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Reliability and Validity of a Novel Instrument to Quantify Psychology Students' Perception of Statistics Learning

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Abstract

This study reports on the validity and reliability of a modified survey tool based on the extended Technology Acceptance Model (TAM). The tool was designed to help identify the factors that affect psychological sciences students' perceptions of the ease of use and usefulness of statistical concepts and their application in psychology using the statistical software, SPSS. The proposed survey instrument was tested for its reliability and structural validity using data from 530 students enrolled in a first-year statistics for psychology subject during the global pandemic**.** First, exploratory factor analysis (EFA) was conducted on 168 of 191 respondents who completed a pre-intervention survey to explore the structure of the constructs of students' attitudes, confidence, and perceptions. Out of the 42 questions which were divided into 8 sections, five factors of confidence, attitude, dependent learner belief, independent learner belief, and mindfulness were identified. These findings provide a valid and reliable assessment of students' attitudes, confidence**,** and beliefs toward statistics learning for predicting academic performance. Consequently, this may help as a guide for effective decision-making in the design and development of the study of statistics for non-mathematical background students. This research is conducted in accordance with La Trobe University's ethics approval license- HEC19013.

Introduction

Statistics is commonly a core requirement for psychological science degrees across the globe. Psychology students are required to have a strong understanding of statistical concepts and applications due to the nature of their field. Many variables such as attitudes, anxiety, and confidence are not directly observable variables and require a sound understanding of complicated statistical analyses. However, this subject itself is one of the anxiety-provoking and less popular subjects for psychology students (Jones & Goldring, 2017; Onwuegbuzie & Wilson, 2000; Rendulic & Terrell, 2000; Schneider, 2011). Evidence-based studies have shown that s*tatistics anxiety* is one of the learning obstacles affecting social science students during their undergraduate and postgraduate studies (Chew & Dillon, 2014a; Chew & Dillon, 2014b; Chew, Dillon, & Swinbourne, 2018; Macher, Paechter, Papousek, & Ruggeri, 2012; Papousek et al., 2012; Siew, McCartney, & Vitevitch, 2019). Since the 1950s, various survey instruments have been developed to measure students' attitudes such as student beliefs, feelings, and behavioural predispositions toward statistics (Nolan, Beran, & Hecker, 2012). Based on the Expectancy Value Theory of Eccles and Wigfield (2020), students' beliefs, values and goals could influence their motivation and performance. Moreover, as the demand for psychologists is increasing due to the increased levels of stress during the global pandemic (Torales, O'Higgins, Castaldelli-Maia, & Ventriglio, 2020), there is a consequent urgency for highly-trained clinical psychologists. Social sciences degrees, such as psychology, draw our attention to the pervasive problem of statistics anxiety in the context of university studies (Macher et al., 2012; Paechter et al., 2017). If students who have a negative attitude towards statistics are identified, they can be assisted through educational interventions which, in turn, may improve their confidence and attitude and consequently their ability to understand statistical concepts.

Consequently, statistics educators need to design and develop a statistics subject that not only educates psychology students in statistical concepts but also encourages them to develop a positive perception of the usefulness and ease of use of statistical concepts and their application in psychology. Many publications in the literature use psychometric survey tools to gauge non-mathematical students' statistics anxiety when taking a statistics subject and assess their reliability and validity (Vigil-Colet, 2008; Chiesi et al., 2011; Oliver et al., 2014), for example, the Statistics Anxiety Scale (SAS) validity was examined by Vigil-Colet (2008)and the Statistics Anxiety Rating Scale (STARS) validity was examined by Chew (2017) and Hanna, Shevlin and Dempster (Hanna, Shevlin & Dempster, 2008) in search of a reliable and valid survey tool.

During the global pandemic, to reduce students' statistics anxiety, we designed and developed an online mindfulness intervention. The link was embedded in the Learning Management System (LMS) of an introductory statistic for psychology subject in the second semester of 2020. The teaching methodology of this subject and the contents of the mindfulness intervention have now been published (Jazayeri, Li, Morris, Laurence, & Loch, 2022). Before the effect of the mindfulness intervention was examined in the published article, the validity and reliability of the online survey tool were examined. The adopted survey tool design was based on the Technology Acceptance Model (TAM) (Chuttur, 2009). It was modified to suit the researchers' purpose and was emailed to the participating students two weeks before the start of the semester via the university-endorsed survey tool, Qualtrics (Qualtrics, 2002).

Technology Acceptance Model (TAM)

The survey tool based on TAM is robust and valid (King & He, 2006) originating from the psychological theory of reasoned action and the theory of planned behaviour. This survey tool has been widely used in the information technology field for around 25 years (Marangunić & Granić, 2015). TAM has been utilised extensively to predict human behaviour in relation to adopting technology. Almost two decades ago, advancements in technology enabled statistical teaching in universities around the world to evolve from mostly introducing theories and using formulas to proving the theories, to teaching intuitive statistical concepts and using limited formulas to solve real-world problems (Bakker, 2004).

Surveys based on TAM have been used to examine the effects of behavioural constructs such as attitude, statistics anxiety and self-efficacy on the perceived ease of use and usefulness of computer software packages (Brezavšcek, Šparl, & Žnidaršic, 2017; Hsu, Wang, & Chiu, 2009). To investigate the influential factors in the adoption of a software statistical package, Hsu et al. (2009) investigated the four constructs of software efficacy, computer attitude, behavioural intentions, and statistics anxiety on users' beliefs such as perceived ease of use and usefulness, during the online delivery of an introductory statistics subject. They claim that computer attitude and statistical software self-efficacy have significant positive effects on perceived usefulness while statistics anxiety has a significant negative impact on perceived usefulness, perceived ease of use and behavioural intentions. The application of survey tools based on the TAM model in higher education and examining learners' willingness to accept e-learning systems was researched by Brezavšcek et.al (2017). They applied an extended survey tool based on the TAM model to investigate the factors influencing the behavioural intentions of students in Slovenia when learning statistics. They also reported that the two most influential factors on students' learning are statistics anxiety and statistics learning value. As discussed in this article, we students' statistics anxiety can manifest in their confidence and attitude. This may have a major effect on students' learning of statistics. Understanding these factors is crucial for developing effective educational strategies to improve students' performance and reduce anxiety in learning statistics.

The aim of this article is to explore the validity and reliability of the modified survey tool based on the TAM model. In this empirical research, the modified version of the survey tool based on the extended TAM model is utilised to investigate the factors affecting students' statistics learning in the fully online delivery of statistics for first-year psychology students during the global pandemic. Our questionnaire represented every component of the modified survey tool based on TAM. Before the analysis, we reversed the scales of all the eight items of the statistics anxiety section which were negatively keyed in the questionnaire.

Due to the increased anxiety levels resulting from the global pandemic and the added challenge of learning statistics in a fully online environment, to understand students' self-awareness of their mental health, a section was added to the extended TAM survey. Mental health, as defined by Skehan, Fox, & Fitspatrick (2022), is related to the social and emotional wellbeing of individuals and communities. The added section to our adopted survey tool was related to the self-awareness of students' mindfulness prior to studying statistics and its software. According to University of California, Berkeley (2022), 'mindfulness' means awareness of our thoughts and feelings without judging them on a moment-to-moment basis through a kind and nurturing lens.

Validity and Reliability

Rubio et al. (2003) describe *validity* as the degree to which a survey measures what it aims to measure. They also state that there are three types of validity: face, content, and logical validity which can be evaluated by a panel of experts. In this article, the utilised survey tool was evaluated for its validity and modified accordingly by a team consisting of two academics from the education and psychology departments in addition to the lecturer of the subject and the statistical consultant involved in this project.

Reliability is concerned with the ability of an instrument to measure consistently (Tavakol & Dennick, 2011). In other words, as explained by Danner (2016), reliability describes the precision of measures such as cognitive abilities, confidence and anxiety which are non-observable variables or so-called latent variables.

In 2012, Nolan et al. (2012) published a systematic review to report on the validity and reliability of the survey tools utilised to investigate students' attitudes, confidence and anxiety towards statistics. They found fifteen different survey instruments from 35 peer-reviewed articles.. It is evident that only a few of the included survey instruments had published measures of validity and reliability and the remainder only reported the reliability scores for the different scales in their utilised survey instruments. As highlighted by Nolan et al. (2012), a very important tool for predicting students' academic performance is the valid and reliable assessment of students' attitude, confidence and anxiety towards learning statistics. As pointed out by Eisinga, Grotenhuis, & Pelzer (2013), the higher the use of multiple subscales in a survey tool such the higher the construct's validity. Consequently, in this research, to increase the validity of the survey tool, we used multiple subscales in the survey. To test the survey design for its precision and consistent measurement capability, the response dataset was analysed by obtaining Cronbach's alpha reliability scores for each section of the survey followed by conducting factor analysis.

Methods

Participants and method of data collection

A total of 530 students enrolled in statistics for psychology were invited via email to take part in the study two weeks prior to the start of the second semester of 2020. In the email invitation, students were directed to a link to complete the survey online. The survey tool based on the modified and extended TAM model was conducted via the university-endorsed online survey tool Qualtrics (Qualtrics, 2002). This research was conducted with La Trobe University ethics approval, licence HEC19013. Of the invited participants, 168 responses were obtained prior to the start of the semester. The survey consisted of 42 questions which were divided into 8 sections. Participation in the survey was voluntary and the research and ethics information was emailed to the students prior to survey administration. The same survey was modified and sent out via Qualtrics to the same cohort during the final week of the semester. However, only 46 pre- and post-intervention responses to the survey were obtained for the analysis. The students had ten days to submit their completed survey. The pre- and post- data was analysed separately. The respondents were asked to rate the degree to which they agreed or disagreed with the statements on a 5-point Likert scale. This article focuses on the validation of the survey instrument, however the details of the teaching methodology of STA1PSY and its transformation to fully online delivery are reported in (Jazayeri et al., 2022).

Statistical analysis

After obtaining the reliability scores for six of the eight sections of the survey instrument, exploratory factor analysis (EFA) was conducted to explore the structure of the survey questions and to find the main factors in the dataset. Factor retention in EFA was determined by factor eigen-values above 1.0, the scree plot criterion (Ledesma, Valero-Mora, &

Macbeth, 2015) and findings from parallel analysis utilizing the web-based application by Donavan, Vivek, Singh, and Mishra (2017). Due to the multi-item nature of the survey, five factors were explored in the EFA phase. This was followed by confirmatory factor analysis (CFA) to test the validity of the constructs of belief, attitude, confidence, independent learner perception and dependent learner perception for students utilizing jamovi 1.1.9.0 (*Jamovi*, 2020) and IBM SPSS AMOS (Version 26) (SPSS, 2020) statistical packages.

There were 191 respondents initially, but only 168 of them completed the entire survey. Some of the 191 respondents only answered the first question. All the responses were reviewed and 168 that had completed the survey were selected. However, within these 168 completed responses, less than 12% of the data was missing, meaning there were some unanswered questions. Data imputations were performed to address these missing responses. . The percentage of missing data (12%) allowed for data imputation (Kyriazos, 2018). The multiple imputation of the missing data is a valid statistical inference when data is missing at random and it fills in missing values multiple times using the information contained in the observed data (Dong & Peng, 2013). Consequently, a complete dataset had to be obtained via multiple imputation techniques using IBM SPSS AMOS (Version 26) (SPSS, 2020) predictive analytics software.

We confirmed the assumption of missing at random (MAR) by explaining that the data was missing by design. In this analysis, the utilised survey subscales are latent variables, which means that the probability of missing data is independent of other observed variables. According to Dong & Peng (2013), this design ensures that the missingness is unrelated to the unobserved data, thereby supporting the MAR assumption.

To generate random values, for data imputation, Mersenne Twister active generator (Jagannatam, 2008) in SPSS was utilised. The multiple imputation approach to handling missing data involved three key steps: (1) imputing the missing data five times to create five complete datasets, (2) analysing each dataset using standard statistical procedures, and (3) combining the results from the five analyses. This method ensured that the imputed values accurately reflected the variability and relationships in the observed data, maintaining consistency and integrity in our statistical analysis. The model was refined to improve the fit, utilising Modification Indices (MI) in IBM SPSS AMOS (Version 26) software. The MI approach predicts which path, if added to the structural diagram, would decrease the chi-squared fit statistic the most (Steiger, 1990). Based on the authors' teaching experience, new parameters (paths in CFA model) were added to the latent variables (constructs) with the highest MIs. After the first run of the CFA, due to a poor fit, the model was modified. The five specified constructs and their correlations were obtained. The set of survey items measuring each construct/factor is detailed.

Results

Of the 530 invited students, 191 respondents (15%) were males and 339 (85%) were females, with ages ranging from 18 to 46 years with an average age of 20.4 (SD=4.6) years. There were 168 completed pre-intervention surveys and of these, there were 46 completed post-intervention survey responses.

The distribution of the background education of the students is as follows: 9% studied up to year 10 mathematics in high school, and 7% had a year 11 mathematics background. As for year 12, 59% studied Further Mathematics, 22% studied Mathematical Methods and 3% studied Specialist Mathematics. 80% of the participants were from the main campus of the university and 20% of the participants were from regional campuses.

The survey participation rate of the 20-year-olds and the 40-year-olds was the same. However, the majority of the participants in the under 19-year-old age group did not participate in the post-intervention survey. Distributing the survey via the university-endorsed online survey tool and conducting this study in the second semester of 2020 coincided with the adverse effect of Covid-19. This could be one of the major contributing factors for the low response rate.

Reliability score

Cronbach's alpha for all measures across the five sections of the modified survey based on the TAM model used in the pre- and post- intervention process were all greater than or equal to 0.80 except for perceived ease of use which was equal to 0.682. In the survey, two sections on self-efficacy and one section on demographic background were not included in these reliability measures due to their irrelevance to the questions for the reliability test. After the reliability analysis had been conducted for each section, we found that no items/questions in the sections could be left out from the analysis because the values of each item's Cronbach's alpha were larger compared with the overall Cronbach's alpha for that section. The power of the reliability tests for each section with a minimum acceptable value of the coefficient 0.7, and significance level 0.05, one-tailed and not adjusting the *p*-value, ranged between 95% to 96% (Arifin, 2017-2022).

The items/questions included in the first four sections of the survey tool (Table 1) were only minorly modified using the original questions in the TAM model to match the participants in the survey. However, the items/questions included in the last four sections of our survey tool presented in Table 1 were either majorly modified or were introduced as new items to that section. Table 1 shows the items in each section of the survey instrument, together with the mean and standard deviation of the responses to each item on 5-point Likert scale measurement. For consistency, only the order from 1: strongly disagree to 5: strongly agree, for the section 'Statistics Anxiety' has been reversed.

Table 1: List of sections, the items in each section, and the means and standard deviations of the responses on the 5-point Likert scale measures (1: strongly disagree to 5: strongly agree). The order of the measurements for eight statistics items has been reversed. The scores presented in the table are after the reversal.

Sections	Question (variable)	Mean, Sd
Attitude	I have confidence in learning statistics (Bel_1)	3.26, 0.948
	I love to study statistics (Bel_2)	2.73, 0.853
	I believe statistics is fun (Bel_3)	2.67, 0.879
	I always liked statistics and am interested in statistics in psychology (Bel_4)	2.86, 1.04

Belief	Statistics develops skills and knowledge required for the jobs of the future in psychology (SBel_1)	4.15,0.606
	Statistics stimulates my thinking (SBel_2)	3.89, 0.746
	Statistics can help solve questions about psychology (SBel_3)	4.17, 0.635
	Statistics helps explain psychological issues (SBel_4)	4.10, 0.706
	Statistics gives opportunity to satisfy my curiosity in relation to psychological matters (SBel_5)	3.67, 0.851
Statistics anxiety	I wonder whether I will ever use statistics in real life (RevAnx_1)	2.88, 1.15
	Statistics is worthless to me being a psychologist (RevAnx_2)	4.07, 0.845
	Statistics is a waste of time (RevAnx_3)	4.18, 0.644
	I don’t think statistics will be useful in my career (RevAnx_4)	3.98, 0.875
	I don’t think statistics will be required in solving psychological issues (RevAnx_5)	4.08,0.777
	I am afraid to ask statistical questions (RevAnx_6)	2.91, 1.09
	Statistics is very difficult subject for me, and I cannot get my head around it (RevAnx_7)	2.64, 1.04
	I feel very anxious studying the subject Statistics for Psychology (STA1PSY) (RevAnx_8)	2.33, 1.14
Intention to actual and future use	I use statistics in problem solving in many psychological issues arising in my professional life (IntAct_1)	2.83, 0.951
	I always try to use statistical concepts /cases in my daily life (IntAct_2)	2.72, 0.994
	There will be several occasions/cases in my future career where I can use statistics and software (IntFut_1)	3.76, 0.798
	I intend to increase the use of statistics and software in my future career. (IntFut_2)	3.70, 0.881
Self-efficacy software	I best learn to use SPSS statistical software if:	
	someone first shows me how to do the analysis (SoftLearn_1);	4.43, 0.664
	someone first helps me get started (SoftLearn_2);	4.38, 0.723
	I learn it myself and call for help when I get stuck (SoftLearn_3);	2.75, 1.09
	I watch the steps of the analysis using a video (SoftLearn_4);	4.03, 0.806
	I read the instructions using the online manual (Stat Lab) (SoftLearn_5);	3.44, 1.05
	I first practice mindfulness and relaxation techniques before I start using SPSS software (SoftLearn_6).	2.77, 1.04
Self-efficacy statistical	I best learn and remember statistical concepts and procedures if:	

concepts	I watch the steps of the analysis using a video (Learn_1);	4.03, 0.803
	someone first helps me get started in an online practice class/computer lab (Learn_2);	4.28, 0.729
	I learn it myself by reading the lecture notes and the book and call for help when I get stuck (Learn_3);	3.02, 1.08
	I watch mini-animation videos with a summary of the objectives and some music (Learn_4);	3.43, 0.985
	I first practice mindfulness and relaxation techniques before I start working on statistics (Learn_5).	2.72, 1.10
Perceived ease of use	Statistical concepts are easy to understand (PercEase_1)	2.66, 0.878
	I find it easy to connect statistical concepts to statistical software such as SPSS (PercEase_2)	2.42, 0.807
	I find it easy to learn statistical concepts by solving problems (PercEase_3)	3.06, 0.894
	I find it easy to learn statistical concepts by surfing on the internet (PercEase_4)	2.79, 0.969
	I find it easy to learn statistical concepts by going through the book chapters (PercEase_5)	2.98, 0.962
	I find it easy to learn statistical concepts by going through the online videos in LMS (PercEase_6)	3.47, 0.895
	I can learn statistical concepts by attending the face-to-face lectures (PercEase_7)	3.86, 0.834
Perceived usefulness	Statistical concepts can improve my study/research/professional performance (PercUse_1)	4.11, 0.657
	Statistics use in my study/result/work can increase my productivity (PercUse_2)	3.89, 0.819
	Statistics use in my life can make me more competitive (PercUse_3)	3.54, 0.898
	Statistics use in my life can make me look at (solve) problems objectively and efficiently (PercUse_4)	3.92, 0.804

Exploratory Factor Analysis

Based on psychometric theorems, three different statistics were obtained to confirm the suitability of the matrix of the response variables for our survey. The preliminary analysis of the correlation matrix indicated the suitability of using EFA because all the correlations between the variables in the response data were above 0.3. Moreover, based on Kaiser and Rice (1974), the results of the Kaiser-Meier-Olkin Measure of Sampling Adequacy (KMO MSA) presented meritorious factorability (0.833). In addition, for Bartlett’s test of sphericity (Dziuban & Shirkey, 1974; Kaiser, 1976; Reddon & Jackson, 1984), the *p*-value was <0.001. The small p-value resulting from Bartlett’s test of sphericity suggests that the correlation matrix significantly deviates from an identity matrix. Given that exploratory factor analysis (EFA) depends on the existence of correlations among variables to unveil underlying factors, a small p-value indicates the presence of meaningful patterns of relationships among variables, which EFA can effectively identify and interpret. Rejecting the null hypothesis of an identity correlation matrix justifies the application of factor analysis and confirms the assumption that the data can be reduced to smaller factors.

The lowest correlation on the main diagonal of the anti-image correlation matrix was 0.683, which again confirms the suitability of the inclusion of these variables in the factor analysis. To find the number of factors that account for the correlations among the variables, the extraction method used was Principal Axis Factor using Promax rotation (so it is an oblique rotation, and we allow for the factors to be correlated) with factors minimum threshold loading of 0.4 which converged in the 7th iteration. Table 2 represents the pattern matrix of the factors of the pre-survey dataset. The five factors are:

1. Confidence,
2. Attitude,
3. Independent learner,
4. Dependent learner
5. Mindfulness

As can be seen, the eight sections which comprise forty-two items in the survey instrument are presented as five constructs or factors. The name of each factor/construct is based on the items included in that factor/construct group. In Table 2, the percentage of variance accounted for by each factor/construct is presented in the bracket next to their name in the first column. In addition, the total variance and itemized factor loadings for each factor are presented in the columns of Table 2.

The items/questions included in the last three factors in Table 2 are mostly the newly introduced questions to the original survey tool based on the TAM model which we modified and used. Interestingly, the 'statistics anxiety' section questions referring to Table 1 in our survey were distributed among the two constructs of 'Confidence' and 'Attitude'. The first five questions included in the 'statistics anxiety' section based on TAM are now loaded on the factor we called 'Confidence'. These questions are all related to considering statistics learning being a waste of time and useless (Table 1). However, the last three questions in the 'statistics anxiety' section of the survey are all related to being anxious or afraid of studying statistics. In this study, they are loaded on the factor called 'Attitude'. Consequently, the three distinct factors of 'Independent-learner', 'Dependent-learner' and 'Mindfulness' are constructed from this analysis.

Table 2- Pattern matrix showing each factor's order number (from highest to lowest), name, total variance, and percentage of variance accounted for by each factor together with factor loadings of items across these five factors.

	Factor number (total variance)				
	1(10.22)	2(3.96)	3(2.30)	4(2.09)	5(1.61)
Construct (Percentage of variance accounted for by each factor					
Confidence (23.77 %)					
1. Perceived values (part B) SBel_1	.761				
2. Perceived values (part B) SBel_2	.413				
3. Perceived values (part B) SBel_3	.659				
4. Perceived values (part B) SBel_4	.748				

5. Perceived values (part B) SBel_5	.537				
1. Anxiety (part A3) RevAnx_1	.403				
2. Anxiety (part A3) RevAnx_2	.723				
3. Anxiety (part A3) RevAnx_3	.811				
4. Anxiety (part A3) RevAnx_4	.759				
5. Anxiety (part A3) RevAnx_5	.838				
1. Intention to actual use (part C) IntAct_1	.420				
1. Intention to future use (part C) IntFut_1	.695				
2. Intention to future use (part C) IntFut_2	.592				
1. Perceived usefulness (part G) PercUse_1	.637				
2. Perceived usefulness (part G) PercUse_2	.518				
4. Perceived usefulness (part G) PercUse_4	.414				
Attitude (9.21%)- cumulative 32.97%					
1. Attitude (part A2) Bel_1		.724			
2. Attitude (part A2) Bel_2		.738			
3. Attitude (part A2) Bel_3		.697			
4. Attitude (part A2) Bel_4		.513			
6. Anxiety (part A3) RevAnx_6		.564			
7. Anxiety (part A3) RevAnx_7		.851			
8. Anxiety (part A3) RevAnx_8		.852			
1. Perceived ease of use (part F) PercEase_1		.736			
2. Perceived ease of use (part F) PercEase_2		.476			
3. Perceived ease of use (part F) PercEase_3		.602			
Independent learner (5.34%-cumulative 38.32%					
3. Independent Learn- (part D) SoftLearn_3			.437		
5. Independent Learn - (part D) SoftLearn_5			.515		
1. Independent Learn (part E) Learn_1			.534		
3. Independent Learn (part E) Learn_3			.589		
4. Independent Learn (part E) Learn_4			.455		
Dependent learner (4.85%- cumulative- 43.17)					
1. Dependent Learn (part D) SoftLearn_1				.788	
2. Dependent Learn (part D) SoftLearn_2				.926	
2. Dependent Learn (part E) Learn_2				.681	
4. Dependent Learn (part D) SoftLearn_4				.403	
Mindfulness (3.73%- cumulative 46.91)					
6. Mindfulness (part D) SoftLearn_6					.646
5. Mindfulness (part E) Learn_5					.651

Confirmatory Factor Analysis of the data

Pre-survey data (with missing values) were first imported to IBM SPSS AMOS (Version 26) predictive analytics software and the initial model with correlations existing between all the latent variables was obtained. The confirmatory factor model consisted of the five latent variables (constructs): confidence, attitude, independent learning belief, dependent learning belief and mindfulness. The sixteen items of the survey tool (5 ‘perceived value, 5 ‘anxiety’, 3 ‘intention to actual and future use’, and 3 ‘perceived usefulness’) were hypothesized to measure the ‘confidence’ factor. The ten items of the survey (4 ‘attitude towards statistics’, 3 ‘anxiety’ and 3 ‘perceived ease of use’) were hypothesised to measure the ‘attitude’ factor. The six items of the survey (6 ‘independent-learn’, in statistics and software) were hypothesized to measure the 'Independent learner belief' factor. The four items in the survey (4 'dependent-learn' belief in statistics and its software) were hypothesized to measure the 'dependent learner' factor. Finally, two measures of self-awareness of feelings (1 software statistics learning, 1 self-awareness of feeling) were hypothesized to measure the 'mindfulness' factor.

Primarily, the results show that the Tucker-Lewis index (TLI) and Comparative Fit Index (CFI) values were 0.744 and 0.762 respectively with the root mean square error approximation (RMSEA) value of 0.085 CI (0.079, 0.092). Based on Jöreskog (1993) this was an acceptable but not a close fit. To modify the model, the missing values were first evaluated to make sure that data were missing at random and not systematically. Next, by choosing the Mersenne Twister in the active generator and setting the seed value, five multiple imputations of data were conducted. In Amos, to further refine the model, the 5th imputed dataset was utilised. Conducting an analysis of a complete dataset enabled the analysis to test for normality and outliers, as well as the extraction of the 'Modification Indices' (MI) in the output tab of the 'Analysis Properties' in this procedure. Three small covariances between the following constructs 'Confidence' and 'independent-learn', 'Confidence' and 'dependent-learn', 'mindfulness' and 'dependent-learn', were omitted in the final model which improved the TLI and CFI to 0.830 and 0.843 respectively with RMSEA of 0.070 CI (0.063, 0.076). The path diagram of the final best fit model is shown in Figure 2.

Measurement Invariance Test
In the configural invariance step of the analysis, (to investigate whether each obtained construct had the same meaning across repeated measurements of pre- and post-intervention), due to the major differences in the estimates, we were not able to utilize the same EFA and CFA for both pre- and post-intervention data. Therefore, the same underlying construct could not be measured across both pre- and post- intervention data. The post-intervention data needed to be analysed separately for EFA and CFA modelling. However, due to the low number of responses compared with the large number of variables, this part of the analysis could not be delivered.

Discussion

Teaching statistics to students in the psychological and social sciences at a tertiary level requires a different approach compared with other STEM students. Previous research emphasized the importance of the effects of students' statistics anxiety on their attitude and confidence and consequently on their performance (Eccles & Wigfield, 2020). To develop an efficient and effective statistics subject, while introducing an intervention to reduce students' statistics anxiety, research into the structure of these factors was conducted. A survey based on the modified and extended TAM was conducted in the second semester of 2020 at the start of the global pandemic. This survey was constructed as multiple, heterogeneous indicators making up eight different subscales. The subscales of the survey based on the TAM model were a) attitude, b) belief, c) statistics anxiety, d) intention to actual and future use, e) self-efficacy software, f) self-efficacy statistical concepts, g) perceived ease of use, and h) perceived usefulness. The modified survey tool included questions on the students' learning style as well as mindfulness in these subscales. Participants were first-year psychology students who had completed the survey two weeks prior to the start of semester and in the last two weeks of semester. The Cronbach's alpha reliability score for each section was obtained utilizing jamovi software. Due to the utilization of multiple sections in the survey tool, it was highly likely that the constructs of interest would be identified.

This was followed by EFA and CFA in structural equation modelling utilizing AMOS software in IBM SPSS to check the reliability and the structural validity of the survey. EFA was conducted on the pre-intervention dataset, which consisted of 168 completed surveys. Of the eight sections in the survey, five factors were observed, namely Confidence, Attitude, Independent learner belief, Dependent learner belief and Mindfulness. These five factors explain the variances in the total scores for the full-scale survey tool. Interestingly, statistics anxiety' subscale items were loaded on two main factors of Attitude and Confidence. The first five items of the statistics anxiety section of the survey, perceived usefulness of statistics study and perceived value of studying statistics were loaded on the 'Confidence' construct. Moreover, Confidence explained more than 23% of the variability among the total scores for the full-scale survey. The second main factor, namely, Attitude, consisted of the last three items of the statistics anxiety section plus the four items of belief of statistics concepts were easy and fun, and three perceived ease-of-use of statistics. Attitude explained about 10% of the variance in the total scores for the full-scale survey. The remaining three factors, Dependent-learner belief, Independent-learner belief and Mindfulness awareness, each explained about 5% of the variance in the total scores for the full-scale survey. The results of the CFA which indicated that there was next to zero correlation between the constructs of 'confidence' and 'dependent-learner belief' or 'confidence' and 'independent-learner belief' directs this research towards whether a student's motivation of learning statistics is independent of his/her confidence level. This raises the question as to whether intrinsic learning motivation has any effect on students' performance. The lack of correlation between the dependent-learner belief and awareness of one's state of mind (mindfulness) is also interesting. Do students who believe they need step-by-step guidance in their learning have no awareness of their state of mind?

The factor analysis was followed by the measurement invariance test for the pre- and post-intervention data to investigate the possibility of the meaningfulness of the same constructs for the post-intervention survey responses. However, due to the low number of post-intervention respondents, the measurement invariance test was not conducted.

This article presents the important findings in the factorial structure of the modified and extended survey tool based on the TAM model in this setting, indicating that the intercorrelation pattern of the eight sections in the survey can be explained by five factors. The validation studies support the usefulness of the self-awareness of students' mindfulness status on their confidence and attitude. In addition, this study emphasizes the importance of consideration of the requirement of preparation of teaching material for dependent learners and independent learners separately at the university level. Further studies are necessary to have a sufficient sample to be able to conduct the measurement invariance test.

The main limitation of this study is the modest pre- and post-intervention response rates (the pre-intervention response rate was 36% whereas the post-intervention response rate reduced to 8%). As explained by Kyriazos (2018), the higher the sample size, the more valid the results of the analysis of the EFA and CFA. However, based on Memon et al. (2020), large samples can make statistical significance overly sensitive, which can result in a Type 1 error. According to Wolf, Harrington, Clark, & Miller, (2013), a sample size between 100 to 200 responses is adequate for a valid CFA analysis.

One of the key reasons for the low response rates could be the increase in the number of Covid cases when the pre- and post-intervention surveys were introduced. The lower age bracket of non-responders could be due to this cohort's time management and placing the survey in the non-urgent basket which could result in missing the opportunity to submit the survey on time. Some students could have missed the survey due to having too many assignments due at the same time.

Future research could investigate the effect of demographic variables such as sex, age, socioeconomic background, and students' educational levels on the observed relationships of the constructs.

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