To what extent is mathematical ability predictive of performance in a methodology and statistics course? Can an action research approach be used to understand the relevance of mathematical ability in psychology undergraduates.

Abstract

Research methods and statistical analysis is typically the least liked and most anxiety provoking aspect of a psychology undergraduate degree, in large part due to the mathematical component of the content. In this this first cycle of a piece of action research, student's mathematical ability is examined in relation to their performance across different assessments. A maths test, including only components relevant to psychological research and analysis, was designed and subsequently completed by 427 students. Factor analysis revealed three distinct facets: understanding of mathematical procedures, interpretation of findings and understanding the semantics of mathematics. Only the procedural and interpretative factors were predictive of overall course performance. Higher scores on both factors predicted better performance on multiple choice questions assessment and an unseen exam, whereas only the interpretation factor predicted performance on a critical thinking assignment and a lab report. The findings are considered with a view to developing another cycle of action research that more actively involves students.

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Introduction

Psychology is a popular subject for undergraduate studies in the UK with over 90,000 students enrolled in 2011/12 (HESA statistics). To some extent, the undergraduate curriculum is determined by the accreditation requirements of the British Psychological Society. This includes training in research and statistics, typically forming a large proportion of first and second year modules. However, a common experience among educators is that statistics is one of the more challenging topics to teach, partly because students often have very negative perceptions of statistics. These negative views typically come from two sources: not understanding the relevance of research methods and statistics within a psychology degree (e.g., Murtonen et al., 2008), and anxiety about the mathematical component of statistical analysis (e.g., Hanna et al., 2008). In this paper I describe and evaluate an intervention that aims to specifically address the second of these negative views; a “Maths Test” for psychology students. The aim of this intervention was two-fold. First, I wanted to make it clear to students which elements of mathematical ability (i.e., the ability to successfully complete a range of mathematical problems) are needed within a psychology degree. Second, having collected the data from the test across three cohorts, I was interested to find out whether specific components of mathematical ability can predict performance on different elements of a research methods and statistics module.

According to Lewin’s (1951) initial outline of action research, the approach is cyclical in nature with a view to understanding and improving practice. Such an approach is ideally suited to pedagogical research regarding course design as academics and teachers are strongly encouraged to reflect on our courses and any changes we implement. Action research allows for this level of reflection and course development, whilst enabling changes to be grounded in a research evidence base. Within the action research cycle there are four stages: to *plan* the practice of interest, to then *act* and implement the new practice, to outcomes are then *observed/collected*, and these findings then feed into the final stage of *reflection* that feeds back into the planning of subsequent changes to practice. This piece of research very much represents a first cycle of an ongoing Action Research Project. With the opportunity to develop a new research methods and statistics module, I was very much aware that one of the greatest barriers for students is anxiety about the mathematical component of the course content. I reflected on the existing literature (summarised in this introduction) and my prior experiences teaching statistics with a view to developing course content that might alleviate some of this anxiety.

Upon entering their psychology degree, around 45% of students are not aware that statistics is part of the typical psychology curriculum and do not see the value of it (Ruggeri et al., 2008). It can therefore be quite a shock to students to learn that up to one quarter of most BPS accredited psychology degrees focus on research methods and statistical analysis. Students often go onto to report that statistics is the most difficult component of a psychology degree (Barry, 2012), and that they do not understand the relevance of statistics to psychology and future careers (Murtonen et al., 2008). Importantly, these negative attitudes can impact on a student’s learning style within a statistics module, with those who do not see research skills as important typically taking a more superficial approach to their learning (Murtonen et al., 2008).

Negative attitudes towards research methods and statistics are not just an issue for new entrants into a degree. Ruggeri et al. (2011) asked students "How useful/difficult/enjoyable is statistics in comparison to other topics within psychology?" at four time points across the first year of their degree. For the "useful" question, there was no significant change across the year, with means of around three out of five indicating that students only saw statistics as slightly useful. For the "difficult" question, there was again no significant change in perceived difficult with students typically rating statistics as difficult with means of nearly four out of five. In contrast, the "enjoyable" question did show a significant change across the year, with scores significantly dropping from around four to around two out of five. This shows that negative attitudes that students hold towards statistics at the beginning of their degree can persist, or even increase across the first year of their study. From my own professional experience as well as from the literature I believe that it is therefore important to consider interventions very early in their degree studies to attempt to reduce negative attitudes towards statistics. As Ruggeri et al. (2011, p 39) note, "If the basic nature of statistics is truly having such a tremendous impact on students, then there is clearly a need to focus more on basics until they have acquired a stable foundation of the discipline. Without this, it is unlikely that they will be able to progress beyond what has been taught to them once out of their course." As such, if students can gain confidence with the basic mathematical skills required within a psychology degree, then they are like to progress more successfully through the course.

In addition to having negative attitudes towards research methods and statistics, statistics is often the most anxiety provoking aspect of the psychology degree (for a review of the literature see Onwuegbuzie & Wilson, 2003). A great deal of research has attempted to understand the various components of statistics anxiety in psychology students, and the way in which statistics anxiety is associated with a range of other individual difference and performance measures. Currently, the most frequently used measure within this field of research is the Statistics Anxiety Rating Scale (STARS; adapted for UK students by Hanna et al., 2008). This scale reliably shows that statistics anxiety comprises of six distinct components: worth of statistics (perceived usefulness), interpretation anxiety, test and class anxiety, computation self-concept (perception of their own mathematical ability), anxiety when asking for help, and fear of statistics teachers. Hanna and Dempster (2009) found that the six scales within the STARS predicted both the student's own predicted exam score and their actual exam score. Overall, STARS was a significant predictor of both exam score measures, but computation self-concept was the best predictor of the student's estimated exam score, whereas worth of statistics and interpretation anxiety were the best predictors of actual exam scores. This clearly shows that students with lower understanding of the relevance of statistics, a lack of confidence in their own mathematical ability, and a lack of confidence in their ability to interpret statistics, are likely to both perform less well, and feel that they will perform less well in a statistics assignment.

The STARS measurement clearly identifies a student's perceived mathematical abilities as an important component of statistics anxiety and a predictor of performance. This relationship has been further examined, particularly in light of research showing that students mathematical knowledge decreased significantly from 1992 to 2002 (Mulhern & Wylie, 2004). However, GCSE maths grade has not been found to predict either performance in in first year undergraduate statistics course (Gnaldi et al., 2006) or final degree classification (Huws et al., 2006). One potential problem with using GCSE maths grade as a predictor of undergraduate performance is that many aspects of the GCSE mathematics curriculum is not relevant to the use of statistics within psychological research. Consequently, Harvey (2009) devised a one-hour maths test, based on GCSE questions, that was split into four component parts: arithmetic, fractions/decimals/percentages, descriptive statistics and algebra. Scores on this maths test were used to predict performance in statistics exams at the end of year one and year two. Although there were some significant correlations, regression analysis showed that arithmetic ability predicted better performance on the year one exam, but none of the scales predicted performance on the year two exam. Therefore, Harvey concluded that mathematical ability is not a good predictor of undergraduate statistics performance. However, it is possible that the components of mathematical ability that he evaluated do not fully represent the differing components of mathematical ability needed within psychological statistics, and the use of a statistics exam as a performance measure may not reflect all aspects of performance on a statistics course, which is likely to involve multiple components including exams and coursework assignments.

The first stage in any piece of action research is to identify the key problem to be addressed. The literature reviewed clearly identifies anxiety over statistics/mathematics as a key difficulty when teaching psychology students. As such, this piece of action research began by attempting to make clear to students which elements of mathematical ability are relevant within a psychology degree. This may then alleviate statistics anxiety in some students. In 2011 I designed a new, yearlong, research methods and statistical analysis course to be taught in the first year of the psychology undergraduate degree. With the complete redesign and implementation of a new module design, I felt it was important to integrate as many elements as possible into the course design to maximise students understanding of the relevance of research and statistics to their degree and career, and to minimise their anxiety about the statistical analyses they would be learning. In this paper, I describe one aspect of this, an intervention within a timetabled lab class, which included a “Maths Test”, given to students in the fourth week of their studies.

The primary aim of the “Maths for psychology” lab class was to explicitly identify for students which aspects of mathematical ability are needed within psychological statistics, to explain why each aspect is relevant and important for psychological research, and to allow students to create their own profile of mathematical strengths and weaknesses. This fits within Kolb’s (1984) Experiential Learning Model by taking advantage of the reflective observation stage in the learning model, by allowing students to further understand their strengths and weaknesses and to reflect on how these might impact on their wider learning within the module. Hanna and Dempster (2009) identified three aspects of statistics anxiety that could predict student performance: understanding of the relevance of statistics, a lack of confidence in their mathematical ability, and a lack of confidence in their ability to interpret statistics. Consequently, the maths test was designed to cover both the interpretation of analyses (i.e., through graphs and tables) and the calculation of mathematical problems (e.g., negative numbers, power, equations). The maths test included ten different sections: graphs, tables, the “language” of maths, the use of ‘<’ and ‘>’ symbols, number sequences, rounding, decimals and percentages, negative numbers, power and square roots, and solving equations.

I designed the maths test to cover the various mathematical skills that were necessary for calculating and interpreting statistics within psychological research, hence using a more specific measure than the broad GCSE grade used in previous research (Gnaldi et al., 2006; Huws et al., 2006). By developing a customised and specific test it was possible to explicitly show student exactly which aspects of mathematical ability they would need within the course, and by dividing it into ten component parts it was possible for students to identify their own strengths and weaknesses. With their weaknesses identified through their scores on the different components of the maths test, they were given further advice so that they could seek out further support to revise any aspects that they did not perform well in before needing these skills within the course. As such, students gain formative feedback that is accurate, provided immediately, and personalised to the students. All of these elements are important for effective formative feedback (for a review see Shute, 2008).

The course has now run for three cohorts of students (2011-12, 2012-13 and 2013-14), and feedback from students has been overwhelmingly positive, often commenting on the "approachable" design of the course. I therefore felt that it would be timely to look back at student's performance on the "Maths Test" and to consider whether any of the component parts could predict performance across different elements of the summative course assessment (weekly multiple choice quizzes, a critical thinking assignment, three lab reports, and an exam). Previous research has considered whether mathematical ability is predictive of performance on statistics exams (e.g., Harvey, 2009), however different types of assessment may require different mathematical skills, and therefore it is of interest to examine how different aspects of mathematical ability may predict performance across different methods of analysis. In an action research sense this was the issue which would form the starting point for my professional practitioner reflections. In essence, the way I analysed and interpreted the data were intertwined with my concerns and motivations as a psychology tutor to develop appropriate course content and interventions that would be effective in supporting students, particularly those who might find maths and statistics anxiety provoking.

Methods

Participants

Data were collected across three cohorts of first year psychology undergraduate students. Complete datasets were provided by 427 students; 127 in the 2011-12 cohort, 139 in the 2012-12 cohort and 161 in the 2013-14 cohort. Data were not collected on the age and sex of participants, but the intake is representative of typical psychology undergraduates with about 85% females and a mean age of about 19 years. All students were taking a single honours BPS accredited psychology degree at a university in the UK with an entrance requirement of AAB.

Overview of the course and assessment

The course was a yearlong first year module, taught over twenty weeks, with integrated teaching of research methods and statistics. It was a one unit module with sixty contact hours of teaching. All of the statistical content was taught with students doing all calculations by hand (SPSS was not introduced until the second year). Each week the teaching structure was the same. There was a one hour lecture that covered a topic within research methods and/or statistical analysis. This was followed on the same day by a one hour workshop, facilitated by lab tutors, in which students worked through worksheet exercises to practice the content learned in the lecture. Later in the week there was a two hour lab class, where students were taught by the same lab tutor as they had for their workshop, that was mainly problem based learning (e.g., designing studies, critiquing papers)_ and allows students to develop skills in designing, running, analysing, finding and critiquing psychological research.

The summative assessment for the module comprises six distinct assessments. Students complete a ten question multiple choice quiz on the virtual learning environment each week. Questions cover both the theoretical content taught in the lecture and the answers to the exercises in the workshop. There are a total of twenty weekly quizzes across the course, which comprises 10% of the module mark. The first written assignment for the course is a critical thinking assignment, which is worth 10% of the module. In this assignment students are given a target paper, and their assignment has two aims; first to critique the paper and second to find and discuss more recent papers that have furthered this area of research. Over the remainder of the year, students complete three lab reports, each worth 10% of the course and focussing on a different statistical analysis (chi square, t test and correlation). The remaining 50% of the module mark comes from a three hour open book exam in which students are asked to design a study, analyse and interpret datasets, and to answer questions linking research design and statistical analysis.

Maths test

The “Maths Test” occured during the lab class in week four of teaching during term one. The aims of the lab class were to identify students mathematical strengths and weaknesses, to explain which elements of mathematical ability are necessary for calculating and understanding statistics within psychology, and to make clear why and how each element is relevant. A copy of the maths test and associated lab resources can be obtained by emailing the author.

The lab class started with students completing the maths test. They were told about the test in advance, and it was also made clear that the “test” was formative and primarily to allow them to identify their own mathematical strengths and weaknesses. The test comprised ten separate sections (see Table 1 for details and example test items). There was no time limit for the test and students were not allowed to use calculators or discuss their answers with their peers.

[Insert Table One about here]

Once all students had completed the test the lab tutor worked through each section of the test with the class. Students marked their own tests and submitted their answers to the lab tutor, and they also completed a page that summarised their “Mathematical Ability Profile” and provided them with advice and resources if there were any elements of the maths test that they found particularly challenging. By dividing mathematical ability into ten component parts and identify specific elements that a student may have difficulties with they can seek more targeted support if necessary. The lab tutor explained the correct answers to each question and gave guidance regarding how to successfully complete this type of mathematical problem. They then explained how this element was relevant to statistics within psychology.

Results

Analysis of the maths test results

As each section of the maths test was measured on a different scale, scores were converted to percentages to allow for easier comparison across the different components of the test. First, a two-way mixed design ANOVA was run to test for significant differences across the ten components of the maths test and across the three cohorts. A 10 (maths test component, repeated measures) by 3 (cohort, independent measures) mixed ANOVA was run, with percentage score as the dependent variable. Cohort was included as a factor in case there were any marked changes in ability across the year groups.

There was a significant difference across the ten components of the maths test (F (9, 3816) = 54.5, $p < .001$; partial $\eta^2 = .114$). See Table Two for descriptive statistics. Rank ordering the ten components from best to worst performance: rounding off, graphs, decimals and percentages, power and square, less/greater than symbols, equations, negative numbers, number sequences, tables and the language of statistics.

[Insert Table Two about here]

There was a significant main effect of cohort (F (2, 424) = 4.1, $p = .017$; partial $\eta^2 = .019$). The 2011-12 and 2012-13 cohorts did not differ significantly ($p = .482$, means of 93.7% and

92.5% respectively), nor did the 2012-13 and 2013-14 cohorts ($p = .446$, mean for 2013-14 = 91.3%). However, scores were significantly higher for the 2011-12 cohort than for the 2013-14 cohort ($p = .013$). There was no significant interaction between the different components of the maths test and the cohort sitting the test (F (18, 3816) = 1.5, $p = .093$; partial $\eta^2 = .007$).

As can be seen from Table Two, most of the components of the maths test are significantly and positively correlated, albeit with small effect sizes. In order to reduce the ten components into a more manageable dataset for subsequent analyses, a factor analysis was run, using varimax rotation. Three factors were extracted, explaining a total of 51.6% of the variance in the total maths test. The first factor had an eigenvalue of 2.2 and explained 21.7% of the variance in the questionnaire after rotation. This factor contained four components: equations, power and square, number sequences and rounding off. The second factor had an eigenvalue of 1.5 and explained 15.4% of the variance in the questionnaire after rotation. This factor contained three components: graphs, tables and decimals and percentages. The third factor had an eigenvalue of 1.5 and explained 14.5% of the variance in the questionnaire after rotation. This factor contained two components: language of statistics and negative numbers. One component, less/greater than symbols, loaded equally on both factor two and three. It was felt that this component fitted best within factor three, and therefore was added to factor three. Factor one represents the *procedural* understanding of mathematical processes, factor two represents the *interpretation* of mathematical information, and factor three represents the *semantics* necessary for mathematical understanding. Factor scores (i.e., with a mean of 0 and standard deviation of 1) were used in subsequent analyses.

Analysis of the relationship between mathematical ability and performance on the different components of a research skills module.

Standard multiple regression analyses were used to examine whether mathematical ability was predictive of performance across the different assessment tasks of the research skills course. The predictor variables were the three different factor scores and the outcome variable was the mark awarded for each component of the module mark, or the final module mark. Consequently, seven separate multiple regression analyses were run predicting: multiple choice quizzes, critical thinking assignment, each of the three lab reports, the exam and the final course mark. The full results of the zero order correlations and regression analyses are summarised in Table Three.

[Insert Table Three about here]

Mathematical ability was, overall, a significant predictor of performance on the multiple choice quizzes, explaining 1.9% of the variability in performance. Mathematical procedural understanding was a significant predictor, with higher scores on this component of mathematical ability predicting higher scores on the multiple choice quizzes. Mathematical interpretation was also a significant predictor, again showing a positive relationship with scores on the quizzes. Mathematical semantics was not a significant predictor.

Marks on the critical thinking assignment were also significantly predicted by mathematical ability, with 2.2% of the variability explained. For this course component, only mathematical interpretation was a significant predictor, with higher scores on this factor predicting higher marks on the critical thinking assignment. Mathematical procedure and semantics were not significant predictors.

Looking across all three of the lab reports, the first lab report was not significant, although the model was approaching significance with mathematical ability predicting 1.8% of the variability in lab report marks. For this first lab report, only mathematical interpretation was significant, with higher scores on this factor predicting higher marks on this report. Mathematical procedure and semantics were not significant. For the second and third lab reports, neither the overall models nor any of the individual predictors were significant. This suggests that, whilst mathematical ability may impact on lab reports completed early in a first year undergraduate course, this effect reduces with subsequent assignments.

The exam was the component of the course that was best predicted by mathematical ability, with 4.9% of the variance explained. Both mathematical procedure and interpretation were significantly and positively associated with mark on the exam, but mathematical semantics was not a significant predictor.

Looking at the overall course mark, weighted appropriately across the six different components of the course (i.e., each component worth 10%, other than the exam, which was worth 50%), mathematical ability was a significant predictor of performance, explaining

4.5% of the variability in performance in the research skills course. Again, higher scores on mathematical procedure and interpretation predicted significantly higher marks on the course, whereas mathematical semantics was not a significant predictor.

Discussion

This study has shown positive relationshipsbetween specific aspects of mathematical ability and performance on different aspects of a first year research skills course. For the course overall, students who scored higher on mathematical procedure and interpretation gained higher marks. This was also found to be the case for the multiple choice quizzes and the exam, both of which are quite reliant on the more computational side of statistical analysis. In contrast, the critical thinking assignment and lab reports require a wide range of academic skills, and this is reflected in the findings. Mathematical interpretation, but not mathematical procedure, is a significant predictor of higher scores for the critical thinking assignment and the first lab report. The finding that none of the aspects of mathematical ability were predictive of marks on lab reports two and three suggests that students with difficulties in mathematical interpretation are able to overcome these weaknesses with repeated assessments. Interestingly, mathematical semantics was not a significant predictor of performance on any component of the research skills course.

Previous research has suggested that mathematical ability was not predictive of performance in a psychology statistics course (Gnaldi et al., 2006; Harvey, 2009; Huws et al., 2006). The present study shows that there is a relationship, albeit with small effect sizes, however it is necessary to identify aspects of mathematical ability that are very specific to psychological research and to consider a range of different styles of assessment. The specificity of these relationships may be of benefit when developing interventions as particular skills can be targeted.

In this study, I found that mathematical ability is not predictive of all elements of a course assessment. This has two important implications for good practice when designing a statistics course for psychologists. First, it is important to design assessments that all students can perform well on. Based on the findings of the present study, it is recommended that a range of different assessment styles are adopted so that students who struggle with their mathematical ability are able to excel on some of the assessments. Second, the relationship between mathematical interpretation ability and performance on lab report performance was significant for the first report, but not for subsequent reports. This suggests that students with weaker mathematical abilities may have difficulties when they first attempt a particular style of assessment, but that their academic development in subsequent comparable assessments eliminates this negative relationship. Therefore, it is recommended that students are able to gain repeated experience with particular styles of assessment.

It is important to acknowledge the limitations of this study. First, performance on the maths test was generally very high, with there being a negative skew in the data and some ceiling effects. This was particularly the case on the Graphs and Tables sections of the test. This suggests that performance was generally of a high standard. Second, the amount of variability explained within the regression models was up to 5%. Whilst this was a significant amount of variance, it does mean that mathematical ability has a relatively small impact on performance, and clearly a number of other factors are far more important. It is also possible that the Maths Test served to reduce any relationships with course performance if those who performed badly in the test then sought help to improve their mathematical skills, consequently reducing the magnitude of any effects reported in this paper. This could be considered in future cycles of this research project by repeating the Maths Test at a later date and considering how any improvement in mathematical ability may be related to course performance. In the future, it might be reassuring for students to inform them as to the limited impact of their own mathematical ability on performance. This may function as a method for reducing statistics anxiety in any further pedagogical developments. Finally, part of the rationale behind the Maths Test intervention was that it may reduce student's statistics anxiety, however no measure of this was included in this study. This is clearly an element that would be important to add in future cycles of this research project. In particular, it would be important to consider whether the relationship between mathematical ability and course performance is either mediated or moderated by statistical anxiety.

This piece of research was framed as action research in the introduction to this paper, and it is important to discuss the findings within this framework, which leads to two important points for consideration. First, one model of action research is participatory action research, as originally suggested by Paulo Freire (1972), who emphasised the importance of students not simply being the passive subjects of pedagogical research, but instead that they should be active participants in the research process. Chevalier and Buckles (2013) define three key components that are essential within action research: involvement of the *participants* in the research, that it informs *action* for a cycle of changes to be executed, and that the *research* is rigorous and can extend knowledge. The element that is noticeably missing from this piece of research is the involvement of the participants, the students taking the course. It would be helpful to run focus groups to gain an important insight into how students view mathematical ability and anxiety within the course. The research in this area tends to rely on questionnaires and performance data, and then makes inferences from their findings. Greater insights may be gained from discussing these issues with students within a focus group or interview setting. It may also be fruitful to more directly involve students in the design of future cycles of research and, perhaps more importantly, the development of targeted interventions in light of the present research findings.

The second point for consideration relates to Lewin's (1951) original conception of action research as cyclical, as outlined in the introduction of this paper. The present research very much represents the first cycle in a piece of action research, whereby a problem was identified (lack of confidence in mathematical ability) and a first action step was taken (development of the "Maths for Psychology" lab class and the "Maths Test"). The analyses presented within this paper have then evaluated this first step and has showed how specific aspects of mathematical ability are associated with different components of assessment. It is important to now consider these findings of this first cycle of research with a view to developing a second cycle of action research, specifically developing and evaluating a further interventions to further support students.

Interventions to be applied in the future will need to address three separate issues. First, it will be necessary to further establish with students the relevance of maths within psychological research, and the relevance of psychological research within their degree and future career plans. Murtonen et al. (2008) found that psychology students who view quantitative methods as relevant to their future career are more "task oriented" and experience fewer difficulties on the course. Whilst this relevance is highlighted earlier in the course, there is scope to expand the "Maths for Psychology" lab class to include further interactive exercises to emphasise the relevance and need for maths within their degree and their future careers. Currently, there are very explicit learning aims to identify how each element of the Maths Test is relevant to psychological research, but this is not expanded to the relevance for their different potential career paths. In the future the lab class could be re-designed to include exercises showing how the lab class content is relevant to career paths for psychology students.

The second issue that could be addressed in a future cycle of action research would be to address the negative perceptions that students tend to have about research and statistical analysis. Hood and Neumann (2013) developed a workshop that attempted to reduce student's negative perceptions of statistics. The workshop had various components including to clarify and normalise the anxiety that students were experiencing, to identify learning strategies that could improve self-efficacy in their statistical studies (e.g., avoiding procrastination) and discuss different learning styles that can be effective in reducing anxiety (i.e., auditory, visual and tactile strategies). At the beginning of the course students completed the STARS questionnaire, and those with above average scores were invited to attend the workshop. Although only seventeen students attended the workshop, those who did experienced significantly improved self-efficacy and improved attitudes towards statistics. In the future, elements of the workshop designed by Hood and Neumann could be integrated into a lab class, to support all of the students taking the course, rather than to a subset of self-selecting and highly anxious students. However, there may also be some negative consequences that arise from obliging non-anxious students to attend, and this would need to be taken into consideration in any further development of this intervention.

A third development could be more targeted at additional support for students who are experiencing high levels of statistics anxiety and who are struggling with the course content. One way to achieve this could be to develop a peer-assisted learning scheme for the module. Within the psychology degree curriculum, peer assisted learning is perhaps most often used within the statistics and methods modules, probably as these are the least liked and most anxiety provoking modules of the degree. Stone and Meade (2012) introduced a peer assisted learning scheme, with final year undergraduates and Masters level postgraduate providing support for a first year statistics course. The student learners gave very positive feedback on the peer assisted learning sessions and reported that they helped learning and improved both confidence and understanding. The student facilitators also reported the participating in the scheme was beneficial, with improved confidence, interpersonal, communication and leadership skills. Consequently, a peer assisted learning scheme is likely to be of great benefit to both learners and facilitators, and could be a strong intervention to introduce in a subsequent phase of this piece of action research.

This piece of research formed the first cycle in a programme of action research that intends to improve the student experience on a research methods and statistics course by addressing two key elements: making statistics relevant to psychological research and future careers, and to reduce the statistics anxiety that many students experience. It was found that different aspects of mathematical ability predicted performance on some, but not all, aspects of module assessment. In light of these findings, various interventions are possible and the implementation and evaluation of these will form the basis of future cycles of research within this project.

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Table One: Overview of the maths test given to students (for a full copy, please email the author).

<table>
<tr><th>Section</th><th>Marked out of</th><th colspan="2">Example items</th></tr>
<tr><td>Graphs</td><td>10</td><td colspan="2">Students are given a graph of the results of a psychology study on a “memory wonder drug” and asked questions including: How much does 6mg improve memory in comparison to no drug? What would you guess a person’s memory score would be if 9mg were taken?</td></tr>
<tr><td>Tables</td><td>10</td><td colspan="2">Students are given a table of the results of a psychology study on children’s emotion processing and asked questions including: What was the sample difference between boys and girls? How much does emotion processing in boys change from age 5 to 9 years?</td></tr>
<tr><td>Language of statistics</td><td>5</td><td colspan="2">What does each of the following symbols mean? (Five items total)
Σ a. Solve b. Average c. Sum d. Square root</td></tr>
<tr><td>< > than symbols</td><td>10</td><td>Are the following expressions true or false? Five items total.
$999 > 1$
$56 \geq 55$</td><td>For each number, is it < .050? Five items total.
.049
.001</td></tr>
<tr><td>Number sequences</td><td>5</td><td colspan="2">Identify the missing number in the series from the options given on the right. (Five items in total)
3, 6, 11, 18, ? 30 22 27 29 31</td></tr>
<tr><td>Rounding off</td><td>10</td><td>Round off the numbers to a whole number. Five items total.
2.3
6.6</td><td>Round off the numbers to one decimal place. Five items total.
2.321
4.565</td></tr>
<tr><td>Decimals and percent</td><td>10</td><td>Convert these decimals into percentages. Five items total.
.33
.05</td><td>Convert these percentages into decimals. Five items total.
65%
1%</td></tr>
<tr><td>Negative numbers</td><td>20</td><td>Rearrange the numbers in ascending/descending order.
-6 9 0 -4 2
-10 -4 1 -8 7</td><td>Complete the following sums. Ten items total.
$-5 \times -3 =$
$+12 \div -4 =$</td></tr>
</table>

Power and square	10	Solve the following. Ten items total. 9^2 $\sqrt{64}$ 3^3 $\sqrt{16}$
Equations	10	Solve the following. Ten items total. $5 * (12 / 2^2) =$ $(4 + -2) / (\sqrt{9} - 1) =$

Table Two: Descriptive statistics and zero order correlations for the total maths score and ten components of the maths test.

	Descriptive statistics				Zero order correlations between components of the maths test									
	Min.	Max.	Mean	SD	2	3	4	5	6	7	8	9	10	11
1: Total	53	100	92.8	6.9	.379**	.509**	.486**	.428**	.450**	.396**	.501**	.688**	.647**	.700**
2: Graphs	50	100	96.8	6.7		.202**	.107*	.195**	.137**	.131**	.152**	.189**	.124*	.171**
3: Tables	10	100	86.7	15.6			.172**	.143**	.163**	.119*	.245**	.146**	.215**	.228**
4: Language of statistics	0	100	84.9	18.7				.241**	.162**	.040	.159**	.255**	.264**	.296**
5: < > than symbols	0	100	93.7	13.2					.096*	.078	.162**	.175**	.103*	.099*
6: Number sequences	20	100	90.2	14.5						.213**	.181**	.130**	.377**	.407**

7: Rounding off	20	100	98.0	7.9								.246**	.135**	.276**	.279**
8: Decimals and percent	0	100	95.8	11.8									.159**	.291**	.236**
9: Negative numbers	25	100	91.7	13.3										.290**	.364**
10: Power and square	10	100	94.4	11.2											.626**
11: Equations	0	100	91.9	14.8											

Note: * indicates $p < .050$, ** indicates $p < .010$.

Table Three: Summary of the zero order correlations and regression analyses, using mathematical ability to predict performance on a research skills course.

			Multiple choice quizzes	Critical thinking assignment	Lab report 1 (χ^2)	Lab report 2 (t)	Lab report 3 (r)	Exam	Course total
Zero order correlations	Procedure		***.098****	.079	.063	.040	.089	***.133*****	***.137*****
	Interpret		***.097****	***.123****	***.111****	.060	.012	***.158*****	***.153*****
	Semantics		.006	.018	-.041	.010	.024	.076	.048
Model statistics	F		***2.8***	***3.1***	2.6	0.8	1.2	***7.2***	***6.6***
	p		***.042***	***.026***	.052	.517	.297	***< .001***	***< .001***
	R^2		***.019***	***.022***	.018	.005	.009	***.049***	***.045***
Predictor statistics	Procedure	B	***1.2***	0.7	0.6	0.5	1.1	***1.1***	***1.0***
		t	***2.0***	1.7	1.3	0.8	1.8	***2.8***	***2.9***
		p	***.042***	.101	.189	.407	.066	***.005***	***.004***
	Interpret	B	***1.2***	***1.1***	***1.1***	0.7	0.2	***1.3***	***1.1***
		t	***2.0***	***2.6***	***2.3***	1.2	0.3	***3.3***	***3.2***
		p	***.044***	***.011***	***.021***	.214	.802	***.001***	***.001***
	Semantics	B	0.1	0.2	-0.4	0.1	0.3	0.6	.3
		t	0.1	0.4	-0.9	0.2	0.5	1.6	1.0
		p	.893	.708	.398	.833	.622	.112	.309

Note: For the correlations, * indicates p < .050, ** indicates p < .010. Significant findings are bold and italicised.