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Measuring risks associated with students of introductory statistics: Scale development and implementation

Abstract

A lack of understanding of statistics, and being unable to apply its techniques, not only has a negative impact on the pass rates of students studying introductory statistics, but also affects the potential usefulness of these students when they enter the marketplace. I report here a novel scale developed to measure various factors that may be associated with the risk of failing an introductory statistics module at university. Various scales are available, but a single scale succinctly combining the factors was not available. The risks students face were explored by creating a 17-item instrument, named the Statistics Students' Risk Questionnaire (SSRQ). The resulting SSRQ scale consists of four dimensions (motivation, attitude towards statistics, statistical anxiety and academic procrastination) that were identified through exploratory factor analysis. The model was confirmed using confirmatory factor analysis. The reliability of the scale was determined, and its usefulness was demonstrated to identify at-risk students. The scale can be applied to determine overall risk but can also be used to reveal which factors contribute to the risk. The scale can be supplemented by including the mathematical history of students of concern as an additional risk factor. This enables the statistics lecturer to select an appropriate support plan to assist at-risk students based on which factors are flagged as risks.

Keywords: *Statistics students at risk, statistical anxiety, attitude towards statistics, motivation, academic procrastination, mathematical history, scale development.*

1. Introduction

Statistics is a crucial discipline for students, irrespective of what they are studying, since it is needed not only to evaluate empirical evidence but also to reinforce empirical research through the application of statistical techniques (Ridgway, Nicholson & McCusker, 2007). High failure rates in introductory statistics modules lead to increased costs for the students and the institution as well as to undergraduates being delayed entering their careers (Gultice, Witham & Kallmeyer, 2015). Since students often struggle with their statistics course, they develop negative attitudes towards

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it (León-Mantero *et al.*, 2020). The effectiveness of teaching statistical courses is therefore critical (Ramirez, Schau & Emmioglu, 2012).

The purpose of this study was to develop a scale that can be used as an efficient detection tool to identify students who may be at risk of failing an introductory statistics module. Various scales exist, but currently no single scale measures the statistical anxiety, the attitude towards statistics, the tendency to procrastinate when faced with statistical assignments and the motivation of a student. The scale presented in this study measures all these factors in one concise questionnaire.

This scale can be applied as a screening instrument to identify potentially at-risk undergraduates early in a semester, after which they should receive appropriate assistance. This is a better strategy than waiting for test results to identify those at-risk by their subsequent failure, since by then valuable time has been lost and foundational knowledge for the module has not been mastered (Gultice, Witham & Kallmeyer, 2015). It also provides valuable information on what contributes to the risk, making it easier to determine an appropriate course of action for someone identified as weak.

This scale's ability to identify at-risk students can be compared to existing scales. Universities can then decide if they prefer using only this scale in future, or in combination with other available scales.

2. Literature review

Numerous studies have been conducted to illustrate reasonably valid indicators of students studying statistics who are likely to fail (Alston, Lane & Wright (2014); Elder, Jacobs & Fast (2015); Dupuis *et al.* (2012); Duru, Duru & Balkis (2014); Galagedera, Woodward & Degamboda (2000); Macher, Paechter *et al*. [2013]; Ratanaolarn (2016)).

Research shows that factors such as statistical anxiety and attitude towards statistics affect the performance of students in subjects such as business statistics (Zanakis & Valenzi, 1997), research methodology (Mji & Onwuegbuzie, 2004) and introductory statistics for psychology students (Chiesi, Primi & Carmona, 2011). It has also been shown that procrastination and statistical anxiety are related (Onwuegbuzie, 2004). Studies have further revealed that statistical anxiety is influenced by previous mathematical experience and skills (Baloğlu, 2003). Various motivational regulation strategies can be indirectly linked to high academic performance via academic procrastination (Grunschel *et al.*, 2016) and learning effort (Schwinger & Stiensmeier-Pelster, 2012).

These studies indicate that the following factors are important when determining a statistics student's risk: statistical anxiety, attitude towards statistics, motivation, academic procrastination and mathematical foundation. Each of these concepts will be defined and its effect on performance in statistics courses, discussed.

Statistical anxiety is "a performance characterized by extensive worry, intrusive thoughts, mental disorganization, tension, and physiological arousal…when exposed to statistics content, problems, instructional situations, or evaluative contexts, and is commonly claimed to debilitate performance in a wide variety of academic situations by interfering with the manipulation of statistics data and solution of statistics problems" (Zeidner, 1991: 319).

Statistical anxiety is a relatively common problem among students in the social and behavioural sciences (Onwuegbuzie & Wilson, 2003; Einbinder, 2014), management sciences

(Zanakis & Valenzi, 1997) and health sciences (Welch *et al.*, 2015). It adversely affects a student's ability to understand research articles, data analysis and the interpretation of these analyses (Onwuegbuzie, 1997). It also has an adverse effect on academic performance in statistics (Macher *et al.*, 2013).

Attitudes towards statistics can be defined as "a disposition to respond favourably or unfavourably to objects, situations or people related to statistics learning" (Chiesi & Primi, 2009: 309). Such attitudes include anxiety, cynicism, fear and even contempt (Hopkins, Glass & Hopkins, 1987). According to Ratanaolarn (2016), students' grades in statistics are influenced positively by their attitudes towards the subject. Not only do these attitudes affect their performance, they also have an effect on the extent to which they may be willing to use statistics later in their careers (Zanakis & Valenzi, 1997, Montcalm, 1999).

Academic success is influenced by various aspects of motivation; one of the important ones is self-regulation. This includes a student's ability to direct his or her thoughts and behaviours towards the attainment of their goals (Dunn *et al.*, 2012).

Academic procrastination can be seen as the daily postponement of duties and responsibilities that relate to school (or college or university), or to delay them to the eleventh hour (McCarthy, Haycock & Skay, 1998). A significant number – between 80% and 95% – of college students apparently engage in procrastination (Wilson & Nguyen, 2012). Steel (2007) reports a correlation of –0.19 between academic performance and procrastination. The negative effect on academic performance is because passive procrastination limits not only the quantity but also the quality of a student's work (Dunn *et al.*, 2012).

Owing to the numerical nature of statistics, students lacking a strong mathematical foundation tend to struggle with statistics. Dupuis *et al.* (2012) explain in their research that a strong mathematical background benefits a student later when studying statistics, since those with such a history enrolled for more difficult statistics courses and obtained higher grades. However, Galagedera *et al.* (2000) found no significant correlation between prior mathematical performance and statistical reasoning.

3. Research objective

The primary objective of this study was to develop a scale that can be used as a detection tool to identify students at risk of failing an introductory statistics module. The dimensionality of the scale was determined, and its effectiveness was illustrated by comparing students' risk to fail, based on the scale, with the marks they obtained. Finally, guidelines have been provided on how to use it to identify and assist at-risk students.

Research questions that were addressed are:

- Does the SSRQ scale meet the requirements for goodness of fit?
- Is the scale reliable?
- Do the items demonstrate good discrimination?
- Do the constructs display discriminant validity?
- Is a high mean risk (as calculated from the SSRQ) associated with a low mark in an introductory statistics course?
- Is there a difference in the performance of students in statistics, based on the type of mathematics taken in matric?

4. Research method

The target population for this study was BA and BCom students who were enrolled for an introductory statistics module at a leading South African university. Permission was obtained from the ethics committee to conduct the research; ethical clearance number is ECONIT-2016-028.

In order to develop a suitable scale and test its usability, a cross-sectional correlational study was used. First, the literature was reviewed to identify possible risks. Existing scales that measure these risks were considered. A scale was then developed – which we call the Statistics Students' Risk Questionnaire (SSRQ) scale – using some questions from different scales to form one concise scale that measures the identified risks. Statistics lecturers were asked to comment on the scale and amendments were made. After completing a pilot study, the final questionnaire consisted of the scale's questions as well as questions pertaining to a student's mathematical foundation and performance in the statistics course. The questionnaire was distributed among students of an introductory statistics course, which they voluntarily completed. Construct validity was investigated using exploratory and confirmatory factor analysis. Reliability and discriminant validity were determined. To assess if the scale provides a good measure to predict which students may be at risk, the mean risk of a student was compared to the student's performance in the course.

In constructing the scale items of the Statistics Students' Risk Questionnaire (SSRQ) used to assess the students, three resources were used: information from the literature, inputs from colleagues, and students' opinions. Possible risks were identified: statistical anxiety, attitude towards statistics, motivation and academic procrastination. Established scales that measured these risks were identified and considered (the Statistical Anxiety Rating Scale [STARS] (Cruise, Cash & Bolton, 1985); Attitude Toward Statistics Scale [ATS] (Wise, 1985); the General Procrastination scale [GP] (Lay, 1986); the Adult Inventory of Procrastination [AIP] (Díaz-Morales *et al.*, 2006), and Motivated Strategies for Learning Questionnaire [MSLQ] (Dunn *et al.*, 2012). Drawing on these scales, a new scale was devised. A pilot questionnaire was constructed that contained questions that measured each of the possible risks mentioned above. Statistics lecturers were asked to evaluate the original, proposed questionnaire, and as a result some changes were made. The questionnaire was then distributed online, and 170 students voluntarily completed it. A final pool of 19 items was formed, assessed using a five-point Likert scale. The final SSRQ was distributed to 274 participants in the introductory statistics classes during the following year. The collected data were uploaded and analysed using SAS 9.4.

5. Results

5.1 Sample profile

A total of 274 responses were captured for analysis. The race distribution in the sample was black (81%), white (11%), coloured (6%) and Indian (2%). Most of the students were registered for BCom (54%) and the rest for BA (46%) degrees. As many as 78% had not failed statistics modules previously, 17% had failed a statistics module once, whereas 5% had failed it twice or more times. Moreover, 54% passed mathematics and 46% passed mathematical literacy in Grade 12.

5.2 Exploratory factor analysis (EFA)

Four measures were used to evaluate the appropriateness of the data set for factor analysis: sample size, sample to variable ratio, Kaiser's Measure of Sampling Adequacy (MSA), and Bartlett's test of sphericity. The sample size obtained was 217 (57 observations had missing values). This is acceptable because the recommended minimum sample size is 150, according to Pallant (2013). The number of variables considered for the EFA was 19. The sample to variable ratio was 11.4 cases per variable. This is greater than 5, which is the minimum acceptable ratio of cases per variable (Pallant, 2013). The overall MSA yielded a value of 0.822. According to Hair *et al.* (2014), a value of 0.80 or above is meritorious. A high MSA is associated with a large sample size, high average correlations and a low number of factors. MSA for the individual variables ranged from 0.70 to 0.87, which are all above the minimum requirement of 0.50 (Hair *et al.*, 2014). In addition, Bartlett's test of sphericity was significant ($p < 0.0001$). This tests if the correlation matrix shows significant correlations among the variables. The data set was considered appropriate for factor analysis (Hair *et al.*, 2014).

Three criteria were used to determine the number of factors to be extracted: latent root criterion, scree test and cumulative percentage variance explained. According to the latent root criterion, an eigenvalue represents the amount of variance associated with each factor. Four eigenvalues were greater than one. The "elbow" of the scree plot indicates that four factors should be extracted. Four factors represented 60.3% of the total variation of the 19 variables. Based on these three criteria, it was decided to extract four factors using the principal component extraction method with varimax rotation.

All the constructs were one-dimensional, meaning that each construct loaded high on one of the factors but loaded significantly lower on the others. All the factor loadings were significant – above 0.40 (Hair *et al.*, 2014). The item-total correlation of the items ranged from 0.23 to 0.53. Typically, the minimum value should not be lower than 0.30. Items 18 and 19 (out of 19) were the only variables with values less than 0.30. It was therefore decided to remove them and redo the factor analysis. After removing these two items, the total variance of the 17 items explained by the four factors was 58.1%. Preferably, the communalities should not be less than 0.50 (Hair *et al.*, 2014). In this case, they ranged from 0.483 to 0.702, which was deemed acceptable.

The results of the factor analysis are shown in Table 1 below. The four-factor SSRQ scale was further refined and validated through confirmatory factor analysis (CFA).

Table 1: Results obtained from the factor analysis and item analyses

Factors/ Dimensions	Item No.	Factor loading value	Item–total correlations [a]	Lower–upper groups difference t-value	Cronbach's α [b]	Eigen-value [c]	Variance explained
Statistical Anxiety	2	0.831	0.494	–8.29**	0.837	4.848	28.5%
	1	0.778	0.535	–8.61**			
	5	0.769	0.481	–9.78**			
	4	0.761	0.530	–8.75**			
	3	0.647	0.482	–7.09**			

Factors/ Dimensions	Item No.	Factor loading value	Item–total correlations [a]	Lower–upper groups difference t-value	Cronbach's α [b]	Eigen-value [c]	Variance explained
Procras-tination	9	0.760	0.486	-8.39^{**}	0.789	2.125	12.5%
	7	0.734	0.509	-7.59^{**}			
	6	0.655	0.470	-7.58^{**}			
	10	0.644	0.475	-7.32^{**}			
	8	0.633	0.382	-6.01^{**}			
R-At *Attitude****	13	0.764	0.382	-6.30^{**}	0.702	1.158	6.8%
	14	0.697	0.348	-7.10^{**}			
	12	0.650	0.316	-4.01^{*}			
	11	0.580	0.513	-8.82^{**}			
R-Motivation***	17	0.783	0.391	-5.48^{**}	0.620	1.758	10.3%
	16	0.633	0.373	-6.67^{*}			
	15	0.552	0.418	-6.83^{**}			

$^{*}p < 0.001$ $^{**}p < 0.0001$ ***Attitude and motivation were reverse coded.

a. Item–total correlations are all above 0.3.

b. Cronbach's α values are all above 0.6.

c. Eigenvalues are all above 1.

5.3 Confirmatory factor analysis

The indicator items measured were assigned to latent constructs. CFA was run for all the constructs through structural equation modelling (SEM), using Proc Calis of SAS 9.4. The SSRQ scale with four factors collectively comprised 17 items.

Various goodness-of-fit indices were used to assess the SSRQ scale. SEM allows for testing of the interrelationships among a set of related variables through multiple regression procedures. The overall fit of the model is indicated by the chi-square test (χ^2). For the SSRQ scale $\chi^2 = 256.82$, $df = 113$, $p < 0.0001$ was obtained. However, this test is viewed as an overly strict indicator of model fit, given its power to detect even inconsequential deviations from the proposed model (Hair *et al.*, 2014). The normed chi-square ratio χ^2/df should ideally be less than 3 (Hair *et al.*, 2014). The SSRQ scale met the required condition, since $\chi^2/\mathrm{df} = 2.273$.

A number of model fit indices were used to assess model fit: goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI) and comparative fit index (CFI). A perfect fit is obtained when indices are close to one (1), whereas those close to zero (0) represent no fit (Hair *et al.*, 2014). The results of the fit indices were 0.888 for GFI, 0.849 for AGFI, and 0.880 for CFI. Concerning the root mean square error of approximation (RMSEA), there is a good model fit if RMSEA is less than or equal to 0.05 and an adequate fit if it is less than or equal to 0.08 (Blunch, 2016). The RMSEA result for this model was 0.073. Overall, the scale portrayed a very good fit for the data set as indicated by the chi-square ratio test, several goodness-of-fit indices, and RMSEA results. Thus, the 17-item scale SSRQ with four dimensions is valid and robust.

5.4 Reliability

The overall SSRQ scale displayed excellent reliability (Cronbach's α = 0.84). The Cronbach's α reliability of three of the four factors extracted ranged from 0.702 to 0.837. The Cronbach's α reliability of motivation was 0.62, which is somewhat low, but still acceptable (Hair *et al.*, 2014). Cronbach's α reliability of the four factors extracted were all above 0.6, which portray fairly good reliability.

Composite reliability (CR) for statistical anxiety was 0.87, for procrastination, 0.82, for attitude, 0.77 and for motivation, 0.70. This suggests good internal consistency of the scale. Thus, overall, the scale was found to be reliable.

5.5 Item analyses

The results of the item analyses are presented in Table 1. The item–total point correlation of the items in the SSRQ yielded a minimum value of 0.316 and a maximum value of 0.535. Since all the values are higher than 0.30, the items' discrimination is good.

The total scale point was calculated, and the 27th and 73rd percentiles were calculated. Values below the 27th percentile were allocated to the lower group, whereas values above the 73rd percentile were allocated to the upper group. T-tests were used to determine if the items' means differed significantly for the two groups. All the t-values were found to be significant ($p < 0.001$), indicating that the distinctiveness levels for all items are high. Each item, therefore, makes a consistent classification.

5.6 Discriminant validity

Discriminant validity refers to the extent to which the constructs differ from one another (Hamid, Sami & Sidek, 2017). One measure to evaluate discriminant validity is the Fornell and Larcker criterion. Here, the square root of the average variance extracted (AVE) is compared with the correlation of latent constructs (Hamid *et al.*, 2017). The reasoning behind this criterion is that a latent construct should explain the variance of its own indicator better than the variance of other latent constructs. Therefore, the square root of each construct's AVE should be greater than each of the correlations with other latent constructs (Hamid *et al.*, 2017). As can be seen in Table 2 below, the smallest square root value of AVE is 0.620, which is greater than the largest squared correlation of 0.330. According to the Fornell and Larcker criterion, the scale shows discriminant validity.

Table 2: Squared correlations and the square root of AVE — average variance extracted (on the diagonal)

SSRQ dimensions	Statistical anxiety	Procrastination	Attitude	Motivation
Statistical anxiety	**0.719**			
Procrastination	0.164	**0.646**		
Attitude	0.138	0.082	**0.622**	
Motivation	0.074	0.330	0.301	**0.620**

5.7 Scoring the scale

For each individual whose risk of performing badly in introductory statistics is to be measured, 1, 2, 3, 4 or 5 points were given to the options “Strongly disagree”, “Disagree”, “Neutral”, “Agree”, and “Strongly agree”, respectively. The points were added together and divided by the number of items, to provide a measure of the risk of performing badly. The expected point range is 1.0 (lowest) and 5.0 (highest), where a value of close to 1.0 indicates that the student is not at high risk, whereas a value close to 5.0 indicates that he or she is at high risk.

5.8 Identify students at risk

The mean risk was calculated for each participant in the survey as explained above and compared to the student’s participation mark (made up of marks for tests and assignments). As can be seen from the statistics provided in Table 3, low participation marks are associated with high mean risk, and high participation marks with low mean risk. The correlation between the mean risk and the participation mark is $r = -0.446$ ($p < 0.0001$), indicating a moderately negative relationship. Correlations between the participation mark and the individual factors are $r = -0.322$ ($p < 0.0001$) for statistical anxiety, $r = -0.232$ ($p = 0.0002$) for academic procrastination, $r = 0.353$ ($p < 0.0001$) for motivation and $r = 0.328$ ($p < 0.0001$) for attitude towards statistics. The negative association found between performance and statistical anxiety is stronger than the correlation ($r = -0.035$) reported by Paechter *et al.* (2013), who used the STARS instrument. The results of the SSRQ also compare favourably with the correlation of –0.19 that Steel (2007) reports between academic performance and procrastination. Chiesi & Primi (2010) also found a positive effect between performance and attitude.

Students awarded a participation mark of 59 or less can be considered still at risk of failing the exam, therefore a cut-off value of 2.80 may be used. Students whose mean risk value is higher than 2.80 may be at risk of failing the module, whereas those with a mean risk of less than 2.80 have a low risk of failing.

Table 3: Risk statistics for different intervals of the participation mark: mean, standard deviation and sample size

Participation mark	Mean risk	Standard deviation of risk	Sample size
0–39	2.98	0.75	12
40–49	2.89	0.58	29
50–59	2.93	0.63	42
60–69	2.70	0.50	58
70–79	2.44	0.58	54
80+	1.99	0.57	35

The analysis of variance indicates that the mean risk differs significantly for different participation mark groupings ($F = 13.92$, $p < 0.0001$). This data set does not indicate a linear relationship. However, the fact that the number of students in the first two classes (0–39 and 40–49) is small ($n = 12$ and 29, respectively) may be the reason why these two classes behave differently from the expected. No model can perfectly distinguish performers from non-performers because other factors often play a role that were not determined at the time the study was conducted, for example illness.

Another way of identifying students at risk is by looking at how many of the four factors have a mean value greater than 3. As Figure 1 indicates, the more factors that have mean values greater than 3, the higher the mean risk of a student failing. A student with no risk factors with values greater than 3 will typically have a low risk of failing. When a student has two or more factors that have been flagged, the risk becomes high, and action should be taken to support that person.

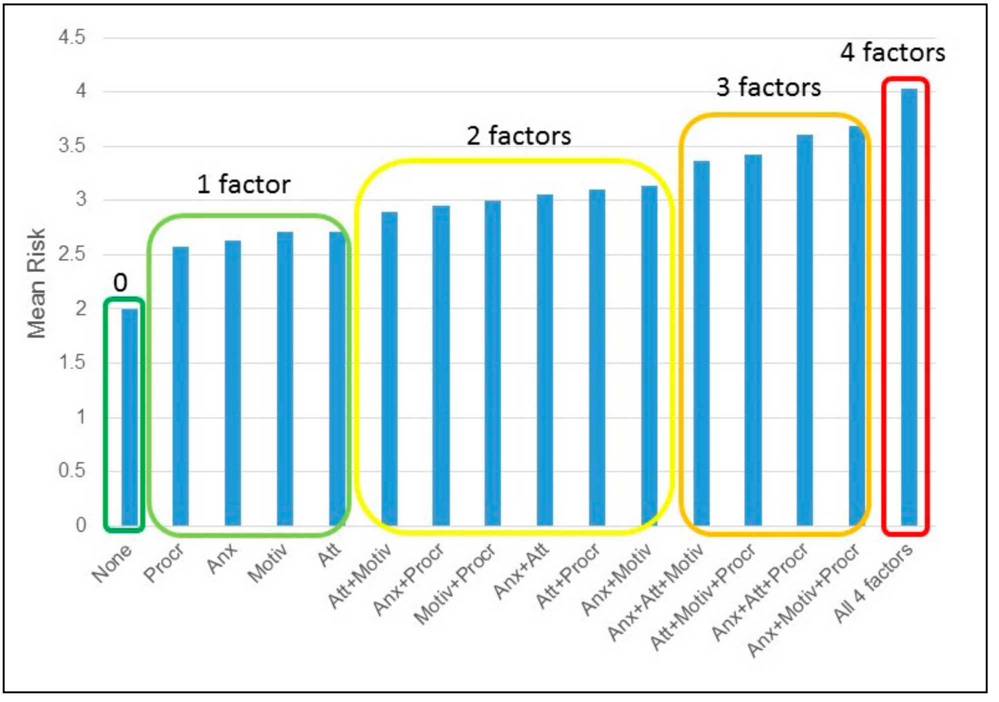

Figure 1: Risk factors (having mean values greater than 3) versus mean risk. The more factors that have been flagged as representing a risk, the higher the mean risk is.

Another factor that may be added to the four factors of the SSRQ is the student's mathematical background. In South African state schools, learners can matriculate either with mathematics or with mathematical literacy. This study indicates that students who matriculated with mathematical literacy are at a significantly greater risk of performing poorly in statistics than those who matriculated with mathematics. Of the students who scored less than 50% for their participation marks, 69% had matriculated with mathematical literacy. On the other hand, 76% of the students who obtained 70% or more had taken mathematics (= 33.16, $df = 3$, $p < 0.0001$). Figure 2 shows the relationship between mathematical type and participation mark.

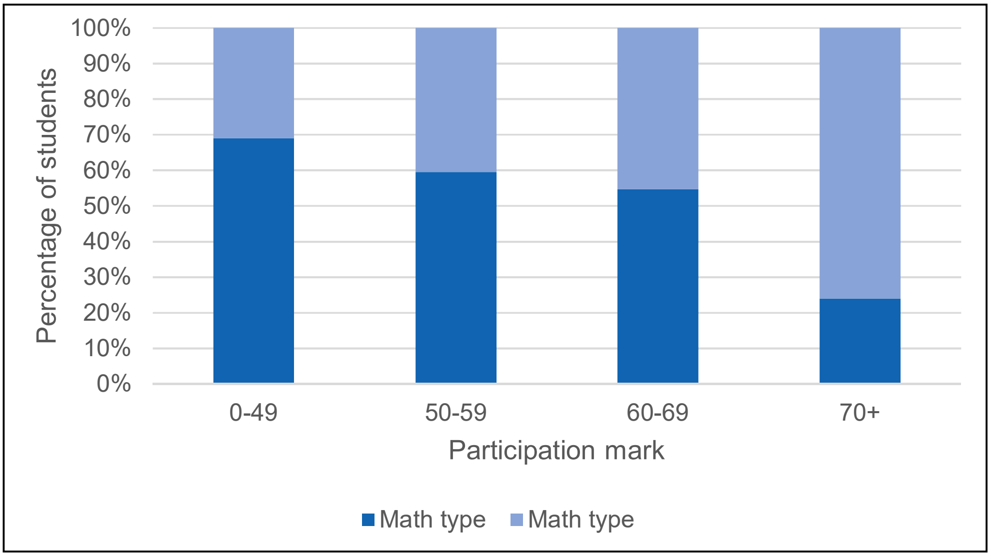

Figure 2: The effect of the mathematics exam taken for matriculation on participation mark.

Having matriculated with mathematical literacy is more associated with low participation marks whereas having mathematics as a subject in Grade 12 is more associated with high participation marks.

6. Discussion

6.1 Development and performance of scale

The SSRQ scale was developed to measure the potential risk that a university student will fail an introductory statistics module. The aim of the tool was to have a measure that quantifies a student's risk of failing a statistics module early in the semester, so that these at-risk students can be identified and special care provided for them.

The results have shown that the SSRQ scale consists of four dimensions that are valid and robust. The overall scale shows excellent reliability with good internal consistency, while each of the factors individually has satisfactory reliability. The scales' items show good discriminant validity.

The SSRQ consists of 17 items, each measured on a five-point Likert scale. The PCA revealed four underlying factors, namely Statistical Anxiety, Attitude towards Statistics, Motivation, and Academic Procrastination. These factors accounted for 58.1% of the total variance. High levels of statistical anxiety and academic procrastination, together with low motivational levels and a negative attitude towards statistics are indicators of an at-risk student.

The Cronbach's alpha reliability of the whole scale was 0.84, which compares well with 0.88 for STARS and 0.82 for SATS that were administered to South African students (Mji, 2009). The scale compares well with a scale developed by Ratanaolarn (2016), which combined STARS, SATS and the Course Experience Questionnaire. The χ^2/df of the CFA of SSRQ was found to be 2.27 (compared to 1.07 of Ratanaolarn's instrument) and the RMSEA was 0.07 (versus 0.02). Furthermore, the GFI, AGFI and CFI were 0.89 (versus 0.93), 0.85

(versus 0.91) and 0.88 (versus 0.99), respectively. The CR ranged from 0.697 to 0.871 for the four factors, indicating good reliability. The Fornell and Larcker criterion had a minimum square root value of 0.620, which is greater than the maximum squared correlation of 0.330, indicating discriminant validity. The Lower–Upper Groups Difference t-values are all significant ($p < 0.001$), indicating that each item makes a consistent classification.

When comparing the SSRQ to the SATS and the STARS, which are widely used to determine attitudes towards statistics and statistical anxiety, it should be noted that the SATS consists of 36 response items and 51 for the STARS. Regarding procrastination, the GP and the AIP scales consist of 20 and 15 items, respectively. The MSLQ scale, which measures motivation, consists of 81 items. The final SSRQ in this study featured only 17 items, measuring not only attitude towards statistics and statistical anxiety, but also academic procrastination and motivation.

The SSRQ can obviously not measure each of the factors in the same depth as the established other scales mentioned above. However, its advantage is that it is relatively short and can easily be administered during a class to all the students to determine which, if any, of the risk factors may potentially cause any of them to struggle. Since the SSRQ is a short questionnaire, the chances of careless responding due to questionnaire fatigue may be minimised, as proposed by Gibson & Bowling (2020).

The mean risk for each student was calculated based on the SSRQ scale and compared to the student’s marks. High mean risks were associated with low marks and vice versa ($r = -0.446$), indicating the ability of the scale correctly to detect at-risk students.

6.2 Implementation of scale

This study therefore puts a tool in the hands of a statistics lecturer to determine which students are at risk. To implement the scale in practice, the lecturer can assess the overall risk by calculating the mean risk over all the factors. If this mean risk is greater than 2.80, a student is considered to be at risk. However, the lecturer can also look at which specific factors are flagged for a particular individual. If only one factor is indicated – that is, the mean value of a particular factor is greater than 3 – the risk is relatively low. As the number of flagged factors increases, the risk of the particular student failing, increases.

Another factor that can be added to the risk assessment instrument is whether a student matriculated with mathematical literacy, since it was found that undergraduates with this particular qualification in matric have a significantly lower participation mark on average than their counterparts who matriculated with mathematics.

6.3 Strategy to assist at-risk students

By considering which factors contribute to the risk, a customised plan of action can be adopted. If, for instance, it is found that a student has a problem with anxiety, this person may complete the STARS in a follow-up session and thereafter be referred to campus psychological support services. Similarly, the SSRQ may be followed by administering the SATS in the case of an attitude problem, the AIP or GP when faced with a procrastination issue, and the MSLQ to address a lack of motivation. The lecturer may address attitude and motivation by showing students how the statistics module links to their major and where mastering this skill will be used in the workplace. Students who tend to procrastinate may be required to undergo time management training. Those with mathematical literacy may need to take a mathematical bridging course before starting a statistics programme.

6.4 Strengths and limitations

This study is limited by being conducted at only one South African university. It is desirable to repeat it elsewhere – in South Africa as well as abroad – to make it more generalisable. Although the sample size was relatively small, it did provide enough power for the EFA and the CFA. Future studies are needed to investigate test–retest reliability and criterion validity.

The strengths of this research are the reliability and discriminant validity of the overall scale and subscales, high PCA loadings and the clarity of the four-factor model derived from the PCA, which is supported by the CFA, as well as significant correlations between each of the risk factors and academic performance.

7. Conclusion

The SSRQ scale was shown to be effective to detect at-risk students in an introductory statistics module. Lecturers can implement the scale to address students' need to receive the right support, for example assistance to address their statistical anxiety, their negative attitude towards statistics, their lack of motivation to study statistics and their tendency to procrastinate academically once they are revealed to be "at risk". These are all "soft" skills that can be addressed to assist students in their journey to succeed in acquiring the much-needed statistical skills. Where students have an inadequate mathematical background, this may be addressed by a bridging course in mathematics.

8. Disclosure statement

No potential conflict of interest was reported by the author.

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Appendix: The Statistics Students' Risk Questionnaire (SSRQ)

Please note: Items 11 to 17 have been reverse coded (R) for all the analyses

Item	Question	1	2	3	4	5
1	I experience feelings of anxiety when I have to attend a statistics class.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
2	I experience feelings of anxiety when I have to solve a statistical problem.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
3	I experience feelings of anxiety when I need to ask the statistics lecturer a question.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
4	I experience feelings of anxiety when I have to study for a statistics test.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
5	I experience feelings of anxiety while I am writing a statistics test.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
6	I generally delay before starting work I have to do for this module.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
7	In preparing for deadlines for this module, I often waste time by doing other things.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
8	I often start my statistics homework at the last minute and find it difficult to complete it on time.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
9	I tend to procrastinate (wait until last minute) more when studying for statistics than studying for other modules.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree

Item	Question	1	2	3	4	5
10	Because I tend to wait until it is almost too late before starting to study statistics, I don't study efficiently for tests and/or exams.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
11	(R) My attitude towards the content of the statistics course I am doing is	Very negative	Negative	Neutral	Positive	Very positive
12	(R) My attitude towards my statistics lecturer is	Very negative	Negative	Neutral	Positive	Very positive
13	(R) I think statistics will be useful for my job	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
14	(R) I can see how statistics relate to my field of study	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
15	(R) Even when statistics course materials are dull and uninteresting, I manage to keep working until I finish.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
16	(R) When I become confused about something I'm reading for this class, I go back and try to figure it out.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
17	(R) The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Dropped	I work hard to do well in statistics even when I don't like what we are doing.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Dropped	I ask myself questions to make sure I understand the material I have been studying in this class.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree

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