 0.99; NNFI = 0.98.

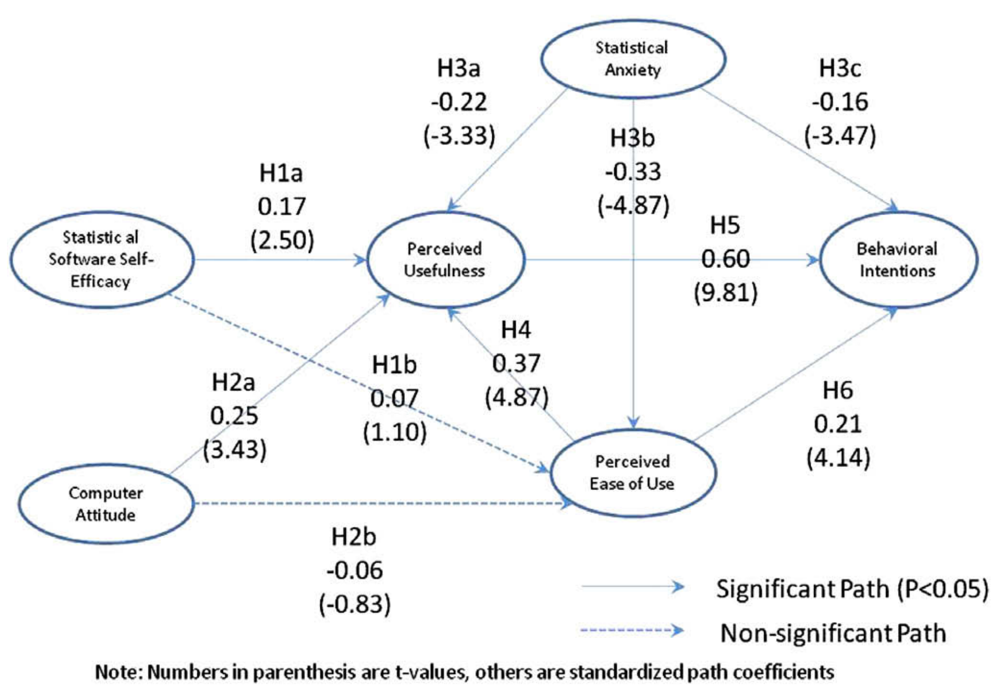

Fig. 2. Outcome of hypothesized framework.

tions (provide no support for hypotheses 1b, 2b; but provide support for hypotheses 4 and 6). Statistics anxiety negatively and significantly influences perceived usefulness, perceived ease of use, and behavioral intentions (support for hypotheses 3a, 3b, and 3c).

15. Discussion

Despite the importance of online learning, the results of research to date do not provide clear guidance in terms of how to help online learners overcome a potentially challenging course and use the tools learned in their job. Responding to the recent call by Yousafzai, Foxall, and Pallister (2007) for more examination of the causal relationship among beliefs and their antecedent factors in a TAM framework, this study sheds light on the possible influence of computer attitude, self-efficacy of using a statistical software package (SPSS), and level of anxiety the online MBA learners have toward the subject background (i.e., statistics) on the behavioral intentions via perceived usefulness and perceived ease of use.

Our empirical results show that both perceived usefulness and perceived ease of use positively influenced learners' behavioral intentions to use a statistical software package, whereas, their statistics anxiety had negative impacts on all three constructs. Furthermore, while both statistical software self-efficacy and attitudes toward computers positively and significantly influenced perceived usefulness, neither of them had significant influence on perceived ease of use.

Perceived usefulness and perceived ease of use have been recognized as the most influential catalysts in a TAM framework. The finding that perceived ease of use has a significant direct and indirect impact (via perceived usefulness) on behavioral intentions is consistent with the TAM findings of Hong et al. (2001-2002) and Thong, Hong, and Tam (2002). Though the standardized coefficient between perceived ease of use and behavioral intentions (0.21) is smaller than its counterpart (0.60), perceived ease of use does have a statistically significant impact on behavioral intentions. Similarly, the significance of the positive relationship between perceived usefulness and behavioral intentions (H5) agrees with the findings of Hong et al. (2001-2002) and Thong et al. (2002). This suggests that the greatest software usage outcome would occur when a statistical software package is perceived both useful and easy to use by the learners.

The outcome of an insignificant relationship between statistical software self-efficacy and perceived ease of use concurs with Chau's (2001) findings, in which 360 college students' computer software usage behavior (e.g., Microsoft Word, Excel, PowerPoint) were examined in an extended TAM framework. Moreover, Chau's study reported an insignificant relationship between computer attitude and perceived ease of use. Interestingly, Chau observed a significant and negative relationship between self-efficacy and perceived usefulness, and his explanation was "an individual with high self-efficacy in computers may see the limitations of a particular IS/IT in addition to its usefulness" (p. 30). A plausible explanation for our finding of a positive relationship is that in this study, the usage was on a particular software package (SPSS) which requires its user to have some basic statistical knowledge while in Chau's study, the focus was on a more general software package (Microsoft Office product). Given that the respondents in this study are less likely to have an advanced knowledge about statistics to observe the software limitations, a significant and positive relationship between self-efficacy and perceived usefulness seems to be reasonable.

To the limited knowledge of the authors, it is the first time that statistics anxiety is introduced to the basic TAM model. The study shows that statistics anxiety has a negative impact on perceived usefulness, perceived ease of use, and behavioral intentions. That is, our empirical findings confirm the counter productive role of statistics anxiety in the higher education context. As more working professionals around the world start to earn an advanced degree in an online environment, professors need to help these online learners overcome possible anxiety toward the course subject.

16. Implications

While online MBA programs are becoming more popular among working adults, studying in isolation poses quite a challenge to students and professors alike. In an online learning environment, professors would be advised to be aware of the online learners' personality traits (e.g., self-efficacy) and use these differences between online learners to the advantage of the curriculum. In particular, as online learners study on their own most of the time, professors need to examine online learners' level of readiness, especially for a course like advanced statistics, and offer them appropriate help in a timely manner.

The significant effects of all three exogenous variables imply that research in technology acceptance should take into account not only factors explicated by TAM but also other potentially important factors, such as personality traits. In this study, we extend the original TAM framework by incorporating three antecedents in the proposed model, presenting a more comprehensive picture of learners' behavioral intentions to adopt/use statistical software. Therefore, theory building in this area could benefit from examining the issues from multiple perspectives to provide additional insights.

Perceived usefulness and perceived ease of use were shown to be important determinants of statistical software usage. 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. If software is easy to use but is not perceived as useful to its potential adopters, then actual usage becomes questionable. Our results also showed, however, that users' individual differences, such as computer attitude, statistical software self-efficacy, and statistics anxiety, can have a direct effect on perceived usefulness. These findings offer insight into statistical software usage and the critical role of perceived usefulness in a higher education setting. Both software producers and business educators cannot ignore user differences but should tailor their selection and training methods to meet the needs of different users.

As to the three external constructs, statistics anxiety has a significantly negative effect on perceived usefulness, perceived ease of use, and behavioral intentions. This means that not only perceived usefulness and perceived ease of use but also anxiety toward statistics are determinates of statistical software using intentions. Business educators should try to eliminate learners' anxiety toward using statistical software, thus, increasing learners' perceived usefulness and perceived ease of use, and finally, their intentions of use. If the reluctance is mainly due to learners' discomfort with the subject matter, introducing a few carefully designed supportive activities may help familiarize the learner with the software and raise comfort levels. In addition, educators may lower online MBA learners' anxiety toward statistics by presenting real-world examples or referring to success stories from recent graduates. In order to effectively reduce students' anxiety in learning statistics, Pan and Tang (2004) recommended the combination of application-oriented teaching methods and instructors' attentiveness to students' anxiety.

If learners are unwilling to use a new software package because they feel it is not useful in their current job, the instructor could motivate learning by explaining how the software could benefit them in the future. It is important to choose user-friendly statistical software to begin with, and we agree with Stephenson and

Bell's (1992) suggestion that textbooks containing a wide variety of computer printouts should be sought.

Both attitude of computers and statistical software self-efficacy have positive and significant effects on perceived usefulness; whereas, insignificant effects on perceived ease of use. This means that both attitude toward computers and self-efficacy had direct effects on perceived usefulness, but they did not have indirect effects on perceived usefulness through perceived ease of use. Therefore, whenever educators try to promote the learning effects of statistical software, they should consider segmenting online MBA learners according to the learners' attitude toward computers and statistical software self-efficacy. Then educators could invest resources to better satisfy online learners' learning needs.

Webster (1992) found that teaching statistical topics such as regressions and analysis of variance is enhanced by using appropriate statistical software. Given that knowledge about statistical techniques can help business professionals amplify the power of their customer databases (Direct Marketing Association, 2008) and make better decisions, educators need to motivate students to learn and use the increasingly user-friendly statistical software packages. With regard to the learners, if they realize that their reluctance to adopt new decision-making tools hamper their learning or job performance, they may ask themselves why they are reluctant. Possible explanations could be the belief that the tools are not useful, are too difficult to use, or the student's anxiety with the subject matter. If one or more of these explanations are true, corrective action may be taken.

17. Limitations and future research

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 online MBA learners' behavioral intentions are included. In particular, some constructs from the innovation adoption literature could also be used to explore learners' behavioral intentions to adopt new technology. Examples of these include compatibility, observability, relative advantage, triability, and complexity (Schach & Stewart, 1991). 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 considered in future research in information technology adoption behavior. In addition, future research may examine whether demographic variables such as gender, educational level, and age could potentially confound the observed relationships using a more diversified sample. Moreover, given that statistics plays an important role in graduate level business research courses and in today's business world, validating the findings in another quantitative-oriented business course or more sophisticated business setting may be warranted. As previous research suggests that the TAM and end-user technology usage may differ across cultural borders, extending this research effort into other countries would be a reasonable next step.

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