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Assessing the utility of an online adaptive tool in a large undergraduate psychology program

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List of acronyms used

APM	Ravens Advanced Progressive Matrices
C	Conscientiousness
CAB-I	Comprehensive Abilities Battery – I
EC	Epistemic Curiosity
Ex	Exam
Go8	Group of Eight
LS	LearnSmart usage
NFC	Need for Cognition
O	Openness to Experience

Executive summary

In recent years there has been growing interest in the use of e-learning tools that are able to adapt to suit the ability levels, needs, or preferences of individual learners (e.g. Gasparinatou, Grigoriadou, & Elsevier Science, 2011; Tseng, Chu, Hwang, & Tsai, 2008; Vandewaetere, Desmet, & Clarebout, 2011). It is generally accepted that individualised instruction is superior to more homogenous approaches (e.g., Bloom, 1984; Cohen, Kulik, & Kulik, 1982; Kulik, Kulik, & Bangertdrowns, 1990), and so in theory adaptive e-learning tools have the potential to increase student motivation and engagement and, in turn, ultimately lead to more positive academic outcomes. It is also possible that individualised e-learning might also lead to lower drop-out rates as many adaptive tools allow students to set the pace of their learning and they are therefore less likely to become overwhelmed by either the volume or depth of understanding that is required of them.

Numerous papers have described how to implement adaptive e-learning tools (see Akbulut & Cardak, 2012 for a review). Further, there are numerous adaptive e-learning tools that are either freely or commercially available for use in a tertiary education environment. Unfortunately, as a number of researchers have noted (e.g., Akbulut & Cardak, 2012; Vandewaetere et al., 2011) there is little in the way of robust empirical evidence available that directly assesses the utility of adaptive e-learning tools in regards to academic outcomes.

In this project we aimed to test the utility of a commercially available adaptive e-learning tool (LearnSmart) within the context of a large undergraduate psychology course across two semesters (Psychology 1A and Psychology 1B). Specifically, we aimed to explore differences in personality traits and intellectual ability between students who did use LearnSmart and those who didn't.

In order to achieve these aims, we measured the personality and intellectual characteristics of users and non-users of LearnSmart in two first-year psychology courses, together with LearnSmart usage, and exam performance. In Psychology 1A, LearnSmart usage was optional, while in Psychology 1B it was mandated as part of the course. In terms of our results, we found significant differences in personality variables with users scoring higher than non-users on Conscientiousness, Openness to Experience, Epistemic Curiosity and Need for Cognition. The data collected in Psychology 1B (when LearnSmart usage was mandated) also showed a difference between users and non-users in terms of the measures of intellectual ability. Unsurprisingly, we also found that intellectual ability was a significant predictor of performance on the end-of-semester exam. Similarly, the two personality traits Conscientiousness and Openness to Experience were found to be significant predictors of exam performance. Further, the two measures of intellectual curiosity that we used (Epistemic Curiosity, and Need for Cognition) were found to predict exam performance in

Psychology 1B, but only Need for Cognition was predictive of exam performance in Psychology 1A.

Most importantly, we found that the strongest predictor of performance on the final exam was LearnSmart usage. Specifically, the data clearly demonstrated that the extent to which students made use of the LearnSmart tool was strongly and significantly related to academic success, and that the strength of this prediction was above and beyond what we would expect it to be based on the psychological factors alone. In other words, the data validated the utility of the LearnSmart tool as a study aid in the context of this undergraduate course.

The project team recommend the use of similar research programs to test the utility of new learning tools such as this, so that curriculum designers are able to make evidence-based choices when considering their potential inclusion in future courses.

The results of the study were fed back to students, providing them with information that is able to guide them in their continuing studies. Further, aspects of the study have been incorporated into the major practical assignment completed by the students in the second semester of undergraduate psychology at The University of Adelaide, providing future cohorts of students the opportunity to experience pedagogical research first-hand. The project has also formed the basis of three Honours thesis projects, and is directly related to two PhD thesis projects. Furthermore, involvement in the project has led to a Masters student and PhD student presenting research at the Australian New Zealand Association for Health Professional Educators conference (ANZAPHE 2016).

The study also led to the researchers' involvement in a number of "spin-off" projects such as investigations of the impact of other psychological factors such learning style, stress, and motivation on academic outcomes; an investigation of the role that meta-cognitive factors such as calibration can have on academic success; and a comparison of the factors influencing the academic satisfaction of international and domestic students. The results of this study were also presented at a number of different forums within The University of Adelaide including the 'Teaching Large Classes' and 'Online Assessments' communities of practice. These communities of practice are comprised of 15-20 academic staff from a wide range of different disciplines across the university that meet regularly to share information relating to pedagogical best-practice. The study has been presented at one international conference and four national conferences, and the results of the project are currently being written up for submission to an international journal.

The findings of this study have the potential to make a significant impact on the development of curriculum in undergraduate courses, and this has the potential to lead to positive outcomes for students, most noticeably in relation to their academic grades.

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Chapter 1 - Introduction

1.1 Rationale & Outline

In recent years there has been growing interest in the use of e-learning tools that are able to adapt to suit the ability levels, needs, or preferences of individual learners (e.g. Gasparinatou, Grigoriadou, & Elsevier Science, 2011; Tseng, Chu, Hwang, & Tsai, 2008; Vandewaetere, Desmet, & Clarebout, 2011). It is generally accepted that individualised instruction is superior to more homogenous approaches (e.g., Bloom, 1984; Cohen, Kulik, & Kulik,1982; Kulik, Kulik, & Bangertdrowns, 1990), and so in theory adaptive e-learning tools have the potential to increase student motivation and engagement and, in turn, ultimately lead to more positive academic outcomes. It is also possible that individualised e-learning might also lead to lower drop-out rates as many adaptive tools allow students to set the pace of their learning and they are therefore less likely to become overwhelmed by either the volume or depth of understanding that is required of them.

Numerous papers are available describing how to implement adaptive e-learning tools (see Akbulut & Cardak, 2012 for a review). Further, there are numerous adaptive e-learning tools that are either freely or commercially available for use in a tertiary education environment. Unfortunately, as a number of researchers have noted (e.g., Akbulut & Cardak, 2012; Vandewaetere et al., 2011) there is little in the way of robust empirical evidence available that directly assesses the utility of adaptive e-learning tools in regards to academic outcomes.

In this project we aim to test the utility of a commercially available adaptive e-learning tool (LearnSmart) within the context of a large undergraduate psychology course.

1.2 The LearnSmart tool

LearnSmart is an online adaptive e-learning tool developed by McGraw-Hill to supplement the content presented in their textbooks. Each chapter in the textbook has an associated online LearnSmart module which course coordinators can assign for the purpose of formative or summative assessments. LearnSmart works by presenting students with questions based on core chapter content to which the students are required to provide an answer and an indication of their confidence on a four point scale (i.e., 'I know it', 'Think so', 'Unsure', or 'No idea').

Based upon the accuracy of the student's response and their associated confidence rating, LearnSmart adjusts the difficulty level of subsequent questions. In this way, students that demonstrate a clear and confident understanding of the content area can be challenged with more difficult questions, and students who are struggling are given the opportunity to master the more basic concepts before being presented with more difficult material.

According to the McGraw-Hill Education website, the use of LearnSmart within undergraduate curricula has resulted in improved student retention, and better academic outcomes (http://www.mheducation.com/highered/ideas/educator/connect-student-discover.html). However, there is little in the way of independent empirical evidence assessing the efficacy of the LearnSmart tool, and the results of these investigations have been mixed.

James (2012) assessed the tool in the context of an introductory biology class (N = 193 students) in which the tool was made available to the students but usage was not compulsory. They found that for students that used the tool there was a weak but significant relationship between the degree of usage and performance on the final exam. However, there was no significant difference between the academic performance of those students that chose to use the tool, and those that did not.

Griff and Matter (2013) compared the performance of undergraduate physiology students using the LearnSmart tool as a study aid with those using a traditional non-adaptive online quiz. Students were randomly assigned to either condition, and group comparisons were made across six separate courses with class sizes ranging from 20 to 200+ (total N = 587). The analyses indicated that for two of the courses, students in the LearnSmart condition performed significantly better than students in the non-adaptive quiz condition, but for one of the courses the opposite effect was found. Overall the investigators found no significant difference between the two groups of students in regards to academic performance.

Owens & Moroney (2015) investigated the effect of LearnSmart tool usage in a bioscience unit of a nursing degree (N = 263). Students were required to use the tool in order to obtain course credit. The results of their analyses indicated that there was a significant relationship between tool usage and final grade for the subject.

Gurung (2015) investigated the efficacy of the tool in the context of an introductory psychology course (N = 251) where students were required to use the tool for course credit. They found that the amount of time that students used the tool was significantly related to exam performance. However, when students' grade point average was taken into account, the overall strength of the relationship weakened – in other words, smarter students were doing better on the final exam, but they were also tending to use the tool more than the other students.

This finding from Gurung (2015), that the existing differences between the intellectual abilities of the students affected the strength of the relationship between tool usage and academic outcomes, is of direct relevance to the present study and will be discussed further in the following section.

1.3 Psychological Predictors of Academic Achievement

Within a given cohort of students a wide range of different intellectual abilities, personality traits, and preferences for different learning styles exist. Further, there is a large body of evidence indicating that these individual differences can have a significant impact upon a given student's ability to succeed within a tertiary education environment (e.g., Conard, 2006; De Feyter, Caers, Vigna, & Berings, 2012; O'Connor & Paunonen, 2007).

One obvious individual difference that impacts upon academic achievement is intellectual ability. Numerous studies have clearly demonstrated that the more intelligent a student is, as measured by standardised IQ tests, the higher their grades tend to be, with some studies indicating that up to 25 percent of the variance in academic achievement is accounted for by intellectual ability (e.g., Busato, Prins, Elshout, & Hamaker, 2000; Chamorro-Premuzic & Furnham, 2003b; Powell & Nettelbeck, 2014).

Individual differences in personality traits have also been demonstrated to have a significant influence on academic outcomes. Of particular importance are the 'Big Five' personality traits described by the Five Factor model of personality – neuroticism, extraversion, openness to experience, conscientiousness, and agreeableness (Costa & McCrae, 1992). The Five Factor model is currently considered to be the dominant conceptualisation of individual differences in personality and has been shown to be stable across time, culture and context.

In regards to academic achievement the two most important personality traits appear to be conscientiousness and openness to experience. Conscientious individuals are associated with behaviours such as efficiency, organisation, self-discipline, deliberation, achievement-orientation and motivation. Further, this trait has been demonstrated to predict a range of academic outcomes including ongoing assessments, exam performance, and grade point average (e.g., Busato et al., 2000; Chamorro-Premuzic & Furnham, 2003a; De Feyter et al., 2012).

The trait openness to experience is associated with behaviours such as curiosity, imagination, aesthetics, and having a broad range of interests. The findings regarding openness and academic achievement are more mixed – a number of studies have demonstrated that there is a positive and significant association between the two factors (e.g., Dollinger & Orff, 1991; Farsides & Woodfield, 2003; Rothstein, Paunonen, Rush, & King, 1994), but this has not always been found (e.g., Chamorro-Premuzic & Furnham, 2003a; O'Connor & Paunonen, 2007). It is possible that this discrepancy is due to differences between the courses focussed on in these studies, or some other extraneous variable that is not being adequately controlled for (O'Connor & Paunonen, 2007).

In addition to these two traits from the Five-Factor model, there are a number of other psychological constructs that have been implicated as potentially contributing to academic outcomes. Two constructs that (like openness to experience) broadly measure intellectual curiosity and a desire to learn are epistemic curiosity (Litman & Spielberger, 2003) and need for cognition (Cacioppo & Petty, 1982). Both of these measures have been demonstrated to correlate positively and significantly with academic achievement (e.g., Powell & Nettelbeck, 2014; von Stumm & Ackermann, 2013).

The evidence linking these psychological factors to academic achievement is of obvious importance in regards to any attempt to assess the utility of a given e-learning tool. Specifically, there are interdependencies between the behaviours and attitudes associated with the psychological variables, behaviours associated with the e-learning tool usage, and the academic outcomes of interest.

In our project we aimed to test the impact that the LearnSmart tool had upon academic achievement while controlling for these known psychological predictors of academic success.

Chapter 2 - Method

2.1 Setting

The following study was conducted at The University of Adelaide, a research-intensive, Group of Eight (Go8) tertiary institution. All of the participants were undergraduate students studying the first-year psychology subjects Psychology 1A (first semester) and Psychology 1B (second semester). In order to major in psychology students must pass these two subjects, along with the methodology subject Research Methods in Psychology.

Just under half of the students were enrolled in the Bachelor of Psychological Science program (45 per cent), with the remaining students enrolled in a wide range of programs including Bachelor of Health Sciences (21 per cent), Bachelor of Science (9 per cent), Bachelor of Arts (7 per cent), Bachelor of Commerce (5 per cent), and Bachelor of Teaching (5 per cent). The cohort has a wide range of tertiary entry scores, and cite a wide range of motivations for studying psychology, ranging from simply filling an elective in first year (29 per cent) to a desire to obtain a Masters (18 per cent) or Doctoral (14 per cent) level qualification.

2.2 Participants

This study was granted ethics approval from the School of Psychology Human Research Ethics Sub-Committee at The University of Adelaide (reference number: H-2015/05).

Of the 601 students enrolled in the first semester course Psychology 1A we had full data-sets for 459 students. Of the 564 students enrolled in the second semester course Psychology 1B we had full data sets for 515 students.

The following analyses are based on the data from 627 individuals in total – 347 studied both Psychology 1A and 1B; 112 studied Psychology 1A only; and 168 studied Psychology 1B only.

2.3 Measures

2.31 Cognitive Abilities Measures

The participants completed two measures of intellectual ability – the Raven's Advanced Progressive Matrices short form (APM-SF), and the Comprehensive Ability Battery – I (CAB-I).

The APM-SF (Bors & Stokes, 1998) is a set of 12 perceptual analytic reasoning tasks that requires the participant to determine which one of eight potential pieces fits into a blank space in order for a rule to be specified.

The CAB-I (Hakstian & Cattell, 1978) is a set of 12 inductive reasoning tasks that require the participant to solve a problem according to a set of rules. For example, if the participant were presented with the following stimuli: (a) BBLJ (b) TTRU (c) FWZP (d) XXBK (e)MMEO, and asked which of these sets of letters did not follow the rule, the answer would be (c) as this set doesn't start with two identical letters whereas the other sets do.

2.3.2 Personality Measures

The participants completed two subtests of the NEO Personality Inventory Revised (Costa & McCrae, 1992); Conscientiousness and Openness to Experience. They also completed two additional measures of intellectual engagement; Need For Cognition (Cacioppo & Petty, 1982), and Epistemic Curiosity (Litman & Spielberger, 2003).

In each case the psychological construct is measured by the participant indicating the extent to which a given behaviour or attitude applied to them. For example, one of the items in the battery of questions relating to conscientiousness was "I am an efficient person" which the participant would respond to on a seven-point scale ranging from "never" to "always".

2.3.3 LearnSmart Usage

LearnSmart usage was calculated as the proportion of each LearnSmart module that the student completed, averaged across the six modules that were set for each course. Each LearnSmart module comprised 40 questions in total.

2.3.4 Academic Performance

Academic performance was measured as each student's grade on the end-of-semester exam. The format of the exam was identical for both of the courses, comprising 60 multiple choice questions (10 questions for each of the 6 modules covered in the course). Students were given 90 minutes to complete the exam under supervised conditions. In each case the exam was worth 55 per cent of the final grade for the course. The exam questions were not drawn from the LearnSmart test-banks, but were generated by the main lecturer for the module, and were based upon the core concepts covered in the lectures.

2.4 Procedure

The data collection procedures for the two courses were slightly different, and so we will describe them in turn.

Students enrolled in Psychology 1A were encouraged to use the LearnSmart tool, but it was not a compulsory component of the course. Furthermore, the 112 students that completed Psychology 1A, but did not go on to study Psychology 1B completed the cognitive abilities and personality measures as part of a related study, for which they obtained a small amount of course credit (5 per cent of final grade).

Students that were enrolled in Psychology 1B were required to complete the LearnSmart modules for course credit (5 per cent of final grade). They were also required to complete the cognitive abilities and personality measures as part of a practical assignment which was assessed.

In each case the cognitive abilities, personality and LearnSmart usage data were matched to each student's exam grade for the respective course.

Each LearnSmart licence cost the individual student A$38 (although this was slightly less if they purchased the licence along with the textbook). Sixteen students demonstrated financial hardship and were provided with a license for free.

Chapter 3 - Results

3.1 Descriptive statistics

Table 1 shows some basic descriptive statistics for the two samples. As can be seen, the mean age was in the early twenties, and roughly a third of the students were men. Further, less than 10 per cent of the students were from overseas.

Table 1. Descriptive statistics for the Psychology 1A and Psychology 1B students

	N	Mean Age	% Males	% International
Psychology 1A	459	21.04	30.28	9.80
Psychology 1B	515	20.76	31.36	6.99

3.2 Group Comparisons

As indicated earlier in Chapter 2, students had access to the LearnSmart tool in Psychology 1A but it was not a course requirement to use it. As can be seen in Table 2, the sample for Psychology 1A was fairly evenly split between users of the tool and non-users. Further, the data indicate that there were significant differences between these two groups of students in regards to the personality variables and measures of intellectual engagement, with users having significantly higher scores on Conscientiousness, Openness to Experience, Epistemic Curiosity and Need for Cognition. Interestingly, the data indicate that there was no significant difference between users and non-users in terms of their intellectual ability (Ravens APM and CAB-I).

This pattern of results is interesting as it confirms some of the expectations that any teacher or course coordinator might have – that is, certain students are more likely than others to make use of the pedagogical tools and materials that are made available to them, and psychological variables such as Conscientiousness are a good predictor of distinguishing between these students, and those that do the basic minimum. At the same time, academic success can be thought of as a complex optimisation problem for which there is no singular solution method. There is no 'one way' to obtain a good grade, and the strategies employed by different students will vary in their optimality according to factors such as intellectual ability. In this regard, intelligent students *may* make use of tools such as LearnSmart, but they are just as likely to ignore the tool and perhaps employ strategies that have previously proven successful (or simply rely on their superior intellectual ability to succeed).

The pattern of results for Psychology 1B is similar in most respects to the Psychology 1A sample, but differs in one important way. This reflects a difference between the two courses in regards to the Learn Smart tool – specifically, in Psychology 1B students were required to use the tool for a small proportion of course credit (10 per cent of the final grade). As a result, the data show a similar pattern in regards to the personality variables with users scoring higher than non-users on Conscientiousness, Openness to Experience, Epistemic Curiosity and Need for Cognition. However, the Psychology 1B data also show a difference between users and non-users in that one of the measures of intellectual ability (the Cognitive Abilities Battery - I) shows a significant difference between users and non-users, and the group comparison for the other measure (Ravens APM) approaches significance. The explanation for this difference is relatively straightforward – intelligent students likely recognise the importance of completing all components of course assessment, whereas less intelligent students may lack the ability to optimise their time and therefore fail to complete tasks such as this. Happily, the vast majority of the students in the 1B sample engaged with the task as required.

3.3 Relationships between the variables

The inter-correlations between the psychological variables, LearnSmart usage and the final exam grades are shown separately for Psychology 1A (Table 3) and Psychology 1B (Table 4). However, the basic pattern of results is almost identical across the two samples. As could be expected the two measures of intellectual ability correlate strongly with each other, and they are also significant predictors of performance on the end-of-semester exam. In other words, students with high intellectual ability tend to do well on the exam. Similarly, in line with the results of many previous studies the two personality traits Conscientiousness and Openness to Experience are significant predictors of exam performance, and as expected the strength of the relationship is weaker than that observed for the measures of intellectual ability.

The two measures of intellectual curiosity (Epistemic Curiosity, and Need for Cognition) are strongly and significantly related in both samples, suggesting that they are measuring a similar psychological construct. For Psychology 1B both of these variables are significantly (if weakly) related to exam performance, however only Need for Cognition is a significant predictor of exam performance in Psychology 1A.

Importantly, for both Psychology 1A and Psychology 1B, the strongest predictor of performance on the final exam was LearnSmart usage. However, as can be seen, there are significant relationships between LearnSmart usage and the psychological variables (with the exception of Ravens APM). For example, highly conscientious students are likely to use the LearnSmart tool, and also do well on the exam. In other words, it is difficult to determine if performance on the exam is being driven by the students' use of the LearnSmart tool, or if it is due to underlying personality traits such as Conscientiousness.

Table 2. Comparison of the psychological variables and exam scores for LearnSmart users and non-users in Psychology 1A and Psychology 1B.

	Psychology 1A Users = 254, Non-Users = 205		Psychology 1B Users = 425, Non-Users = 90	
	t(457)	Cohen's *d*	*t*(513)	Cohen's *d*
Ravens APM	0.67	0.06	1.83	0.21
Cognitive Abilities Battery - I	1.61	0.15	**3.27**	0.38
Conscientiousness	**4.09**	0.38	**4.00**	0.46
Epistemic Curiosity	**3.82**	0.35	**2.93**	0.34
Need For Cognition	**3.76**	0.35	**2.57**	0.29
Openness to Experience	**2.93**	0.27	**2.41**	0.28
Exam	**5.68**	0.53	**7.78**	0.90

Note 1: Significant *t*-values ($p<0.05$) are indicated in bold font.

Table 3. Inter-correlations between the psychological variables, LearnSmart usage and final exam score for Psychology 1A

	1	2	3	4	5	6	7
1. Ravens APM	-						
2. Cognitive Abilities Battery - I	**.54**	-					
3. Conscientiousness	.01	.04	-				
4. Epistemic Curiosity	.05	.01	**.36**	-			
5. Need For Cognition	**.18**	**.12**	**.42**	**.67**	-		
6. Openness to Experience	**.13**	**.14**	-.07	**.33**	**.31**	-	
7. LearnSmart Usage	.04	**.13**	**.19**	**.10**	**.13**	**.10**	-
8. Exam	**.27**	**.27**	**.16**	.05	**.13**	**.16**	**.30**

Note: Significant *r*-values ($p<0.05$) are indicated in bold font

Table 4. Inter-correlations between the psychological variables, LearnSmart usage and final exam score for Psychology 1B

	1	2	3	4	5	6	7
1. Ravens APM	-						
2. Cognitive Abilities Battery - I	**.52**	-					
3. Conscientiousness	.01	.03	-				
4. Epistemic Curiosity	.06	.02	**.30**	-			
5. Need For Cognition	**.19**	**.10**	**.39**	**.66**	-		
6. Openness to Experience	**.12**	**.14**	-.02	**.37**	**.30**	-	
7. LearnSmart Usage	.07	**.13**	**.21**	**.13**	**.13**	**.10**	-
8. Exam	**.32**	**.26**	**.19**	.12	**.14**	**.17**	**.34**

Note: Significant *r*-values ($p<0.05$) are indicated in bold font

3.4 Regression Analyses

The results of the group comparisons and the correlation analyses indicate that there is a complex pattern of relationships between the psychological variables, the students' tool usage behaviour, and the academic outcome of interest. In order to obtain further insight into the relative impact that the psychological and behavioural variables have upon the students' academic success we employed regression analysis.

As the previously reported data and the results of numerous previous studies have indicated, psychological constructs such as cognitive ability and personality traits are predictive of performance on academic tasks. Our data also indicate that there is a relationship between LearnSmart usage and academic success. In order to determine the impact that students' use of the LearnSmart tool had upon academic success above and beyond what we would expect to see based upon the psychological variables alone we compared two regression models.

The first of these regression models (Model 1) estimated the proportion of the variance in exam performance that was accounted for by the six psychological constructs. The second model (Model 2) estimated the proportion of variance in exam performance that was accounted for by the six psychological constructs *plus* LearnSmart usage. The models and the results of the analyses are summarised in Table 5 for both Psychology 1A and Psychology 1B.

In regards to Psychology 1A both of the models made significant predictions of the exam results. Model 1, based on the psychological constructs alone was able to account for 14 per cent of the variance in the final exam score. However, Model 2, in which the students' LearnSmart usage was also included, was able to account for a larger proportion of the variance in exam results (19 per cent). Further, an *F*-test indicated that this change in R^2 was significant ($F[1,451] = 30.85$, $p < 0.001$).

The results for Psychology 1B were very similar, with Model 1 accounting for 16 per cent of the variance in the exam score. However, in this case when LearnSmart usage was included in the equation the model accounted for a slightly larger proportion of the exam performance variance (R^2 change = 7 per cent). Unsurprisingly, this change in R^2 was also significant ($F[1,507] = 49.71$, $p < 0.001$).

The results of these regression analyses clearly indicate that the psychological variables alone are able to predict a significant proportion of the variance in exam performance. However, when the LearnSmart data are included in the equation the strength of prediction increases significantly.

In order to determine the extent to which each of the variables was making an independent contribution to the prediction we employed relative importance regression analysis (Gromping, 2006). The results of these analyses are displayed in Table 6 for both Psychology 1A and Psychology 1B. As can be seen, for Psychology 1A the two cognitive abilities together accounted for 42 per cent of the Model 2 R^2, and the four personality traits accounted for around 23 per cent. However, the greatest single contribution to the model prediction was made by the LearnSmart usage data at 35 per cent.

For the Psychology 1B data the pattern is highly similar. The combined contribution of the cognitive abilities measures is approximately 42 per cent of the variance, and the four personality traits account for approximately 20 per cent. Finally, the LearnSmart data are making a slightly larger contribution to the model predictions, accounting for a total of approximately 38 per cent of the explained variance.

Table 5. Regression model comparison for Psychology 1A and Psychology 1B

	F	*df*	*p*	R^2	R^2 Change
Psychology 1A					
Model 1. Ex = APM + CAB-I + C + EC + NFC + O	12.48	6, 452	> 0.001	0.14	
Model 2. Ex = APM + CAB-I + C + EC + NFC + O + LS	15.82	7, 451	> 0.001	0.19	0.05
Psychology 1B					
Model 1. Ex = APM + CAB-I + C + EC + NFC + O	16.99	6, 508	> 0.001	0.16	
Model 2. Ex = APM + CAB-I + C + EC + NFC + O + LS	23.06	7,507	> 0.001	0.24	0.07

Note: Ex = Exam; APM = Ravens APM; CAB-I = Comprehensive Abilities Battery – I; C = Conscientiousness; EC = Epistemic Curiosity; NFC = Need for Cognition; O = Openness to Experience; LS = LearnSmart usage.

Table 6. Relative Importance Regression Analysis on Model 2 predictions for Psychology 1A and Psychology 1B.

	Proportion of Model 2 variance accounted for	
	Psychology 1A	Psychology 1B
Ravens APM	0.23	0.29
Cognitive Abilities Battery - I	0.19	0.13
Conscientiousness	0.10	0.10
Epistemic Curiosity	0.01	0.02
Need For Cognition	0.03	0.02
Openness to Experience	0.09	0.06
Learn Smart	0.35	0.38

Chapter 4 - Discussion

4.1 Summary

The results of our study broadly replicate those of previous studies investigating the role that individual differences in students' intellectual ability and personality traits have upon academic success. Specifically, the more intelligent a given student is (as measured by standardised measures), the more likely they are to succeed academically. Similarly, the more conscientious, open to experience, and intellectually curious a student is, the more likely they are to succeed academically.

Importantly, however, the data also clearly demonstrated that the extent to which students made use of the LearnSmart tool was strongly and significantly related to academic success, and that the strength of this prediction was above and beyond what we would expect it to be based on the psychological factors alone. In other words, the data validate the utility of the LearnSmart tool as a study aid in the context of this undergraduate course.

4.2 Comparison with previous studies involving LearnSmart

It is not clear why the strength of the effect attributable to LearnSmart was found to be so large in our study compared to previous investigations involving the tool. It is possible that this can be explained by differences in the way these courses were structured, or the way that the tool was employed in the context of these courses, however there is not enough detail provided in the previously published studies to make a meaningful comparison along these lines.

An alternative explanation is that the methodology employed in the previous studies was not sufficient to detect any effect if there were indeed an effect to be found. One of the strengths of the current study was the ability to control for any potential impact of individual differences in personality and intellect on the academic outcome. As demonstrated in Gurung (2015) the strength of the observed effect decreased when a proxy measure of the students' intellectual ability (i.e., grade point average) was controlled for. However, it is also important to point out that failing to control for individual differences might potentially lead to the opposite outcome – with any potential relationship between the tool and academic success being obscured by these other variables.

4.3 Voluntary versus mandatory usage

It is worth noting that this effect was found regardless of whether the students' use of the tool was voluntary (as it was in Psychology 1A) or mandated for course credit (as it was in Psychology 1B). However, as can be seen from the results of the regression analyses, the strength of the effect attributed to the LearnSmart tool was slightly greater in the second semester data set in which the tool usage was mandated. It is not clear why this should have been the case. Indeed, our initial expectations were that we would find the opposite pattern, with the LearnSmart tool having a greater impact when its usage was voluntary, as the voluntary users would have been more intrinsically motivated to make “good use” of the tool rather than simply completing the assigned task for credit.

One potential explanation for this may be that the minimum proscribed usage of the LearnSmart tool actually comprised a significant proportion of the time that students spent in independent study. In other words, there is the very real possibility that forcing students to use the tool forced them to do study that they would not have done otherwise.

It is difficult to determine if this was indeed the case – our previous attempts to ascertain the time that students actually spend studying have indicated that the students themselves don’t seem to have much insight into their study habits. Self-reported estimates that we have obtained from students vary markedly and are likely to be biased by social desirability effects. More pertinently, when students are asked to rate their confidence in the accuracy of their estimates, the responses tend to be very low. In other words, the students themselves know that they don’t know how long they spend on revision activities.

4.4 Potential reasons for LearnSmart’s efficacy

One of the potential reasons underlying the tool’s efficacy may have been the adaptive nature of the assessment. Specifically, it is possible that adjusting the difficulty of the assessment to suit the understanding of individual students may lead to overall improvements across a cohort because the assessment is not being focussed at the mean of the distribution of abilities. Rather, the adaptive component of the tool may lead to students in the bottom and top tails of the distribution being respectively supported and challenged in their learning.

Given that the tool was developed by a third-party for commercial use, in the current study we were not able to manipulate the extent to which the tool was able to adapt to the student’s level of understanding, and thereby measure any causal relationship between the extent of adaptation and the academic outcomes of interest. However, as was noted in the introduction section, there is a growing body of literature outlining methods for developing and implementing adaptive assessment tools such as this, and one possible future line of investigation might be to develop a tool that can be actively manipulated in regards to adaptation, and then empirically test the relationship between assessment adaptation and academic outcomes.

Another potential explanation for the tool’s efficacy may be related to what is known as the “testing effect” (see McDermott, Arnold, & Nelson, 2013 for a comprehensive review). The testing effect is a well replicated empirical finding related to long-term memory retention. Specifically, it has been demonstrated that the act of being tested on knowledge of a given subject area improves performance on future tests of knowledge for that area above and beyond the improvement observed for studying alone. Furthermore, the more times a student is tested, the greater their overall retention of the material, and if they are provided with feedback, the strength of the effect is even greater (McDermott et al., 2013). As with the role of adaptation, it is not clear the extent to which these factors impacted upon the academic outcomes observed in our study, as we had no control over the direct manipulation of these factors. Again, investigating this in more detail is a potential research direction for future study.

4.5 Student attitudes to LearnSmart

We did not explicitly ask the students about their attitude towards the LearnSmart tool. However, both of the courses underwent a mandatory independent evaluation at the end of the semester in which all students were surveyed in regards to factors such as overall satisfaction with the course, efficacy of teaching, etc. In answer to the open-response question “What were the best aspects of this course?” a number of students made unsolicited remarks about the efficacy and utility of the LearnSmart tool, such as:

“I found the best aspect of this course to be the online learning module - learnsmart, because it enabled a practical application of the information we had learned during the lectures and confirmed and built upon my knowledge of the course.”

“I have found the learnsmart activities … at the end of each course topic particularly useful in helping to synthesise and improve my knowledge in the topics.”

“Learnsmart, it really aids learning and helps you retain information and is good for refreshing.”

“LearnSmart is an effective learning tool, as it helps me recognise what I do and don't know in a specific module”

“The lecture material, textbook and online material (learnsmart) provided a very cohesive understanding of the course content, I found many of the topics much easier to understand due to this excellent repetition & reinforcement of material through these different media.”

“The use of the online technologies like LearnSmart, because it helps to support and solidify understanding of the information in the course.”

“I have found the LearnSmart component very good for learning and retaining information.”

We found very few negative responses from students in regards to the tool, even when its usage was mandated. However, some students felt it was unfair that they had to pay extra for access to the tool, and some indicated that this might have influenced their voluntary uptake of the tool:

“Also it would be great in future if prices for online resources be worked into the course fee, so i don't have to pay an extra $30 off my own back to access the online tests and stuff. Heaps of people i know didn't use the feature because they didn't want to pay for it, whereas if it was part of the course more people might benefit from it.”

Furthermore, it is worth mentioning that some students felt that the *way* they chose to revise should not be mandated:

"I would rather invest my time in my own studying techniques that I feel work better for me."

Of course, we cannot tell if the study methods preferred by this student would have been of more or less benefit than the tool in question.

4.6 Costs associated with using LearnSmart

The previous comments highlight that there are costs associated with the use of tools such as this in undergraduate curricula. As previously indicated, each license cost a student AU$38. We initially justified this cost as being a relatively small one compared to other, larger expenses incurred by undergraduates (such as textbook costs, enrolment fees) and on par with mandatory requirements of many other introductory courses (such as lab coats, safety goggles, etc).

Further, there is a time cost accrued on the part of the students when using resources such as this. For both Psychology 1A and Psychology 1B the minimum time required to complete the LearnSmart modules was estimated at being 3 hours, and this was largely correct. For example, for Psychology 1A the mean length of time that the tool users spent on-task was 3.41 hours.

There is also a cost in regards to the administration time spent by the course coordinator or instructor responsible for maintaining the tool. This will depend on numerous factors such as the technical proficiency of the administrator, the level of technical support available to them, and the size of the class involved.

4.7 Limitations

First, it is important to clarify that while the analyses indicated that LearnSmart usage was a significant predictor of academic performance, we make no strong claim regarding a causal relationship between these two variables. In order to establish a causal relationship it is necessary to employ a true experimental design comparing a control and treatment group. In this case we were simply observing patterns of relationships between the variables and attempting to interpret these in a plausible and reasoned manner.

Second, the present study has controlled for a range of psychological variables that have been implicated in regards to academic success, however it is entirely possible that the relationship that has been observed is due to the influence of other variables that have not been controlled for. For example, we have not controlled for variables such as age, socio-economic status, the extent to which the student works outside of study, or other external commitments of the student, all of which might possibly impact upon the likelihood of using the LearnSmart tool, or upon academic success.

Third, in this study we have employed a relatively simple measure of academic success – that is, performance on the end of semester exam. We recognise that these sorts of assessment tasks represent only a small proportion of the types of tasks that could be used to measure academic success, and that this will differ across different courses. Further, “success” for a given individual may not be best measured as a grade relative to the rest of the class, but rather as measured performance relative to their theoretical potential.

These limitations do not nullify the conclusions of the present study – we include them here as a matter of good practice, and counsel the reader that all research should be interpreted with a degree of caution! At the very least these limitations provide some direction for the design of future studies.

4.8 Conclusions

The results of our study clearly validate the use of the LearnSmart tool as a study aid within the context of this large undergraduate psychology class. Usage of the tool was found to be positively and significantly related to performance on the final exam. Furthermore, the strength of this behavioural relationship was found to be greater than the relationship based upon psychological predictors alone.

Student responses to the tool were largely positive, with a large proportion of the cohort adopting use of the tool regardless of whether its usage was voluntary or mandated. Further, unsolicited qualitative responses indicated that students enjoyed using the tool, found it was motivating, and felt that it had a positive impact on their study habits and overall understanding of course content.

While there was a time and monetary cost associated with the inclusion of the tool in the curriculum, the potential benefits of the tool arguably outweighed these costs.

We strongly advocate the use of similar research programs to test the utility of new learning tools such as this, so that curriculum designers are able to make evidence-based choices when considering their potential inclusion in future courses.

Chapter 5 – Impact, Dissemination and Evaluation

Given the criteria outlined in the IMPEL framework (https://www.education.gov.au/resources-grant-and-fellowship-holders) we can outline the following project outcomes in regards to impact, dissemination and evaluation:

At the level of *team member*, the results of the study have directly informed the team members approach to curriculum development, specifically in relation to the continuing use and further adoption of the LearnSmart tool (and similar e-learning tools) in the undergraduate curriculum. The study has led to the researchers' involvement in a number of "spin-off" projects such as investigations of the impact of other psychological factors such as learning style, stress, and motivation on academic outcomes; an investigation of the role that meta-cognitive factors such as calibration can have on academic success; and a comparison of the factors influencing the academic satisfaction of international and domestic students.

At the level of *immediate students*, the results of the study clearly indicate that the students' usage of the tool was associated with academic achievement. Given that these results generalised across semesters, and followed the same basic patterns as was observed in previous years, it is safe to assume that continuing use of this tool and similar tools will have an ongoing positive impact on the immediate undergraduate students' academic outcomes. The results of the study have also been directly fed back to the students providing them with information that is able to guide them in their continuing studies. Further, aspects of the study have been incorporated into the major practical assignment completed by the students in the second semester, providing future cohorts of students the opportunity to experience pedagogical research at first-hand. The current project and the fore-mentioned ''spin-off" projects have also directly impacted upon students studying at an Honours and post-graduate level, as they have formed the basis of three Honours thesis projects, and are directly related to two PhD thesis projects. Furthermore, involvement in the project has led to a Master's student and PhD student presenting research at the Australian New Zealand Association for Health Professional Educators conference (ANZAPHE 2016).

At the level of *spreading the word*, the results of this study have been presented at a number of different forums within The University of Adelaide including the 'Teaching Large Classes' and 'Online Assessments' communities of practice. These communities of practice are comprised of 15-20 academic staff from a wide range of different disciplines across the University that meet regularly to share information relating to pedagogical best-practice.

The study has been presented at one international conference and four national conferences:

Adaptive e-learning tools and academic performance in a large undergraduate psychology cohort. OTTAWA 2016 - Perth, 2016

The role of individual differences in personality trait and intellectual ability in curriculum design. ANZHAPE – Perth, 2016

Learning analytics and psychological constructs - predicting academic success in a large undergraduate program. BlackBoard Learning & Teaching Conference – Adelaide, 2015

Assessing the impact of e-learning tools on academic outcomes. The University of Adelaide Festival of Learning & Teaching – Adelaide, 2015

Behavioural and psychological determinants of academic outcomes in an introductory psychology course. 5th Vancouver International Conference on the Teaching of Psychology – Vancouver, 2015

Furthermore, the results of this project are currently being written up for submission to an international journal.

At the level of *narrow and broad opportunistic adoption*, disseminating our findings within The University of Adelaide at forums such as the communities of practice, and to the wider academic community via conference presentations and has led to a number of expressions of interest in regards to adopting the use of this tool (or similar tools) within their curricula. It can be expected that these sorts of opportunistic adoptions of approaches such as this will increase as the results of the study are disseminated more widely via publication in an international journal, and as we continue to research and report our findings.

At the level of *narrow systematic adoption*, the results of this study will be reported within The University of Adelaide to organisational structures such as the office of the Deputy Vice Chancellor and Vice President – Academic. As such there is the potential for the study to influence the positioning of online methods for pedagogical improvement at an institutional level.

At the level of *broad systematic adoption* it is too early to make any strong claims regarding the impact that this research might have on systematic changes to tertiary education at a national level. However, if this study is viewed within the context of a larger program of research, it is reasonable to assume that it has the potential to add incremental weight to evidence-based policy changes regarding the use of online assessments in tertiary education.

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Appendix A

Certification by Deputy Vice-Chancellor (or equivalent)

I certify that all parts of the final report for this OLT grant provide an accurate representation of the implementation, impact and findings of the project, and that the report is of publishable quality.

Name: ……Philippa Levy ………………………………………………...............Date: 09 February 2017