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Factors Influencing the Behavioural Intention to Use Statistical Software: The Perspective of the Slovenian Students of Social Sciences

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ABSTRACT
The aim of the paper is to investigate the main factors influencing the adoption and continuous utilization of statistical software among university social sciences students in Slovenia. Based on the Technology Acceptance Model (TAM), a conceptual model was derived where five external variables were taken into account: statistical software self-efficacy, computer attitude, statistics anxiety, statistics learning self-efficacy, and statistics learning value. The model was applied to the purposive sample of 387 university social sciences students in Slovenia who have been introduced to IBM SPSS Statistics during statistics courses. Data were analyzed using Structural Equation Modeling (SEM). The results indicated that all external variables considered in the model directly or indirectly affect the behavioural intention to use statistical software and are therefore relevant for our study. The most influential factors are found to be statistics anxiety and statistics learning value. The latter one plays a central role in our extended TAM, as its impact is stronger when compared with other external variables. The findings from our empirical study are useful for statistics educators. The recommendations proposed can improve the educational process in order to strengthen students' attitudes towards statistics and to decrease the level of statistics anxiety.
Keywords: statistical software, intention to use, Technology Acceptance Model (TAM), Structural Equation Modeling (SEM), SPSS.

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State of the literature

- Since statistical literacy is vital to all business majors, courses in statistics within university programmes play a very important role in persuading students of the usefulness of statistics in their professional life.
- Students' experiences in learning statistics are often a source of anxiety and produce negative perceptions, especially for students in non-mathematics-oriented disciplines.
- There have been many studies that investigated success in statistics courses. Many of these studies have focused on students' attitudes towards statistics or statistics anxiety, but few have discussed the acceptance of statistical software among students.

Contribution of this paper to the literature

- Statistical software can be understood as a kind of facilitator which potentially reduces the resistance of social sciences students towards learning statistics.
- Despite the fact that there exists a relatively large number of social sciences education studies regarding attitudes towards statistics and statistics anxiety, the role of statistical software support during education still remains a rather under-researched area.
- TAM combined with SEM was used to determine the external factors influencing the actual use as well as the future use of statistical software among social sciences students in Slovenia.
- The most important external variables predicting the actual and consequently the future use of statistical software are statistics anxiety and statistics learning value.

INTRODUCTION

In recent decades statistical methods have become very important in science research and business as well as in general society. They provide valuable information that can only be obtained by analysing data collected from surveys. The demand for information, which not only consists of statistical data but also of the results of sophisticated statistical analyses, is evidently growing (Zapletal & Packova, 2013). Therefore, courses in statistics are an important part of the higher education process. Such courses represent formal exposure to statistical analyses and research methods that many students may find useful in their careers. The broader importance of educating the masses in the art of statistical thinking is stressed by Shaw (as cited in Nolan & Swart, 2015), who believes that statistical thinking will one day be as necessary for efficient citizenship as the ability to read and write.

Despite these facts, statistics courses are not very popular in most universities. Students' personal experiences in learning statistics are often a source of anxiety that produce negative perceptions. Many studies have indicated that courses in statistics are among those that cause the most anxiety, especially for students in non-mathematics-oriented disciplines. Onwuegbuzie and Wilson (2003) report that statistics anxiety is experienced by as many as 80% of graduate students in the social and behavioural sciences and is at least partly responsible for the procrastination of students enrolling in required statistics courses.

Some research has asserted that using computers in statistics classes has been generally successful in lowering statistics anxiety (Stickels & Dobbs, 2007). There are many statistical software packages which can be introduced in a statistic course (e.g., SPSS, SAS, Stata, R). Packages that can provide implementation of statistical techniques with the help of computers have been found to be very useful. They make complex subject matter more accessible and easier to understand. In addition, they combine theoretical and practical aspects in order to help students understand how statistical research can be properly applied to everyday problems and questions.

A literature overview has shown that there are many studies about teaching and learning of statistics in higher education. Many authors investigate the problem of statistics anxiety, its psychometric properties, and the scales and factors affecting statistics anxiety (e.g., Zeidner, 1991; Baloğlu, 2003; Onwuegbuzie, 2004; Pan & Tang, 2004; DeVaney, 2010). A comprehensive summary of the literature on statistics anxiety is provided by Onwuegbuzie and Wilson (2003). Quite numerous also are the studies which analyse students' attitudes towards statistics (e.g., Hilton et al., 2004; García-Santillán et al., 2012; García-Santillán et al., 2013; García-Santillán et al., 2013a; Escalera-Chávez et al., 2014). However, although the idea of introducing technology in the statistics classroom is not new (see e.g., Lawrin & Lawrin, 2011), only a few papers have appeared in recent years discussing the effect of statistical software usage on students' success in and attitudes towards statistics courses. One of these is Zapletal and Pacakova (2013), who highlighted the usage of statistical software to motivate students to study statistics. Furthermore, Jatnika (2015) has studied the effect of an SPSS course on students' attitudes towards statistics and achievement in statistics. The author tried to determine whether there was a significant difference in students' attitudes before and after participating in an SPSS course. Ertuğ et al. (2014) have applied the structure equation modeling technique to analyze students' attitudes towards statistical software and found that behaviours related to statistical software have a strong relationship with benefits attained from positive use of software.

Our motivation for this study was the idea that statistical software can be used as a facilitator with the potential to reduce the resistance of social sciences students towards learning statistics. Better adoption of statistical software among students is one of the important ways to improve the students' statistical knowledge and consequently to strengthen their positive attitude towards statistics (Bastürk, 2005). In our opinion, a positive attitude towards statistical software while studying statistics plays a significant role in building a positive attitude towards statistics itself and can help students realize that statistics courses are both interesting and useful for their future careers. Therefore, it would be worthwhile to identify the main factors that may influence the adoption of statistical software usage and its continued use. However, none of the studies cited above was focused on investigating the main factors influencing the efficient adoption of statistical software among students. In addition, Ertuğ et al.'s (2014) research was performed in a statistics department, where the phenomenon of negative attitudes towards learning statistics is probably expressed less intensively than in social and behavioural sciences departments.

An approach that is frequently used to investigate the factors influencing software adoption is the Technology Acceptance Model (TAM). The TAM was developed by Davis (1986, 1989) to explain the nature and determinants of computer usage. The primary assumption of TAM is that users tend to use technology if they feel the technology will be useful for them and they feel it is easy to use. Therefore, the main antecedents of technology usage are assumed to be perceived ease of use and perceived usefulness. Perceived usefulness and perceived ease of use can be directly influenced by several external variables which indirectly affect attitudes towards technology usage. External variables commonly used in TAM applications refer to organizational, system, and the user's personal characteristics (Yousafzai et al., 2007).

Despite of relatively large number of TAM applications to higher education (see Section Technology Acceptance Model), we noticed a lack of TAM-based research studies examining the adoption and acceptance of statistical software among students. To date we found only the study of Hsu et al. (2009), who proposed extending the TAM model to study the adoption and utilization of statistical software among online MBA students in an Association to Advance Collegiate Schools of Business (AACSB) accredited business school in the Midwest region of the United States. The authors proposed three external variables, computer attitude, statistical software self-efficacy, and statistics anxiety, as the main predictors of statistical software adoption.

Although the idea of Hsu et al. (2009) is very interesting and useful for us, some improvements are needed. Many studies have shown that an important factor for success in learning is students' intrinsic motivation (see e.g., Froiland et al., 2012). Since we have proposed statistical software as a facilitator which stimulates a positive attitude towards statistics, we can therefore assume that students' intrinsic motivation to learn statistics and their attitude towards statistical software are correlated. Therefore, in selecting the TAM's external variables, a student's intrinsic motivation to learn statistics should also be taken into account. Intrinsic motivation as a user's personal characteristic is frequently involved in TAM applications, and it is proposed to affect both of the key TAM components: perceived usefulness and perceived ease of use (see Yousafzai et al., 2007).

Considering the discussion above, the aim of this paper can be expressed as follows:

- The primary aim is to investigate the main factors influencing the adoption and continued utilization of statistical software among full-time university social sciences students in Slovenia. For this purpose, an extended TAM will be derived. In selecting the external variables, students' personal characteristics affecting attitude towards statistical software will be taken into account. Other aspects, like organizational and system characteristics will not be considered in this study. Since there is no clear pattern with respect to the choice of TAM external variables (Legris et al., 2003) this decision is allowed. On the top of the external variables proposed by Hsu et al. (2009), factors related to students' intrinsic motivation to learn statistics will also be involved. To investigate these factors, we will follow Tuan et al. (2005), who presented a methodology to measure students' motivation towards learning science.

- The model will be applied to a sample of students from seven faculties from all three Slovenian public universities with different social sciences programmes. The students involved in the study anticipated the use of IBM SPSS Statistics within statistics courses. We will analyse two aspects of behavioural intention to use statistical software, intention to actually use (during the study) as well as the intention to use it in the future after finishing the study. To examine the relationships among the model components, structural equation modelling (SEM) will be performed. To find the most parsimonious model, the nested models approach will be also applied. Results will be presented and discussed.

TECHNOLOGY ACCEPTANCE MODEL

The TAM is one of the most widely used conceptual models in explaining and predicting behaviour in adopting information technology (Hsu et al., 2009). The TAM is widely known and it has received strong theoretical and empirical support in the literature, having been cited more than 700 times (Padilla-Meléndez et al., 2013).

The original TAM postulates that perceived usefulness and perceived ease of use are the key constructs in determining users' acceptance of technology. As articulated by Davis (1989), these constructs are defined in the following way:

- Perceived usefulness is referred to as the degree to which a person believes that using a particular technology would enhance his/her job performance.
- Perceived ease of use is referred to the degree to which a person believes that using a particular technology would be free of effort.

Perceived ease of use influences perceived usefulness but not vice versa. Both perceived usefulness and perceived ease of use have influence on behavioural intention to use, which is defined as the degree to which a person has formulated conscious plans to perform or not perform some specified future behaviour. The main assumption is that users will have a greater intent to use technology if they feel the technology will be useful for them and they feel it is easy to use.

Perceived usefulness and perceived ease of use can be influenced by several external variables which may affect attitudes towards using a technology. Although external variables are not obligatory for TAM applications, Legris et al. (2003) stressed that it is important to study them because they are the ultimate drivers of technology usage. The authors also noted that there is no clear pattern with respect to the choice of the external variables considered. Some authors suggest that researchers choose external variables that are used widely and have theoretical support (Li et al., 2007). However, Yousafzai et al. (2007) determined that more than 70 different external variables for perceived usefulness and perceived ease of use can be found with practical applications of TAM. This study also provides a useful list of TAM external variables divided into four categories: organizational characteristics, system characteristics, users' personal characteristics, and other variables.

The TAM has been validated over a wide range of technologies and has been identified as a useful model in a relatively large number of applications over the past two decades. A comprehensive overview of the TAM and its variations can be found in Legris et al. (2003) and Chuttur (2009).

The literature review has shown that TAM is frequently used approach to investigate the factors influencing software adoption (see e.g., Hernández et al., 2008; Lee, 2009; Li et al., 2011; Sriwidharmanely & Syafrudin, 2012; Antonius et al., 2015). Furthermore, several papers have been published on the context of application of the TAM in higher education in recent years (e.g., Un Jan & Contreras, 2011; Teo, 2009, 2010, 2011, 2011a; Teo & Zhou, 2014). A number of studies have used the TAM to examine learners' willingness to accept e-learning systems (e.g., Al-Adwan et al., 2013; Cheung & Vogel, 2013; Persico et al., 2014; Shah et al., 2013; Sharma & Chandel, 2013; Shroff et al., 2011; Tabak & Nguyen, 2013) or to predict learners' intention to use an online learning community (Liu et al., 2010). Some papers have focused on validating the TAM on specific software that is used in higher education. For example, Escobar-Rodriguez and Monge-Lozano (2012) used the TAM to explain or predict university students' acceptance of the Moodle platform.

However, in spite of numerous TAM applications in the field of higher education, there is a lack of TAM studies analysing the adoption and acceptance of statistical software among students. The only exception we found to date is Hsu et al. (2009), who developed an extended TAM to investigate the adoption of statistical software among online MBA students of a particular business school.

RESEARCH MODEL DEVELOPMENT

Traditional TAM components

As discussed in the previous section, the traditional TAM components are perceived usefulness (PU), perceived ease of use (PEU) and behavioural intention to use (BIU). In our extended TAM we used their conventional definitions presented in the previous section. According to TAM theory, three conventional relationships are usually formulated in TAM applications, as described by the following research hypotheses (Lee & Letho, 2013):

- Perceived usefulness positively affects behavioural intention to use.
- Perceived ease of use positively affects behavioural intention to use.

- Perceived ease of use positively affects perceived usefulness.

These hypotheses are considered also in our extended TAM: Students intend to use statistical software if they perceive the software to be useful for them and if they feel it is easy to use. In addition, if students find the software easy to use, they will perceive it also as more useful. However, in terms of behavioural intention to use, two aspects of statistical software usage can be analysed: its usage during the student's university education (i.e., actual use) and usage at the professional level after finishing education (i.e., future use). For the following research, both aspects are deemed to be important.

Since introduction of statistical software in a statistics course represents one of the most important ways to improve students' knowledge of statistics and to strengthen their positive attitudes towards statistics (Bastürk, 2005), taking a look at actual statistical software use during the education is meaningful. On the other hand, we cannot neglect the fact that due to an increasing amount of data available to organizations, there is a growing need for use of statistical software in both science research and the business world (Adams et al., 2013). Therefore, looking at future statistical software usage after students finish their studies is also of great importance. Consequently, both aspects of statistical software usage will be taken into account in our extended TAM. Since previous research has proven that past use of a given technology is a key factor in determining its future use (Bajaj & Nidumolu, 1998, as cited in Legris et al., 2003), we can assume that the use of statistical software during the university education (actual use) is an important predictor of its usage in the future after students finish their studies (future use). Therefore, we will assume in our model that the variable behavioural intention to actual use (BIAU) positively affects the variable behavioural intention to future use (BIFU).

External variables

Selection of the model's external variables is based on the following assumptions:

- To prevent model complexity, the number of external variables should not be too large. Usually in TAM applications between three and five external variables are involved. We found only one study with more than nine external variables (Agudo-Peregrina et al., 2013).

- As suggested Li et al. (2007), external variables which have theoretical supports in the literature are preferred. Selection of TAM external variables is based on students' personal characteristics. Organizational and system characteristics will not be considered in this phase of research.

- The population in this study is limited to undergraduate full-time social sciences students in Slovenia. Students from all three Slovenian public universities were involved. All of them attended a traditional in-class introductory statistics course supported by IBM SPSS Statistics. The curricula of the undergraduate introductory statistics courses in all of the social sciences programmes in these universities are very similar. This ensures that the participants of the study come from a relatively uniform and controlled environment.

- Based on the similarities mentioned above, we assumed that every student in the study had a comparable possibility of making progress in statistical knowledge. Therefore, experience with statistics before entering a statistics course was not assumed to be an essential influencing factor for statistics software adoption. Furthermore, since all the participants are undergraduate students, educational level is not assumed to be an essential influencing factor for statistics software adoption. For the same reason we expect low variation in students' age; therefore, this variable is also not presumed to be an essential influencing factor for our study. Similarly to Hsu et al. (2009), the impact of other students' socio-demographic variables (e.g., gender) on statistical software adoption will not be examined in this phase of research.

In selecting the external variables for our extended TAM we first relied on the results of the empirical study of Hsu et al. (2009), whose important external predictors of statistical software adoption were statistical software self-efficacy, computer attitude, and statistics anxiety. All of these factors represent a student's personal characteristics and are therefore also of interest to our study. Since self-efficacy, computer attitude, and anxiety are commonly used external variables in TAM applications (Yousafzai et al., 2007), we expected that they would also be applicable to our model.

However, it must be taken into account that selection of external variables may vary depending on the population studied (Teo & Zhou, 2014). For example, some authors have stressed that there were significant differences between MBA and traditional students. Since MBA programmes are becoming more popular among working adults, many MBA students are full-time employees, who appear to be more capable, savvy, and demanding than traditional students (Bisoux, 2002). We realised that the population of students involved in Hsu et al. (2009) differed considerably from the population addressed in our study. Therefore, we needed to determine whether the external variables proposed by Hsu et al. (2009) would fit our model. For this purpose, we examined a pilot study on a preliminary sample of Slovenian social sciences students (see Brezavšček et al., 2014), which confirmed that the external variables statistical software self-efficacy, computer attitude, and statistics anxiety were applicable to our model.

Drawing on the assumption of correlation between students' motivation to learn statistics and their attitude towards statistical software, our primary focus was to investigate additional external variables that affect students' motivation to learn statistics. There are various theories concerning academic motivation. One of the widely used approaches is the self-determination theory (SDT) that was developed by Deci and Ryan (1985) (as cited in Lavasani et al., 2014). The SDT model claims that a complete analysis of the motivation process must take into consideration three important entities: intrinsic motivation, extrinsic motivation, and a-motivation. We will concentrate on intrinsic motivation, which refers to the motivation that drives individuals towards performing specific tasks and duties spontaneously and intrinsically (Lavasani et al., 2014) and is an important motivating factor for success in learning (Froiland et al., 2012). According to Yousafzai et al. (2007), intrinsic motivation can be used as an external variable in TAM application and is confirmed to be an antecedent of both perceived usefulness and perceived ease of use.

To investigate the external variables regarding students' intrinsic motivation in learning statistics we used the results of the study of Tuan et al. (2005), which reveals that self-efficacy, task value, an individual's goals in a task, and learning environment dominate students' learning motivation. Since Tuan et al. (2005) investigated students' motivation towards science learning, the meaning of the variables needed to be adjusted to the context of learning statistics.

Based on the above discussion the following external variables are included in our extended TAM:

Statistical software self-efficacy

Self-efficacy is defined as belief in one's own ability to perform a particular task (Bandura, 1982, as cited in Teo & Zhou, 2014). Statistical software self-efficacy (SSSE) is defined therefore as the belief that one has the capability to perform a statistical analysis using statistical software. Individuals with lower statistical software self-efficacy will be easily frustrated by obstacles to their performance and will respond by lowering their perceptions of their ability to use statistical software. On the contrary, those with a strong sense of statistical software self-efficacy do not become deterred easily by difficult problems. Therefore, they persist with their efforts and are more likely to overcome any obstacle that is present, which strengthens their intention to use statistical software. Since self-efficacy has been confirmed as an antecedent of both perceived usefulness and perceived ease of use (Yousafzai et al., 2007), we presumed in our study that individuals who have high statistical software self-efficacy will perceive statistical software as being more useful and easier to use. Therefore, such individuals are more likely to use statistical software and feel a higher level of mastery over it both during their university studies and after them.

Computer attitude

Attitudes guide behaviour, and attitude refers to the way an individual responds to and is disposed towards an object (Ajzen & Fishbein, 2005, as cited in Teo et al., 2008). This feeling or disposition may be negative or positive (Teo et al., 2008). According to this definition, computer attitude (CA) can be defined as the degree to which a person likes or dislikes computers. As cited in Hsu et al. (2009), a number of empirical studies have found significant relationships between attitudes about computers and their usage. An increasing amount of research suggests that attitude towards computer use has a strong link to both behavioural intention and actual behaviour (Wong et al., 2013). In the meta-analysis of the

TAM that they performed, Yousafzai et al. (2007) proposed that computer attitude affects both perceived usefulness and perceived ease of use. We therefore postulated in our model that students with positive attitudes towards computers will perceive statistical software as being more useful and easier to use. This in turn positively affects their intention to use statistical software both during their university studies and after them.

Statistics anxiety

Statistics anxiety (SA) refers to the feeling of anxiety experienced by those taking a statistics course or gathering, processing, and interpreting data in the course of undertaking a statistical analysis (Cruise et al., 1985). Statistics anxiety has been conceptualized as being multidimensional (Onwuegbuzie, 2004). As defined in Cruise et al. (1985), it consists of six dimensions: (a) worth of statistics, (b) interpretation anxiety, (c) test and call anxiety, (d) computational self-concept, (e) fear of asking for help, and (f) fear of the statistics teacher. Among these six dimensions, the worth of statistics, a key source of statistics anxiety, refers to students' perceptions of the relevance and usefulness of statistics (Hsu et al., 2009).

Yousafzai et al. (2007) state that anxiety, which is a personal characteristic, is an antecedent of both perceived usefulness and perceived ease of use. Therefore, we propose in our study that a lower level of statistics anxiety increases the levels of both perceived usefulness and perceived ease of use of statistical software. Consequently, such students are more likely to be comfortable using statistical software in class and also later in their jobs. Students with higher levels of statistics anxiety tend to perceive statistical software as being useless as well as difficult to use, which negatively affects their attitude towards both actual and future use of statistical software.

Statistics learning self-efficacy

Similar to statistical software self-efficacy, statistics learning self-efficacy (SLSE) is defined as students' belief in their own ability to perform well in statistics learning tasks. These beliefs can influence students' behaviour either positively or negatively. Low self-efficacy in statistics and insufficient practice with a variety of problems are two of the potential blocks students face when attempting to solve statistics problems (Onwuegbuzie & Wilson, 2003). On the other hand, Cleary (2006) showed that the strategies students use in solving problems can be predicted based on their levels of self-efficacy. Students with higher self-efficacy use more effective learning strategies.

According to social cognitive theory (as cited in Hall et al., 2010), students learn by observing others performing the same or similar tasks. This learning is affected by the reciprocal interactions between (a) personal factors in the form of cognitions and self-efficacy (perceived capabilities), (b) behaviours in the form of cognitive strategies such as providing feedback and self-explanations, and (c) environmental influences such as peer feedback, teacher feedback, and modelling. As students work on tasks and measure their successful progress towards learning goals, their self-efficacy for continued learning is enhanced and their motivation is influenced positively.

We assumed in our study that students with higher levels of self-efficacy in learning statistics tend to perceive statistical software as being both more useful and easier to use, which positively affects the intention to use statistical software both during their university studies and after them.

Statistics learning value

According to the instrument Survey of Attitude Towards Statistics (SATS) developed by Schau et al. (as cited in Hilton et al., 2004; Tempelaar et al., 2007; Judi et al., 2011; Reeinna, 2014) the value of statistics learning is one of six components of attitude towards statistics. It is defined as students' attitudes about the usefulness, relevance, and worth of statistics in personal and professional life. Similarly, Tuan et al. (2005) reveal that learning value is one of the most influential motivational factors in defining students' attitudes towards learning science. If we adapt the definition of Tuan et al. (2005) to our topic, statistics learning value (SLV) can be used to help students acquire problem-solving competency, experience inquiry activity, stimulate their own thinking, and find the relevance of statistics within daily life. If they can perceive these important values, they will be motivated to learn statistics. Higher motivation to learn statistics will both decrease statistics anxiety and increase statistics learning self-efficacy. In addition, we also assumed that students who perceive a higher level of statistics learning value and are therefore more motivated to learn statistics will perceive statistical software as being both more useful and easier to use than students who perceive a statistic course as a necessary evil.

Research hypotheses

On the basis of the discussion in Subsections Traditional TAM components and External variables, the following hypotheses were formulated:

H1a: Statistical software self-efficacy positively affects perceived usefulness.

H1b: Statistical software self-efficacy positively affects perceived ease of use.

H2a: Computer attitude positively affects perceived usefulness.

H2b: Computer attitude positively affects perceived ease of use.

H3a: Statistics anxiety negatively affects perceived usefulness.

H3b: Statistics anxiety negatively affects perceived ease of use.

H4a: Statistics learning self-efficacy positively affects perceived usefulness.

H4b: Statistics learning self-efficacy positively affects perceived ease of use.

H5a: Statistics learning value positively affects perceived usefulness.

H5b: Statistics learning value positively affects perceived ease of use.

H5c: Statistics learning value positively affects statistics learning self-efficacy.

H5d: Statistics learning value negatively affects statistics anxiety.

H6: Perceived ease of use positively affects perceived usefulness.

H7a: Perceived usefulness positively affects behavioural intention to future use.

H7b: Perceived usefulness positively affects behavioural intention to actual use.

H8a: Perceived ease of use positively affects behavioural intention to future use.

H8b: Perceived ease of use positively affects behavioural intention to actual use.

H9: Behavioural intention to actual use positively affects behavioural intention to future use.

METHODOLOGY

Questionnaire

We developed a questionnaire where every component of the extended TAM is represented by several measured items (i.e., questions). The total number of measured items was 37. The complete list is given in **Table 1**. All the items were measured on the 5-point Likert type scale of agreement, where 1 meant strongly disagree, and 5 meant strongly agree. Before the analyses, we reversed the scales of all three items of statistics learning self-efficacy (which were negatively keyed in the questionnaire).

Internal consistency of the questionnaire was assessed to determine the extent to which the measured items within the same latent variable (i.e., the component of our extended TAM) were related to each other. For this purpose, Cronbach's alpha coefficients were calculated for each of the nine subscales. The results in **Table 1** show that the Cronbach's alpha coefficients ranged from 0.80 to 0.93, and all the values reached the bound of 0.8 recommended by Kline (2011). This indicates that subscales in the survey questionnaire exhibited a high internal reliability.

Data collection and sample characteristics

We applied our model to undergraduate full-time social sciences students in Slovenia who attend traditional in-class courses. Seven faculties from all three Slovenian public universities collaborated. All of the participants were enrolled in an introductory statistics course (where students learned basic descriptive statistics and bivariate tests) supported by IBM SPSS Statistics, which is one of the most widely used pieces of software for statistical analysis in the social sciences.

The anonymous web survey (prepared using the open-source application 1KA, available at www.1ka.si) was performed from June 2013 to May 2014. We used a non-probability purposive sampling technique where we asked the lecturers of selected courses to provide the students a link to the web survey during their lab session.

Since Turner et al. (2010) emphasized that future technology use can be predicted by applying the TAM at the time that a technology is introduced, the survey was performed at the final stage of the course when the students have already become familiar with SPSS.

The average time for survey completion was 5.5 minutes. The total number of usable survey responses was 387, with 328 (84.8%) completely filled-out questionnaires. Eleven respondents were excluded from the analysis because they provided only demographic data. The percentage of missing data for individual variables included in the model varied from 0.5% to 5.0%, while the percentage of casewise missingness rates ranged from 0% to 89% with an average value of 5.0%.

Almost all respondents (365) defined their gender, with 270 (74%) females and 95 (26%) males. The average age of respondents was 22.8 years (*SD* = 3.51 years). Participation in the research was completely voluntary and students did not receive any benefits.

A sample size of 387 is sufficient to achieve the statistical power necessary for SEM with three or more measured items per model component (i.e., latent variable), as proposed by Hair et al. (2006), who suggested a sample size between 150 and 400. The sample size satisfies also Loehlin's rule of thumb (as cited in Siddiqui, 2013): the sample size should be at least 50 more than 8 times the number of measured items in the model (which would be 346 in our case).

Research methods

Data obtained from the survey was analysed using the SEM approach (see e.g., Anderson & Gerbing, 1988; Kline, 2011). SEM was employed for its ability to analyse relationships between latent and observed variables simultaneously (Teo, 2011). The analysis was performed using the standard two-stage approach to SEM (Schumacker & Lomax, 2010), where the first step involves validation of the measurement model, which describes the relationships between the observed measured items and unobserved latent variables. In the second step, the structural model is evaluated. This part specifies the relationships among the latent variables.

Within the first step of data analysis a confirmatory approach was used to validate the measurement instrument and to examine the construct validity of the measurement model. A confirmatory factor analysis (CFA) using R-package lavaan (Rosseel, 2012; 2015) was performed in order to determine how well the measured items reflect the theoretical latent variables. More precisely, we examined convergent validity, unidimensionality, and discriminant validity.

In the second step of the data analysis SEM was used to test the structural relationships among the latent variables, i.e., the components of our extended TAM. The results of SEM are presented with the values of the standardized path coefficient β (representing the relationships between the latent variables) together with its z-values (calculated as the ratio of β to its standard error) and the significance level. For each of the endogenous latent variables also a coefficient of determination (R^2) is calculated, representing the percentage of the explained variance of that variable by the set of its predictors.

After evaluating the fit of the initial structural equation model, the trimming process was employed to simplify the model. The Chi-square distance test was used to determine if non-significant paths could be sequentially removed from the initial model (Kline, 2011).

RESULTS

Descriptive statistics

First, descriptive statistics were calculated for nine model components as well as for all 37 measured items. Results are listed in **Table 1**.

Table 1 shows that the means of the items range from 2.15 to 4.19, while the means of the model components vary from 2.37 to 3.98. The means of all components (except for the variable SA) are at least 2.94 indicating that the overall response can be classified as positive. A mean of 2.37 for SA indicates that an average student's anxiety towards statistics is not high. This can possibly be explained by the fact that our survey was performed only at the end of the statistics course, since the students were not familiar with SPSS before that. Perhaps the level of students' anxiety towards statistics was higher at the beginning of the course and decreased during their participation in the course. Similar experiences have been reported by Jatnika (2015). To confirm this assumption further research should be undertaken.

Standard deviations of all items range from 0.734 to 1.127, indicating a fairly narrow spread of scores around the means. The standard deviations of the model components vary from 0.64 to 0.95. The skewness values are in the interval from -0.908 to 0.946, while the kurtosis values are in the range from -0.909 to 0.903, indicating that data are fairly normally distributed. Since Lei and Lomax (as cited in Lee & Lehto, 2013) define absolute values of skewness and kurtosis up to 2.3 as unproblematic, our data are appropriate for CFA and SEM. The average percentage of missing data on individual measured item equals 5.0% (SD = 2.2%), and ranges from 0.5% to 7.5%.

Table 1. Descriptive statistics of the model components and corresponding measured items

	Model component	Item	*N*	*M*	*SD*	Skewness	Kurtosis
Behavioural Intention to	**Actual Use** *M* = 2.85 *SD* = 1.00 Cronbach's α = 0.89	I always try SPSS to conduct a task whenever it has a feature to help me perform it. **(BIAU1)**	360	2.83	1.027	-0.012	-0.493
		I always try SPSS in as many cases/occasions as possible. **(BIAU2)**	358	2.86	1.070	-0.118	-0.721
	Future Use *M* = 3.04 *SD* = 0.95 Cronbach's α = 0.80	SPSS has lots of exciting functions that I intend to use in the future. **(BIFU1)**	359	3.19	0.989	-0.482	-0.192
		I intend to increase my use of SPSS in the future. **(BIFU2)**	358	2.90	1.086	-0.161	-0.673
Perceived Usefulness *M* = 3.55 *SD* = 0.90 Cronbach's α = 0.91		SPSS use can improve my job performance. **(PU1)**	362	3.43	1.016	-0.343	-0.356
		SPSS use can make it easier to do my job. **(PU2)**	360	3.64	1.002	-0.688	0.108
		SPSS use in my job can increase my productivity. **(PU3)**	358	3.51	1.079	-0.503	-0.312
		I find SPSS useful in my job. **(PU4)**	361	3.19	1.083	-0.206	-0.527
		SPSS use would enable me to accomplish statistical analysis more quickly. **(PU5)**	358	3.97	1.016	-0.908	0.386
Perceived Ease of Use *M* = 3.13 *SD* = 0.93 Cronbach's α = 0.91		I find it easy to get SPSS to do what I want it to do. **(PEU1)**	361	3.36	1.056	-0.478	-0.245
		My interaction with SPSS is understandable and clear. (**PEU2**)	361	3.04	1.061	-0.313	-0.529
		I find SPSS to be flexible to interact with. **(PEU3)**	359	3.20	1.047	-0.265	-0.516
		It is easy for me to become skilful at using SPSS. **(PEU4)**	359	2.90	1.039	-0.128	-0.508
Statistical Software Self-Efficacy *M* = 3.79 *SD* = 0.74 Cronbach's α = 0.83		*I could complete a statistical analysis using SPSS …*					
		… If I had seen someone else using SPSS before trying it myself. **(SSSE1)**	362	3.20	1.070	-0.427	-0.576
		… If someone else had helped me get started. **(SSSE2)**	362	3.88	0.851	-0.811	0.903
		…If someone showed me how to do it first. **(SSSE3)**	360	4.02	0.819	-0.733	0.553
		… If I could call someone for help if I got stuck. **(SSSE4)**	362	4.07	0.849	-0.868	0.624
Computer Attitude *M* = 3.98 *SD* = 0.64 Cronbach's α = 0.84		Computers are bringing us into a bright new era. **(CA1)**	369	3.88	0.862	-0.323	-0.521
		The use of computers is enhancing our standard of living. **(CA2)**	367	3.81	0.855	-0.319	-0.415
		There are unlimited possibilities of computer applications that haven't even been thought of yet. **(CA3)**	368	4.19	0.766	-0.631	0.007
		Computers are responsible for many of the good things we enjoy. **(CA4)**	368	4.18	0.734	-0.535	-0.199
		Working with computers is an enjoyable experience. **(CA5)**	368	3.85	0.880	-0.365	-0.266

Table 1. Descriptive statistics of the model components and corresponding measured items *(continued)*

Model component	Item	*N*	*M*	*SD*	Skewness	Kurtosis
Statistics Anxiety M = 2.37 SD = 0.88 Cronbach's α = 0.93	I wonder why I have to do all these things in statistics when in actual life I'll never use them. **(SA1)**	372	2.68	1.100	0.339	-0.506
	Statistics is worthless to me since it's empirical and my area of specialization is philosophical. **(SA2)**	371	2.52	1.076	0.422	-0.428
	I feel statistics is a waste of time. **(SA3)**	372	2.34	1.027	0.726	0.203
	I don't want to learn to like statistics. **(SA4)**	371	2.54	1.127	0.500	-0.544
	I wish the statistics requirement would be removed from my academic program. **(SA5)**	372	2.15	1.114	0.946	0.308
	I don't understand why somebody in my field needs statistics. **(SA6)**	370	2.17	1.014	0.827	0.258
	I don't see why I have to clutter up my head with statistics. It has no significance to my life work. **(SA7)**	371	2.22	0.971	0.656	0.143
Statistics Learning Self-Efficacy M = 3.63 SD = 0.89 Cronbach's α = 0.80	No matter how much effort I put in, I cannot learn statistics (R). **(SLSE1)**	377	3.75	1.061	-0.706	-0.029
	When statistics activities are too difficult, I give up or only do the easy parts (R) .**(SLSE2)**	378	3.39	1.117	-0.241	-0.717
	When I find the statistics content difficult, I do not try to learn it (R). **(SLSE3)**	377	3.76	0.951	-0.609	0.036
Statistics Learning Value M = 3.13 SD = 0.75 Cronbach's α = 0.80	I think that learning statistics is important because I can use it in my daily life. **(SLV1)**	385	3.14	0.918	-0.274	-0.094
	I think that learning statistics is important because it stimulates my thinking. **(SLV2)**	382	3.19	0.961	-0.216	-0.250
	In statistics, I think that it is important to learn to solve problems. **(SLV3)**	382	3.51	0.904	-0.547	0.161
	In statistics, I think it is important to participate in inquiry activities. **(SLV4)**	382	3.10	1.096	-0.060	-0.859
	It is important to have the opportunity to satisfy my own curiosity when learning statistics. **(SLV5)**	382	2.75	1.123	0.038	-0.909

M – Mean, *SD* – Standard Deviation

Construct validity of the measurement model

The aim of construct validity is to determine how well a set of measured items actually reflects the theoretical latent variable they are designed to measure. The construct validity of each scale was assessed using CFA. It was examined through evaluation of convergent validity and discriminant validity.

Convergent validity should be examined as follows (Fornell & Larcker, 1981; Koufteros, 1999):

(a) Estimates of standardized factor loadings should exceed 0.5 (or even 0.7), or absolute values of corresponding z-values (calculated as the ratio of the standardized factor loading to its standard error) should exceed 1.96 or 2.58 to be considered as significant at the 5% or 1% significance level, respectively.

Table 2. Parameter estimates, error terms and z-values for the measurement model

Latent Variable	Item	Unstandardized Factor Loading	Standardized Factor Loading	Error Term	*z*-value
Behavioural Intention to Actual Use	**BIAU1**	1	0.879	-[a]	-[a]
	BIAU2	1.089	0.920	0.064	16.488
Behavioural Intention to Future Use	**BIFU1**	1	0.825	-[a]	-[a]
	BIFU2	1.049	0.865	0.049	22.341
Perceived Usefulness	**PU1**	1	0.872	-[a]	-[a]
	PU2	0.997	0.884	0.043	23.040
	PU3	1.048	0.863	0.047	22.178
	PU4	0.960	0.785	0.051	18.802
	PU5	0.829	0.721	0.051	16.162
Perceived Ease of Use	**PEU1**	1	0.793	-[a]	-[a]
	PEU2	1.131	0.893	0.059	19.303
	PEU3	1.074	0.861	0.058	18.537
	PEU4	1.027	0.829	0.058	17.551
Statistical Software Self-Efficacy	**SSSE1**	1	0.521	-[a]	-[a]
	SSSE2	1.282	0.840	0.127	10.128
	SSSE3	1.308	0.891	0.129	10.140
	SSSE4	1.260	0.829	0.127	9.892
Computer Attitude	**CA1**	1	0.790	-[a]	-[a]
	CA2	0.985	0.781	0.068	14.461
	CA3	0.726	0.645	0.063	11.527
	CA4	0.716	0.665	0.060	11.942
	CA5	0.878	0.679	0.068	12.895
Statistics Anxiety	**SA1**	1	0.806	-[a]	-[a]
	SA2	0.985	0.813	0.054	18.192
	SA3	0.989	0.854	0.051	19.404
	SA4	0.852	0.670	0.061	13.931
	SA5	1.051	0.837	0.056	18.846
	SA6	0.904	0.791	0.052	17.503
	SA7	0.941	0.860	0.048	19.702
Statistics Learning Self-Efficacy	**SLSE1**	1	0.736	-[a]	-[a]
	SLSE2	1.166	0.818	0.096	12.174
	SLSE3	0.894	0.736	0.077	11.580
Statistics Learning Value	**SLV1**	1	0.695	-a	-a
	SLV2	1.082	0.718	0.088	12.269
	SLV3	0.995	0.702	0.085	11.749
	SLV4	1.058	0.616	0.100	10.554
	SLV5	1.108	0.629	0.102	10.875

-[a] Indicates a parameter fixed at 1 in the original solution.

Fit indices: χ^2 = 1263.8, *df* = 593, χ^2/df = 2.13, NNFI = 0.914, CFI = 0.923, RMSEA = 0.054, 90% confidence interval for REMSA = (0.050, 0.058)

(b) Composite reliability (CR) for each latent variable should exceed 0.7.

(c) Average variance extracted (AVE) for each latent variable should exceed 0.5.

The unstandardized and standardized factor loadings together with corresponding *z*-values for each measured item are presented in **Table 2**, which shows that all standardized factor loadings exceed a threshold of 0.5 for convergent validity, while 78% values exceed even the threshold of 0.7. The examination of *z*-values reveals that they exceed the critical value at 1% significance level for each of the loadings.

The values of CR and AVE for all latent variables of the final measurement model are presented in **Table 3**, which shows that the CR of each latent variable easily fulfils the criterion CR > 0.7. All CR values are well above 0.9, with the lowest value being 0.971 for the latent variables BIFU, SSSE, and SLSE and the highest value being 0.993 for the latent variable SA. The AVE measures the amount of variance captured by the latent variable in the relation to the amount of variance attributable to measurement error. In addition, the AVE values for all nine latent variables are well above the desired threshold of 0.5. The lowest value of AVE is 0.905 for the latent variable SLV. The results obtained prove the convergent validity for the set of latent variables and corresponding items in the measurement model. We can therefore conclude that all included items are significantly related to the specified latent variable.

The discriminant validity of the measurement model was examined through the comparison of the square root of AVE of each latent variable to the correlations between the latent variables. The correlations between the latent variables are given in the right panel of **Table 3**. In the correlation matrix, the diagonal elements having a value of 1 are replaced with the values of the square root of AVE. It is evident that the values of the square root of AVE for the corresponding latent variables are all greater than the inter-variable correlations. This indicates that the measured items have more in common with the latent variable they are associated with than they do with the other latent variables. Therefore, the discriminant validity can be inferred for all pairs of latent variables.

The overall fit of the measurement model was assessed based on various set of commonly used fit indices. Since χ^2 statistics itself is sensitive to the sample size, the ratio of χ^2 to the degrees of freedom (*df*) was used. The obtained value $\chi^2/df = 2.13$ ($\chi^2 = 1263.8$, $df = 593$) is lower than 3, which Teo and Zhou (2014) indicate is an acceptable fit. The values of the non-normed fit index (NNFI) and comparative fit index (CFI) that should, according to Koufteros (1999), be at least 0.9 indicate adequate model fit (NNFI = 0.914, CFI = 0.923). The root mean square error of approximation (RMSEA) value should be below 0.06 (Teo & Zhou, 2014), while MacCallum et al. (1996) interpret REMSA values below 0.05 as “good”, and the values below 0.08 as “mediocre”. The RMSEA of our measurement model is equal to 0.054. Furthermore, the upper bound of REMSEA 90% confidence interval (0.050, 0.058) is lower than 0.06. Based on the whole set of fit indices we can conclude that our final measurement model fits to the sample data reasonably well.

Table 3. Composite reliability (CR), average variance extracted (AVE), square root of AVE and correlations among the latent variables

Construct	CR	AVE	Construct								
			BIAU	BIFU	PU	PEU	SSSE	CA	SA	SLSE	SLV
BIAU	0.982	0.964	**0.982** [a]								
BIFU	0.971	0.944	0.863	**0.972** [a]							
PU	0.991	0.957	0.571	0.692	**0.978** [a]						
PEU	0.990	0.960	0.668	0.680	0.565	**0.980** [a]					
SSSE	0.971	0.919	0.189	0.189	0.229	0.136	**0.959** [a]				
CA	0.988	0.944	0.088	0.028	0.093	0.189	0.084	**0.972** [a]			
SA	0.993	0.951	-0.409	-0.559	-0.577	-0.557	-0.193	-0.106	**0.975** [a]		
SLSE	0.971	0.919	0.306	0.390	0.393	0.508	0.009	0.047	-0.617	**0.959** [a]	
SLV	0.979	0.905	0.490	0.586	0.550	0.599	0.195	0.078	-0.776	0.485	**0.951** [a]

[a] The square root of AVE

Evaluation of the initial structural model and hypotheses testing

SEM was used to test the predicted relationships among the constructs in the extended TAM. Since our dataset includes missing values, the full information maximum likelihood (FIML) estimation inside R-package lavaan was used (Rosseel, 2012, 2015). FIML uses information from each observation, including those with missing values. Therefore, an incorporation of partially observed data can contribute to the estimation of all parameters of the model (Beaujean, 2014).

First, goodness of fit of the structural equation model was tested. The results show that the model has a good fit according to the following indices: χ^2/df = 2.19 (χ^2 = 1330.4, df = 608), NNFI = 0.910, CFI = 0.918, and RMSEA = 0.055 with its 90% confidence interval (0.051, 0.059).

Further, the structural model was evaluated. The results are presented in **Figure 1** and **Table 4**. **Figure 1** shows the values of standardized path coefficient β and corresponding z-values, which reflect the relationships among the latent variables in terms of magnitude and statistical significance. For every endogenous latent variable also the coefficient of determination (R^2) has been calculated.

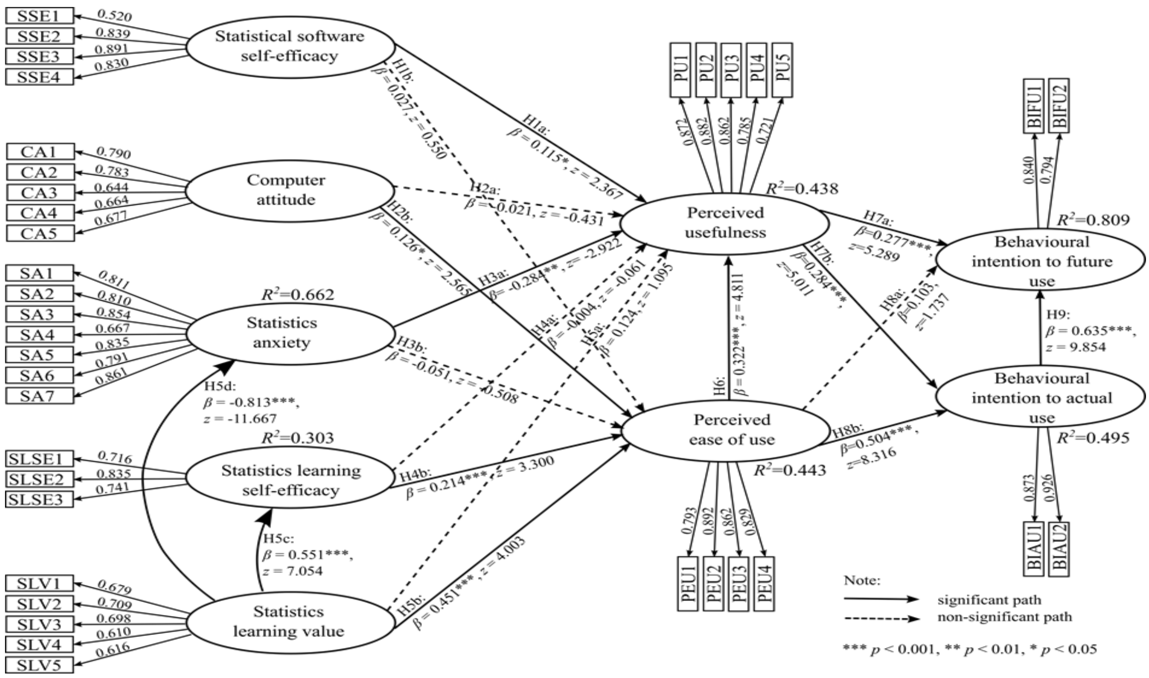

Figure 1. The relationships among the extended TAM components – the initial model

Table 4. Summary of hypotheses testing for the initial structural model

Hypothesis	Path	Expected Sign	Initial model		Final model		Hypothesis Supported?
			Standardized Path Coefficient	*z*-value	Standardized Path Coefficient	*z*-value	
H1a	SSSE → PU	+	0.115	2.367*	0.120	2.502*	**Yes**
H1b	SSSE → PEU	+	0.027	0.550	/	/	No
H2a	CA → PU	+	-0.021	-0.431	/	/	No
H2b	CA → PEU	+	0.126	2.565*	0.128	2.620**	**Yes**
H3a	SA → PU	-	-0.284	-2.922**	-0.369	-6.341***	**Yes**
H3b	SA → PEU	-	-0.051	-0.508	/	/	No
H4a	SLSE → PU	+	-0.004	-0.061	/	/	No
H4b	SLSE → PEU	+	0.214	3.300***	0.213	3.342***	**Yes**
H5a	SLV → PU	+	0.124	1.095	/	/	No
H5b	SLV → PEU	+	0.451	4.003***	0.503	7.057***	**Yes**
H5c	SLV → SLSE	+	0.551	7.054***	0.552	7.091***	**Yes**
H5d	SLV → SA	-	-0.813	-11.667***	-0.817	-11.769***	**Yes**
H6	PEU → PU	+	0.322	4.811***	0.354	6.127***	**Yes**
H7a	PU → BIFU	+	0.275	5.245***	0.303	5.962***	**Yes**
H7b	PU → BIAU	+	0.284	5.011***	0.275	4.892***	**Yes**
H8a	PEU → BIAU	+	0.504	8.316***	0.518	8.577***	**Yes**
H8b	PEU → BIFU	+	0.106	1.776	/	/	No
H9	BIAU →BIFU	+	0.635	9.854***	0.695	11.820***	**Yes**

Statistical significance of standardized path coefficients:
* denotes 5% statistical significance level
** denotes 1% statistical significance level
*** denotes 0.1% statistical significance level

Based on the values of the standardized path coefficient and corresponding z-values, each of the hypotheses proposed in Section Reserach hypotheses is either supported or rejected. A summary of the hypotheses testing is given in **Table 4**, which shows that 12 out of 18 hypotheses were supported, while six of them were rejected. The predictive capability of the proposed model is satisfactory because all coefficients of determination R^2 are higher than 0.3. Falk and Miller (as cited in Escobar-Rodriguez & Monge-Lozano, 2012) have suggested that all overall coefficients of determination should be greater than 0.1.

Fit of nested models

After assessing the model fit of the initial structural model, its fit was then compared to the nested models during the iterative process of model trimming. In empirical based re-specification, the free parameters in the model are eliminated, meaning that the paths are trimmed (sequentially one at a time) if their path coefficients are not statistically significant (Kline, 2011).

The Chi-square difference test was used to test the statistical significance of the decrement of the overall fit when the free parameter was eliminated (thus this path is dropped). It was computed as the difference of model chi-square for the initial model and a nested or trimmed model for one degree of freedom (Kline, 2011). Rejection of the equal-fit hypothesis suggests that the model has been oversimplified while non-significant Chi-square difference indicates the acceptance of the more parsimonious model.

We used the model trimming strategy for nested model comparison to test whether the simplified model fit of the data is at least equally as good as our initial model. The analysis was begun with our initially proposed model shown in **Figure 1**. The model was then simplified by sequential elimination of non-significant paths.

Table 5 presents sequential elimination of paths with corresponding Chi-square differences and p-values. First, from the initial model M_1 the path H4a from SLSE to PU was eliminated. Non-significant Chi-square difference then indicates the acceptance of the simpler model M_2 (p = 0.952). In sequential steps, based on non-significant paths according to smallest z-values of path coefficients, the following paths were eliminated: H2a from CA to PU (we obtained the model M_3, which is simpler than M_2), H3b from SA to PEU (we obtained the model M_4, which is simpler than M_3), H1b from SSSE to PEU (we obtained the model M_5, which is simpler than M_4), H5a from SLV to PU (we obtained the model M_6, which is simpler than M_5), and H8a from PEU to BIFU (we obtained the final model M_7). The Chi-square difference between the final model M_7 and the sixth trimmed model M_6 supports the parsimonious one ($\chi^2_D = 3.1145$, p = 0.078). Since all the paths were significant at 5% significance level, the trimming process was stopped. The final model M_7 is presented in **Figure 2**. The goodness of fit of the final model is as follows: χ^2/df = 2.18 (χ^2 = 1335.5, df = 614), NNFI = 0.911, CFI = 0.918, and RMSEA = 0.055 with its 90% confidence interval (0.051, 0.059).

Table 5. Results of model trimming

Model	Eliminated path	χ^2_M	df_M	χ^2_D	df_D	p
M_1 -Initial model	/	1330.4	608	/	/	/
M_2	SLSE → PU	1330.4	609	0.0037	1	0.952
M_3	CA → PU	1330.6	610	0.1831	1	0.669
M_4	SA → PEU	1330.9	611	0.2551	1	0.614
M_5	SSSE → PEU	1331.2	612	0.3181	1	0.573
M_6	SLV → PU	1332.4	613	1.2196	1	0.269
M_7 - Final model	PEU → BIFU	1335.5	614	3.1145	1	0.078

χ^2_M– chi-square statistic for the model M_i, i=1,…,7
df_M– degrees of freedom for the model M_i, i=1,…,7
χ^2_D – difference between chi-square statistics of the trimmed model M_i and the previous model M_{i-1}
df_D – difference between degrees of freedom of the trimmed model M_i and the previous model M_{i-1}

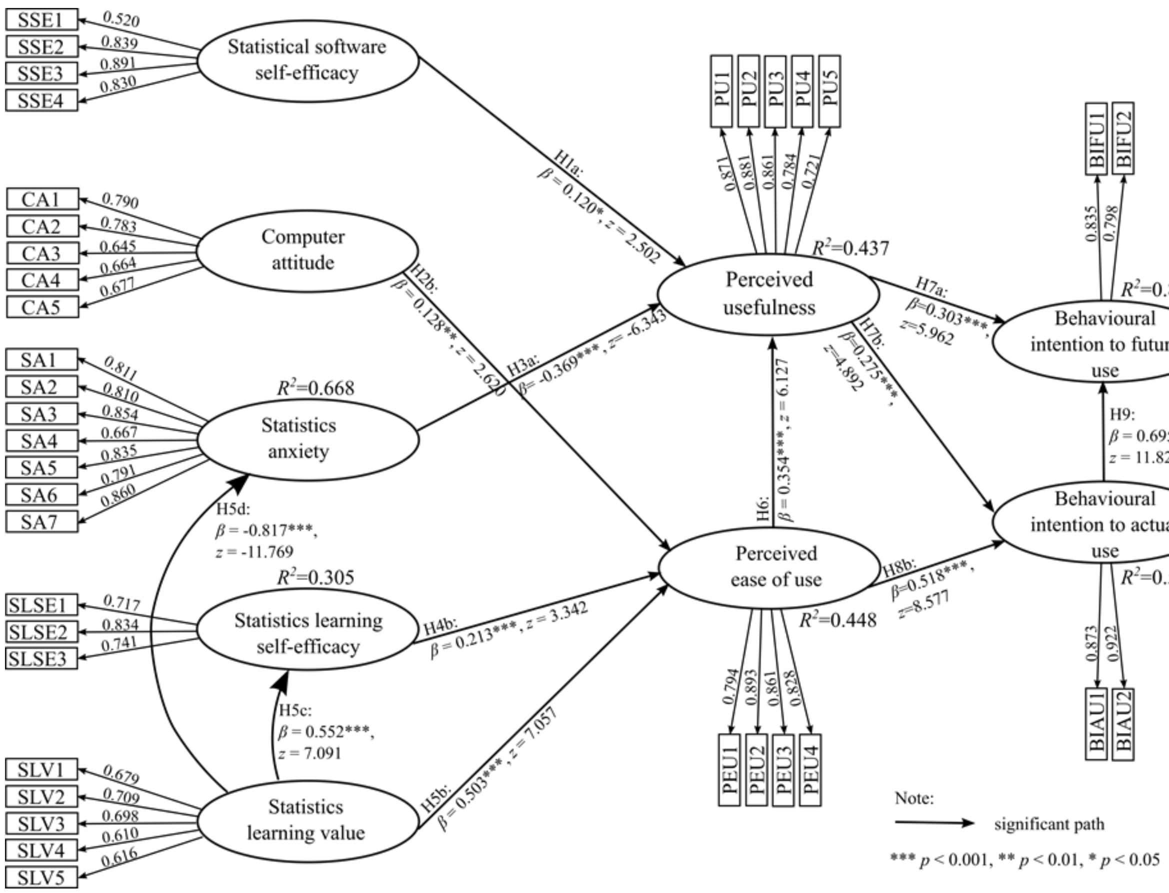

Figure 2. The relationships among the extended TAM components – the final model

Analysis of the final model

The final model, presented in **Figure 2**, will be discussed in two phases. First, the relationship among the traditional TAM components will be analysed. Afterwards, the influence of a particular external variable on the other model components will be investigated.

Analysis of the relationships among the traditional TAM components

TAM theory suggests that there exist positive effects of PU and PEU on BIAU and on BIFU (in our case the hypotheses H7a, H7b, H8a, and H8b). Results confirmed that three of the hypotheses could be supported at 0.1% significance level (H7a: β = 0.303, z = 5.962; H7b: β = 0.275, z = 4.892; H8b: β = 0.518, z = 8.577), while hypothesis H8a was eliminated during the trimming process. We found out that PU and PEU together explain 50.4% of the total variance of BIAU, while PU and BIAU could explain 81.3% of the total variance of BIFU.

Another relationship that is usually predicted in TAM applications is the positive impact of PEU on PU. In our model this relationship is described by the hypothesis H6, which could also be supported at 0.1% significance level (β = 0.354, z = 6.127).

The variable PU has three significant predictors which can explain 43.7% of its total variance. Finally, the variable PEU has three significant predictors which are able to explain 44.8% of its total variance.

Impact of the external variables

Hypothesis H1a predicted a positive effect of SSSE on PU. Results showed that it can be confirmed at 5% significance level (β = 0.120, z = 2.502). Initial hypothesis H1b, which presumed a positive effect of SSSE on PEU, was eliminated and therefore is not included in the final model.

Hypothesis H2a supposed a positive effect of CA on PU, while hypothesis H2b presumed CA's positive effect on PEU. During the trimming process hypothesis H2a was eliminated, so it is not considered in the final model. The standardized coefficient of the path from CA to PEU is positive (β = 0.128, z = 2.620) and significant at 1% significance level, which confirms hypothesis H2b.

In the questionnaire, the negatively stated items for SA were used. This means that higher scores represent a higher level of anxiety towards statistics. The standardized path coefficient of the path from SA to PU is statistically significantly negative (β = -0.369, z = -6.343). This confirms hypothesis H3a at 0.1% significance level, while the path H3b from SA to PEU was eliminated during the trimming process.

The hypothesis H4a predicted a positive effect of this variable on PU, but the results of trimming process suggested elimination of this path from the model. Hypothesis H4b presumed its positive effect on PEU. Results show that hypothesis H4b can be supported (β = 0.213, z = 3.342) at 0.1% significance level.

It has been proposed that SLV has a positive effect on both PU (H5a) and PEU (H5b). However, path H5a was eliminated from the model, while H5b is supported at 0.1% significance level (β = 0.503, z = 7.057). Furthermore, we predicted a positive effect of SLV on SLSE (H5c) and a negative effect on SA (H5d). Both hypotheses are supported at 0.1% significance level (H5c: β = 0.552, z = 7.091; H5d: β = -0.817, z = -11.769). SLV is able to explain 30.5% variance of SLSE and 66.8% variance of SA.

DISCUSSION

The main findings of our study will be discussed on the basis of investigation of the relationships among components of the final model shown in **Figure 2**. Since all of the five external variables (statistical software self-efficacy, computer attitude, statistics anxiety, statistics learning self-efficacy, and statistics learning value) included in the model were found to have direct influence on perceived usefulness or perceived ease of use, we can assert that they also affect the behavioural intention to use statistical software during university education as well as in the future. This justifies the application of TAM to our topic, as well as the selection of external variables considered.

Within the study, we analysed two aspects of statistical software usage, the actual use of software during the university education and future usage after finishing education. We found that behavioural intention towards actual use was influenced by both perceived usefulness and perceived ease of use, whereas the impact of perceived ease of use was rather stronger. However, from the viewpoint of long-term usage, perceived usefulness seems to be more important, while the impact of perceived ease of use is only indirect, through the behavioural intention to use. Therefore, we can conclude that average students will employ statistical software during their university education if they perceive it to be easy to use, but continued utilization of this software will be ensured when during their education students find the software useful. It is also evident that the actual intention to use the software is an important predictor of its future use. This finding is consistent with Bajaj and Nidumolu (1998) (as cited in Legris et al., 2003), and is one of the important results of our study. As the need for statistical software skills in business world is growing, it is therefore worthwhile from an employers' viewpoint to ensure adequate knowledge of statistical software even during university education. This therefore argues for the introduction of statistical software into academic curricula. Since ease of use was found to be an important influencing factor in building students' attitude towards use of statistical software within the class, we can recommend that educators introduce this software to students in a user-friendly manner. Statistical software has to be presented as being flexible and having a variety of possibilities for performing quantitative analyses and presenting the results in an easy way. We also suggest preparing understandable and clear tutorials. Videos and/or other multimedia activities are useful resources to make these tutorials clearer and more applicable.

Perceived usefulness has three significant predictors: perceived ease of use, statistical software self-efficacy, and statistics anxiety, the last one being the most influential. Results therefore indicated that students with low statistics anxiety saw statistical software as a useful tool which could facilitate their tasks and increase their job productivity. On the other hand, low scores of statistics anxiety did not guarantee that students perceived statistical software as being easy to learn and user friendly. Therefore, this again confirms the need for appropriate tutorials, which should include comprehensive step-by-step guides to show how to carry out a particular statistical analysis and interpret the results. As a result of this, we consider the external variable statistics anxiety to be an important component of our model. We can affirm that there exists a significant negative correlation between statistics anxiety and behavioural intention to use statistical software. A high level of statistics anxiety was reflected in a negative influence on students' behavioural intention to use statistical software and vice versa. Positive attitudes towards statistical software therefore reduced statistics anxiety. These results support Stickels and Dobbs (2007), who found significant differences between the levels of anxiety about computer-based and non-computer-based statistics classes. Moreover, statistics anxiety has been found to be the best predictor of students' achievement in statistics courses (Onwuegbuzie, 2004; Ramos & Carvalho, 2011). Students who displayed the highest level of statistics anxiety and consequently rejected the usefulness of statistical software perceived statistics as less important (Baloğlu, 2003) and tended to view it as irrelevant for their future academic or career development (Murtonen et al., 2008). 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. The results of our study also indicate that statistics anxiety can be mitigated by increasing the value of statistics learning. In our opinion, educators should try to introduce carefully designed activities and present real-world examples. Samples based on real data are interesting for students and they motivate them to understand the results obtained. Only such an approach can lead the students to an interest in understanding the statistical methods used. Consequently, this can contribute to better statistical literacy in the general population, which has, according to Ferligoj (2015), received growing attention in the last decade. The author has ascertained that several actions by many (international) statistical institutions, statistical societies, and education institutions to improve statistical literacy have been undertaken. However, to improve the statistical literacy of different segments of the population much remains to be done in the future.

Similar to perceived usefulness, perceived ease of use also has three significant predictors: computer attitude, statistics learning self-efficacy, and statistics learning value, the last being the most influential one. Additionally, a high negative β of the path H5d indicates a very strong negative impact of statistics learning value on statistics anxiety. Therefore, a higher perceived value of statistics knowledge results in a lower level of anxiety towards statistics. In other words, we can say that the students with positive attitudes towards statistics are appreciably less anxious about it. This finding is consistent with much of the literature (e.g., Perepiczka et al., 2011; García-Santillán et al., 2013, 2013a; Escalera-Chávez et al., 2014; Sesé et al., 2015).

Considering the discussion above, we can conclude that statistics learning value is the only external variable that has an influence on both perceived usefulness and perceived ease of use, making statistics learning value the most important external variable of our extended TAM. Thus, we can conclude that the effective use of statistical software during university education and in the future after finishing education depends substantially on the perceived value of the statistical knowledge. To strengthen the value of learning statistics it is therefore necessary for students to gain an insight into where and how one can effectively use statistics in business practice.

Moreover, we treated statistics learning value (together with statistics learning self-efficacy) as one of dominant factors in students' intrinsic motivation to learn statistics. The reasonable next step of our research would therefore be to investigate this area more in detail. As indicated by Tuan et al. (2005), another significant element of students' learning motivation is learning environment. To avoid complexity in our model, this aspect was not considered in the present study, but it provides a research opportunity for the future work. In our opinion, the essential role in the learning environment is played by the teacher and/or the teaching methods being applied. A major concern of those who teach statistics is how to ensure that students understand statistical ideas and are able to apply what they have learned to real-world situations (Garfield, 1995; Garfield & Ben-Zvi, 2007). To do their job effectively, statistics educators should implement a variety of the best practices described in the literature (e.g., Dunn et al., 2007; Garfield & Everson, 2009; Hulsizer & Woolf, 2009). They should experiment with different teaching approaches and activities and monitor the results. They should not be satisfied with using only conventional teaching methods but also try to involve some new, modern concepts. For example, Budé et al. (2009) reported on positive effects of directive tutor guidance in problem-based learning of statistics. Everson et al. (2013) share their own examples of how social media such as Facebook, Twitter, or YouTube can be used within statistics courses. Several useful ideas on how to attract the modern student can be find also in Gould (2010).

However, many social sciences students perceive statistics as difficult and unpleasant. Quantitative methods and statistics courses tend to be the most problematic courses for social science, psychology, and education students (Murtonen et al., 2008). Despite teachers' efforts, abstractions may be difficult for students to understand. Involving different user-friendly instructional resources may help them to clarify abstract ideas.

Finally, students should be encouraged to assess their own learning by giving them opportunities to reflect on the teaching/learning process. Although they often enter statistical courses with negative views, the teacher should help them to recognize that statistical knowledge is a competitive advantage when they apply for a job since many professions and occupations require research and problem-solving skills. Such skills are no longer needed only by those aiming for research work, but they are important to all university graduates regardless of whether they aim to work in research or the public or private sector (Murtonen et al., 2008). Results of previous studies have proven that good performance in statistics or mathematics is equated with ability to process information efficiently and the ability to solve problems. Therefore, the frequently made assumption is that people who are good at statistics will also possess good research and problem-solving skills (Chatzisarantis & Williams, 2006). To variegate the lectures we suggest the teachers to occasionally invite some experts from practice. Their abundant practical experiences will help the students to realize the importance of statistics for their professional careers.

LIMITATIONS AND FUTURE RESEARCH

There are some limitations about the scope of this study that must be addressed, some of which have been already expressed and discussed in Subsection Traditional TAM components. Here we summarize the main points.

The first limitation is the population under consideration. We limited the study to full-time Slovenian undergraduate social sciences students attending traditional in-class courses from seven different faculties at all three Slovenian public universities, which have different but comparable social sciences programmes. All of the students who participated in the survey were taking statistics courses where they used IBM SPSS Statistics. No other statistical software has been considered.

As with every application of the TAM, our study also suffered due to the limited possibility of generalizing the results. One must be aware that the results obtained from our study correspond only to the population under consideration and they cannot be applied entirely to other environments. Lee et al. (2003) stressed that the results obtained from TAM studies where the participants are students cannot be generalized to the real world (as cited in Chuttur, 2009). Furthermore, one has also to realize that selection of external variables as well as the relationships among them may vary depending on the population (Teo & Zhou, 2014). Therefore, if we want to project the results obtained from our study to another environment some caution in interpretation will be necessary.

In our opinion, the main limitation of this study is the fact that all of the external variables involved in our extended TAM refer to students' personal characteristics, while the impact of the organizational, system, or any other characteristics was not taken into account in order to prevent model complexity. However, during the study we came to some important conclusions which should be investigated in our future research. As the impact of statistics learning value is stronger when compared with other external variables, this variable was found to be the most important in our extended TAM. Therefore, the reasonable next step of our study would be to investigate and to analyze the main antecedents of this variable. Furthermore, we recognized the importance of some learning-related organizational and/or system characteristics, such as the learning environment, including support of a teacher, teaching strategies, and students' learning strategies, which we did not consider in this study. Since these characteristics are significant motivational factors that affect students' motivation to learn statistics they should be a focus of our in-depth study in the future.

Moreover, we believe that there are other great opportunities for our future research. Namely, we understand statistical software to be a useful tool which can help to strengthen positive attitudes towards statistics among students. As some authors (Jatnika, 2015) indicate that students' attitudes towards statistics may change after attending a statistics course supported by statistical software, this aspect is worth studying in the future. Future research should also be oriented towards the investigation of pedagogical support for the use of statistical software, as it is seen that the use of statistical software requires an adequate level of motivation in order to reduce students' statistics anxiety. In addition, we could apply the conceptual model to another environment (e.g., students of technical and natural sciences or usage of other statistical software packages than SPSS) and compare the results. Future research may also examine whether demographic variables such as gender, age, and educational level, which were neglected in this study, could potentially confound the observed relationships. As previous research suggests that the TAM and end-user technology usage may differ across the cultural borders (Hsu et al., 2009), we could also extend this research to other countries.

CONCLUSION

Our study was stimulated by the desire to ascertain the positive effects of statistical software applications on statistics education. Statistical software has been recognized as a useful facilitator that can strengthen students' positive attitudes towards statistics and reduce the level of their statistics anxiety. This is especially important for social sciences students whose experiences towards learning statistics are often a source of anxiety that produce negative perceptions.

Despite the fact that there are a relatively large number of studies regarding attitude towards statistics and statistics anxiety in the field of social sciences education, the role of statistical software support during education still remains a rather under-researched area.

In order to identify the external factors which may influence the adoption and continued utilization of statistical software among social sciences students we developed an extended TAM. The model consisted of nine components, where four of them were derived from TAM theory, while the other five represented external variables specific to the field of statistical software application in the education process. The relationships among the model components were described by eighteen hypotheses, which represented the paths between the components of the initial model. The model was applied to the sample of 387 full-time university-level social sciences students from all three Slovenian public universities who anticipated the use of IBM SPSS Statistics within statistics courses. To study the relationships among the model components the SEM approach was used. On the basis of the results of SEM, the nested models technique was applied to find the most parsimonious final model, which had twelve significant paths.

In the conceptual model, we studied two aspects of statistical software usage: actual use during the university education and future use after graduating and completing the education. We determined that students will employ statistical software during the class if they perceive that it is easy to use, but its continued utilization after graduation will be ensured when students find the software useful during the university education. Our empirical results confirmed that the actual intention to use statistical software is an important predictor of its future usage, which is an important finding of our study. To fulfil the future demand for statistical software skills in science research and in the business world it is therefore necessary and worthwhile to introduce statistical software in academic curricula.

Our empirical results also indicated that all five external variables (statistical software self-efficacy, computer attitude, statistics anxiety, statistics learning self-efficacy, and statistics learning value) influence either perceived usefulness or perceived ease of use, which directly affect students' behavioural intention to use statistical software during university education and in the future after graduating. Our study results show that the most influential external variables were statistics anxiety, and statistics learning value. The last one plays a central role in our extended TAM, as its impact is stronger when compared with other external variables. In addition, we recognized statistics learning value as an important factor in students' intrinsic motivation to learn statistics. Furthermore, we recognized the importance while in school of learning environment, including support from a teacher, teaching strategies, and students' learning strategies. We provided some recommendations that we believe can improve the educational process in order to improve students' attitude towards statistics and decrease their levels of statistics anxiety. Certainly, all these findings give us great opportunities for our future research.

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