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

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In this project we test the utility of an adaptive e-learning study tool (LearnSmart) within the context of a large undergraduate psychology course. We measured student usage of the e-learning tool and the effect that this usage has on academic outcomes, while controlling for the effects of intellectual ability and personality traits such as conscientiousness and openness to experience. The results of our analyses indicate that students who made use of the tool performed significantly better on the assessment tasks when compared to non-users. Further, regression analyses indicated that the extent to which students made use of the tool was a stronger predictor of academic performance than four personality variables that had previously been implicated in the literature as related to academic outcomes, and was a stronger predictor of academic performance than intellectual ability for two of the four academic tasks.

Keywords: *LearnSmart, e-Learning, academic achievement, intellectual ability, personality trait.*

Introduction

IN RECENT YEARS there has been growing interest in the use of e-learning tools that are able to adapt to the ability levels, needs, or preferences of individual learners (e.g. Gasparinatou, Grigoriadou, & Elsevier Science, 2011; Tseng et al., 2008; Vandewaetere et al., 2011). It is generally accepted that individualised instruction is superior to more homogenous approaches (e.g. Bloom, 1984; Cohen et al., 1982; Kulik et al., 1990) and so, in principle, 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 higher retention rates because many adaptive tools allow students to set the pace of their learning and, therefore, they are less likely to become overwhelmed by either the volume or depth of understanding that is required of them. Here, we aim to test the utility of a commercially available adaptive e-learning tool (LearnSmart) within the context of a large undergraduate psychology course.

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 instructors can assign for the purpose of formative or summative assessment. LearnSmart works by presenting questions based on core content to which students are required to provide an answer and an indication of their confidence in the correctness of their answer on a four-point scale (i.e. 'I know it', 'Think so', 'Unsure', or 'No idea').

Based upon the accuracy of each response and the associated confidence rating, LearnSmart adjusts the difficulty level of subsequent questions. In this way, students who 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 independent empirical evidence assessing the efficacy of the LearnSmart tool, and the results of these investigations have been mixed.

James (2012) assessed the LearnSmart 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. In the case of students who used the tool James found a weak but statistically significant relationship between the degree of tool usage and performance on the final exam, where tool usage was measured as either the proportion of task completion (R^2 = 0.10), or time spent on task (R^2 = 0.02). However, there was no significant difference between the final exam 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, nonadaptive, formative online quiz. Students were randomly assigned to one of the conditions, and group comparisons were made across six separate courses with class sizes ranging from 20-to-200+ (total N = 587). Overall the investigators found no significant difference between the two groups of students in regards to improvement in academic performance from the start of the course to the end-of-semester exam (F[1, 580.8] = 0.19, p = .67). Post-hoc 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. Further, for students in the LearnSmart group they found no significant relationship between the amount of time students spent using the tool and overall improvement (r = 0.07, p = .25).

Conversely, Owens & Moroney (2015) reported a significant relationship between tool usage (measured as time-on-task) and final grade in their investigation of the effect of LearnSmart tool usage in a bioscience unit of a nursing degree (N = 263) where students were required to use the tool in order to obtain a small proportion of course credit. The authors indicate that 50 minutes of LearnSmart usage was equivalent to a 1 per cent increase in final grade.

Finally, Gurung (2015) investigated the efficacy of the LearnSmart 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 quiz performance, with effect sizes ranging from r = .19 to .32 across four quizzes. However, when student grade point average was taken into account, the overall strength of the relationship weakened (but remained significant), with effect sizes ranging from r = .14 to .22 across the quizzes. In other words, students with higher GPAs were doing better on the final exam, but they were also tending to use the tool more than other students. This finding 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.

Psychological predictors of academic achievement

Within a given cohort of students there are typically a wide range of different intellectual abilities, personality traits, and preferences for different learning styles. Furthermore, there is a large body of evidence indicating that these individual differences can have a substantial influence upon a given student's ability to succeed within a tertiary education environment (e.g. Conard, 2006; De Feyter et al., 2012; O'Connor & Paunonen, 2007). One obvious individual difference variable that influences 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 per cent of the variance in academic achievement is accounted for by intellectual ability (e.g. Busato et al., 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, although findings concerning some of these traits are mixed. Of particular importance are the 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. Conscientiousness is associated with behaviours such as efficiency, organisation, self-discipline, deliberation, achievement-orientation and motivation. 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 et al., 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 focused on in these studies, the types of assessment tasks being predicted, or other extraneous variables that are not being adequately controlled for in these studies. Unfortunately, to date there does not appear to be any clear explanatory pattern relating these factors to academic success (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 (see, e.g. von Stumm & Ackermann, 2013) but there is continuing debate on whether they make an independent contribution to the prediction of academic achievement, or if they simply share variance with variables such as Openness to Experience (e.g. Powell & Nettelbeck, 2014).

The evidence linking these psychological constructs of intelligence and personality factors to academic achievement is of obvious importance in regards to any attempt to assess the utility of e-learning tools. 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.

Study aims

Here we aimed to test the relationship between LearnSmart tool usage and academic achievement while controlling for five known psychological predictors of academic success (intellectual ability, Conscientiousness, Openness to Experience, Need for Cognition and Epistemic Curiosity). We focus on two assessment pieces as measures of academic achievement: a series of module quizzes, and an end of semester exam.

Method

Participants

The following study was conducted at the University of Adelaide, South Australia. All participants were undergraduate students studying the first-year psychology subjects Psychology 1A (first semester) and Psychology 1B (second semester), both of which involve a set of six modules covering introductory level material in areas of study in psychology. The cohort has a wide range of tertiary entry scores, and cites 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 Master (18 per cent) or Doctoral (14 per cent) level qualification in psychology.

Of the N = 601 students enrolled in Psychology 1A in 2015, we had datasets for N = 467. Of the N = 564 students enrolled in Psychology 1B, we had data-sets for N = 542 students. The following analyses are based on the data from N = 648 individuals in total. N = 361 studied both Psychology 1A and 1B; N = 106 studied Psychology 1A only; and N = 181 studied Psychology 1B only.

Measures

Cognitive Abilities Measures. Participants completed two measures of Intellectual ability – the Raven's Advanced Progressive Matrices short form (APM-SF: Bors & Stokes, 1998), and the Comprehensive Ability Battery – Inductive Reasoning (CAB-I: Hakstian & Cattell, 1978). Student performance on these two measures was averaged to produce a single indicator of intellectual ability.

The APM-SF 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 set of inferred rules to be satisfied. The CAB-I 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.

Personality Measures. The participants completed the items comprising the Conscientiousness and Openness to Experience scales from the NEO PI-R (Costa & McCrae, 1992). 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'.

LearnSmart Usage. Each LearnSmart module comprised 40 questions in total, and the students completed six modules per course. Previous studies assessing the effect of LearnSmart have tended to use the system's default measure of the total length of time that students spend logged onto the online tool as an indication of tool usage (generally referred to as 'time-on-task'). However, as has been noted (e.g. Kovanović et al., 2015) measures of engagement such as this can confound 'time-logged-in' with 'time-spent-learning'. In other words a student might be logged into the tool on their web-browser, but not actually be engaged in the task. In light of this, in the current study we adopted a measure of LearnSmart usage based upon the incremental progress that students had made on the task. Specifically, we measured LearnSmart usage as the proportion of each LearnSmart module that each student completed, averaged across the six modules that were set for each course.

Academic Performance. Academic performance was measured via two different assessment pieces: mean grade across six module quizzes, and the grade on the end-of-semester exam. The module quizzes comprised 30 multiple-choice questions drawn from the test-banks supplied by the textbook publisher. Each test-bank contained 100-to-150 questions and covered the same concepts as the LearnSmart test-banks (in some cases the questions were identical, or close to identical). Each student was presented with a different random selection of 30 questions. Students were allowed a fortnight to complete each quiz, but could only submit the quiz once. The format of the module quizzes was identical for both courses and comprised 20 per cent of the final grade for the semester.

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 semester. The exam questions were not drawn from the LearnSmart test-banks or the textbook test-banks, but were generated by the main instructor for each module and were based upon the core concepts covered in the lectures.

The remaining assessment components for each course were based on participation in research activities (10 per cent in Psychology 1A and 5 per cent in Psychology 1B) and a written report (20 per cent in Psychology 1A and 15 per cent in Psychology 1B). Further, students enrolled in Psychology 1A were encouraged to use the LearnSmart tool, but it was not a compulsory component of the course, whereas students that were enrolled in Psychology 1B were required to complete the LearnSmart modules for 5 per cent of their final grade.

The analyses reported in the Results section were based on scores for actual attempts at each of the assessment tasks. Any student that did not attempt a given task was excluded from any analysis related to that particular task, hence the *N*'s (and associated degrees of freedom) vary slightly across the analyses.

Procedure

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). The data collection procedures for the two courses were slightly different. The 106 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. In contrast, the students that were enrolled in Psychology 1B were required to complete the cognitive abilities and personality measures as part of the data collection for a statistical report.

Results

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 outside Australia.

Group comparisons

As indicated earlier, students had access to the LearnSmart tool in Psychology 1A but its usage was not a course requirement.

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

	N	Mean Age (SD)	% Males	% International
Psychology 1A	467	21.0 (5.42 yrs)	30.1	9.63
Psychology 1B	542	20.8 (4.68 yrs)	31.4	6.99

As can be seen in Table 2, the sample for Psychology 1A (when LearnSmart usage did not attract course credit) was fairly evenly split between users and non-users of the tool. Further, the data indicate that there were significant differences between these two groups of students in regards to the personality variables, with LearnSmart users having significantly higher scores on Conscientiousness, Openness to Experience, Epistemic Curiosity and Need for Cognition. The data also indicate medium-to-large and significant differences between these two groups of students in performance on both assessment pieces. However, the data indicate that there was no significant difference between users and non-users in terms of their intellectual ability.

As shown in Table 3, the pattern of results for Psychology 1B is similar in most respects to the Psychology 1A sample, although in this case the data show that fewer students chose not to use the tool, and there was also a significant difference between users and non-users in regards to the measures of intellectual ability, with non-users scoring significantly lower than users. This is potentially a result of the requirement in Psychology 1B to complete the LearnSmart tasks for 5 per cent of the final grade. In light of the disparity between the number of users and non-users in Psychology 1B we also ran non-parametric versions of these group comparisons (Mann-Whitney U). In each case these analyses indicated the same pattern of significant results.

The results of these comparisons suggest the existence of strong interdependencies between LearnSmart tool usage, the measures of intellectual ability and personality, and the academic outcomes for the students. In the following we explore these relationships in more detail.

Correlation analyses

The correlations between the psychological variables, LearnSmart usage and the assessment pieces are shown in Table 4 and as can be seen the basic pattern of results is highly similar across the two samples. The correlations between performance on the assessment pieces were statistically significant and relatively strong. The data also indicate that the measure of intellectual ability was a significant predictor of performance on each of the assessment pieces.

In contrast, the various measures of personality show a mixed pattern of rela-

Table 2: Group comparisons across LearnSmart Users and Non-Users for Psychology 1A

	LearnSmart Users			LearnSmart Non-Users			Group Comparisons		
	N	Mean	SD	*N*	Mean	SD	*t*	*df*	Cohen's *d*
Intellectual Ability (%)	256	69.63	20.15	211	67.24	21.04	1. 25	465	0. 12
Conscientiousness	256	164.21	22.71	211	155.40	22.39	4.20**	465	0. 39
Epistemic Curiosity	256	27.98	5.60	211	25.97	5.14	4.01**	465	0. 37
Need For Cognition	256	89.34	16.80	211	83.57	16.49	3.72**	465	0. 35
Openness	256	169.84	16.41	211	165.06	18.51	2.95**	465	0. 27
Final Exam (%)	254	67.47	12.14	205	60.68	13.38	5.69**	457	0. 53
Module Quizzes (%)	256	84.48	10.58	211	74.44	17.45	7.65**	465	0. 71

Notes: * p<0.05, ** p<0.01.

Table 3: Group comparisons across LearnSmart Users and Non-Users for Psychology 1B

	LearnSmart Users			LearnSmart Non-Users			Group Comparisons		
	N	Mean	SD	*N*	Mean	SD	*t*	*df*	Cohen's *d*
Intellectual Ability (%)	434	72.17	19.74	108	65.51	22.46	3.04**	540	0.33
Conscientiousness	434	161.63	22.15	108	151.31	20.13	4.41**	540	0.47
Epistemic Curiosity	434	27.50	5.44	108	25.79	4.90	2.99**	540	0.32
Need For Cognition	434	87.64	17.21	108	83.36	13.84	2.40*	540	0.26
Openness	434	169.53	17.07	108	165.04	18.11	2. 41*	540	0.26
Final Exam (%)	425	64.67	14.96	90	51.20	14.67	7.79**	513	0.90
Module Quizzes (%)	433	81.92	15.67	107	56.99	24.97	12.91**	538	1.39

Notes: * p<0.05, ** p<0.01.

tionships in regards to the assessment tasks. Conscientiousness and Need for Cognition were significantly and positively related to the assessment tasks for both Psychology 1A and 1B, although the strength of the relationship was relatively weaker for Need For Cognition. Epistemic Curiosity had no significant relationship with either task in 1A, and was only weakly (but significantly) related to performance on the exam in Psychology 1B. Finally, Openness to Experience had a weak but significant relationship with the exam but not the quizzes for both 1A and 1B.

Importantly, Table 4 indicates that for both Psychology 1A and 1B the extent to which students made use of the LearnSmart tool was significantly related to intellectual ability and all four of the personality measures. Furthermore, LearnSmart tool usage was significantly related to performance on both assessment tasks, and the strength of the relationship was moderate to strong ($r = .30$ to $.57$).

Table 4: Correlation coefficients between the test variables for Psychology 1A (above the diagonal) and Psychology 1B (below the diagonal)

	1	2	3	4	5	6	7	8
1. Intellectual Ability	-	.04	.04	.18**	.14**	.10*	.31**	.25**
2. Conscientiousness	.04	-	.37**	.41**	-.06	.20**	.17**	.24**
3. Epistemic Curiosity	.07	.33**	-	.68**	.35**	.10*	.06	.05
4. Need For Cognition	.18**	.37**	.67**	-	.31**	.13**	.13**	.12*
5. Openness to Experience	.16**	-.01	.38**	.32**	-	.11*	.16**	.06
6. LearnSmart Usage	.11*	.22**	.11**	.12**	.10*	-	.30**	.33**
7. Final Exam	.34**	.19**	.12**	.14**	.17**	.34**	-	.53**
8. Module Quizzes	.25**	.26**	.01	.09*	.05	.57**	.52**	-

* p< 0.05, **p<0.01

Regression analyses

To further explore the relative contributions of the LearnSmart tool usage and the psychological variables in regards to the prediction of academic performance we ran a series of regression models. 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 relative contribution that use of the LearnSmart tool made in regards to the prediction of academic performance 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 assessment performance that was accounted for by the five psychological variables. The second model (Model 2) estimated the proportion of variance in assessment performance that was accounted for by the five psychological constructs *plus* LearnSmart usage. Further, 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. Relative importance regression is a computationally intensive approach to the problem of assessing the relative contributions of correlated regressors to a regression model. We used Lindeman, Merenda, and Gold's (1980) approach of averaging over all orderings of regressors in the model, as implemented in the R (R Development Core Team, 2015) package relaimpo (Gromping, 2006). The models and the results of the analyses are summarised in Table 5 for Psychology 1A and Table 6 for Psychology 1B and, for the relative importance analyses, the Tables show the proportion of explained variance attributable to each predictor variable.

The results of the analyses show broad agreement across the courses and assessment pieces. In each case the F-tests indicate that Model 1 (based on the psychological predictors alone) made a statistically significant prediction of the performance of the assessment tasks, with the proportion of variance accounted for being slightly greatest for the final exam than the quizzes. In regards to Model 1, intellectual ability made a significant contribution to the regression predictions for each of the assessment tasks, with relative importance regression analyses indicating the explained variance accounted for ranging from 42 per cent to 63 per cent. Conscientiousness contributed significantly to the predictions for the tasks across both of the courses, and in the case of the module quizzes made a slightly larger contribution than intellectual ability. Openness to Experience made a small but significant contribution to the predictions for the exam, but did not make significant contribution for the module quiz performance. Finally, Epistemic Curiosity made no significant contribution to any of the models, and Need for Cognition only made a relatively minor (but significant) contribution to the prediction of the module quiz in Psychology 1B.

The results of the Model 2 analyses, in which LearnSmart usage was added to the regression equation, also show broad agreement across the courses and assessment pieces. In each case Model 2 accounted for a greater proportion of the variance than Model 1, and in each case the R^2 change was significant. Further, for the module quizzes the relative importance regression analyses indicate that LearnSmart usage made the single greatest contribution to the prediction of performance, ranging from 45 to 74 per cent of the explained variance. In the case of the final exam, the relative contribution of LearnSmart usage was equal to that of intellectual ability for Psychology 1B, and slightly less than that of intellectual ability for Psychology 1A.

In the analyses so far we have measured LearnSmart usage as the proportion of LearnSmart module completion, averaged across the six modules. However, the previous studies investigating LearnSmart efficacy have also employed the amount of time that students spend on-task as a measure of usage. Following this, we re-ran our regression analyses using time-on-task as the measure of LearnSmart usage in the Model 2 predictions and found that the pattern of results were identical to those displayed in Tables 5 and 6, but the effect sizes were weaker. For Psychology 1A the Model 2 predictions the R^2 values were .17 and .14 for the exam and quiz, respectively. For Psychology 1B the corresponding R^2 values were .17 and .21. As with the previous analyses, in each case the F-tests for R^2 change from Models 1 to 2 were significant at a .05 alpha level.

Discussion

The primary aim of this study was to determine if usage of a commercially available online study aid (LearnSmart) was significantly related to academic outcomes in the context of a large undergraduate psychology course. The results of our analyses indicate that students who made use of the tool performed significantly better on the assessment tasks when compared to non-users and this outcome held regardless of whether usage of the tool was voluntary (as in Psychology 1A), or mandatory to obtain a small proportion of course credit (as in Psychology 1B). Further, regression analyses indicated that the extent to which students made use of the tool was a stronger predictor of academic performance than four personality variables that had previously been implicated in the literature as related to academic outcomes, and was a stronger predictor of academic performance than intellectual ability for two of the four academic tasks.

Psychological predictors of academic success

The results of this study provide further insight into the psychological predictors of academic success. In line with the results of numerous previous (e.g. Busato et al., 2000; Chamorro-Premuzic & Furnham, 2003b; Powell & Nettelbeck, 2014), the

Table 5: Regression model comparisons across the assessment tasks for Psychology 1A

	Final Exam				Module Quiz			
	Model 1 F[5, 453] = 14.81** R² = 0.14		Model 2 F[6, 452] = 18.05** R² = 0.19 R² change = 0.05**		Model 1 F[5, 461] = 13.10** R² = 0.12		Model 2 F[6, 460] = 18.05** R² = 0.19 R² change = 0.07**	
	Beta	RI	Beta	RI	Beta	RI	Beta	RI
Intellectual Ability	0.18**	0.61	0.17**	0.41	0.16**	0.44	0.15**	0.26
Conscientiousness	0.11**	0.18	0.08**	0.10	0.18**	0.46	0.14**	0.24
Epistemic Curiosity	-0.19	0.02	-0.16	0.01	-0.25	0.03	-0.23	0.02
Need For Cognition	0.01	0.04	0.00	0.03	-0.00	0.04	-0.00	0.02
Openness	0.11**	0.14	0.09**	0.09	0.07	0.03	0.04	0.01
LearnSmart Usage	-	-	8.21**	0.35	-	-	10.52**	0.45

Notes: * p<0.05, ** p<0.01. Beta weights are unstandardized. RI = proportion of model explained variance attributable to individual regressor

Table 6: Regression model comparisons across the assessment tasks for Psychology 1B

	Final Exam				Module Quiz			
	Model 1 F[5, 509] =19.56** R^2 = 0.16		Model 2 F[6, 508] = 25.73** R^2 = 0.23 R^2 change = 0.07**		Model 1 F[5, 534] = 16.42** R^2 = 0.13		Model 2 F[6, 533] = 56.93** R^2 = 0.39 R^2 change = 0.25**	
	Beta	RI	Beta	RI	Beta	RI	Beta	RI
Intellectual Ability	0.25**	0.63	0.23**	0.40	0.23**	0.42	0.18**	0.11
Conscientiousness	0.14**	0.19	0.10	0.10	0.27**	0.49	0.16**	0.11
Epistemic Curiosity	0.04	0.03	0.03	0.02	-0.50*	0.04	-0.53	0.02
Need For Cognition	-0.03	0.04	-0.03	0.02	0.01	0.03	0.03	0.01
Openness	0.12**	0.11	0.09*	0.07	0.07	0.02	0.01	0.00
LearnSmart Usage	-	-	10.93**	0.40	-	-	25.83**	0.74

Notes: * p<0.05, ** p<0.01. Beta weights are unstandardized. RI = proportion of model explained variance attributable to individual regressor

data indicated that intellectual ability was a major predictor of academic performance. Further, the data also indicated a clear difference in the intellectual ability scores of the LearnSmart users and non-users in Psychology 1B, suggesting that there was a relationship between what might be thought of as optimised study behaviours and intellectual ability. In other words, completing the LearnSmart tasks was a mandatory part of the assessment in Psychology 1B, therefore using the tool was an optimal behaviour (even if it were the case that it had no actual relationship with performance on the exam or quizzes). An alternative possibility is that the lower intellectual ability scores for the non-users could be reflecting a lack of motivation on the part of these students – that is, the students that didn't use the tool may also have put little effort into completing the two measures of cognitive ability, leading to lower scores on these tasks. Such an explanation would also explain the observed differences between users and non-users in regards to Conscientiousness.

In regards to the personality traits, Conscientiousness was found to have significant first-order correlations with each of the assessment tasks and made significant contributions to the regression models. This adds further weight to the results of previous studies suggesting that the behaviours and attitudes associated with the trait Conscientiousness play an important role in academic outcomes. Openness to Experience made a smaller contribution to the predictions, and only significantly contributed to the final regression models for the exam, and not the quiz, which is also broadly reflective of the results of previous studies suggesting that the strength of the Openness/Achievement relationship varies across different academic tasks (O'Connor & Paunonen, 2007). However, interpreting the reason for this difference across the two tasks is not straightforward – it is unclear why the behaviours and attitudes associated with Openness would have an influence upon exam performance and not the module quizzes.

In regards to the two additional measures of intellectual curiosity, Epistemic Curiosity and Need for Cognition, the data provide further support for the conclusions of Powell and Nettelbeck (2014) who suggested that these variables do not incrementally predict academic success. The first-order correlations with Need for Cognition indicated shared variance between the measure and each of the assessment tasks. However, the regression analyses clearly indicated that this variance overlapped with the other variables in the model and as a result it made no unique contribution to the predictions. Epistemic Curiosity only made a significant contribution to the final regression model for the Psychology 1B module quizzes, and the relative weight of this contribution could be considered negligible (2 per cent of the explained variance). Given this, it is highly possible that the observed relationship was merely reflecting random sampling variance, and not any meaningful relationship with academic success.

Comparisons with previous LearnSmart-based studies

The results of the current study replicate the results of James (2012), Owens and Moroney (2015), and Gurung (2015) suggesting that the extent to which students make use of the LearnSmart tool (as either proportion of module completion, or time-on-task) is positively and significantly related to academic performance. Due to differences in the forms of analyses employed in these studies it is difficult to make direct comparisons, but the overall size of the effect of LearnSmart use found in the current study appears to be larger than that found previously. One potential explanation for this may be related to the primary measure of LearnSmart usage employed in this study – proportion of module completion – as opposed to time-on-task (as has generally been employed in previous studies). Our analyses found that the effect sizes for predictions based on time-on-task were weaker than those based on module completion, which follows the same pattern as the results of James (2012). One reason for the disparity between these two measures of tool usage may be that the length of time students spend logged into a particular web-application is not necessarily an accurate indication of the time that the students actually spend engaged in the task – they may be logged in, but engaged in other activities (e.g. reading the textbook, or browsing other websites). This could lead to inflated estimates of tool usage for some students, which may weaken the strength of the overall effect. In contrast, proportion of module completion is a more objectively clear indication of task progress – students have either made incremental progress towards completing a module or they have not. It is interesting to speculate whether Griff and Matter (2013) would have also found a significant positive relationship between tool usage and academic achievement had they used proportion of module completion as a measure rather than time-on-task.

Explaining the efficacy of the LearnSmart tool

There are a number of potential explanations for the observed relationship between LearnSmart usage and academic outcomes. One may be related to the adaptive nature of the tool. 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 focused 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. 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, one possible future line of investigation might be to develop a similar tool that can be actively manipulated in regards to adaptation, and then empirically test the relationship between assessment adaptation and academic outcomes.

An alternative interpretation is that there is nothing specific about the LearnSmart tool itself that has an influence on learning outcomes. In other words, the extent to which students made use of the LearnSmart tool may simply be a proxy measure for the extent to which students study in general – that is, LearnSmart usage may be seen as a form of 'study efficacy'. Students who applied themselves to the use of the LearnSmart tool would likely be students that applied themselves to other (non-LearnSmart) study activities in preparation for the module quizzes and exam. Furthermore, we could expect that variables such as Conscientiousness would share variance with this sort of behavioural construct, which would go some way towards explaining the patterns of inter-correlations observed in this study (and previous studies). Additionally, if LearnSmart usage was indeed directly influencing exam and quiz performance then we could expect it to be moderated by this 'study efficacy' variable.

Unfortunately we have no means of testing this suggestion in our current dataset, and indeed, measuring 'study efficacy' appears difficult regardless. Our previous (unpublished) attempts to measure student self-reported study efficacy seem to indicate that students find it difficult to report the amount of time they spend in study activities, and while other studies have employed strategies such as daily diaries, these self-report measures of study time appear to fluctuate broadly and are highly context-specific (see Plant et al., 2005, for a review). Furthermore, while learning analytics obtained from Learning Management Systems provide some indication of student's online study behaviours, these estimates cannot provide any indication of 'offline' behaviours such as reading textbooks, making notes, discussing concepts with peers, and so on.

A final potential explanation for the relationship found in this study may be related to what is known as the 'testing effect' (see McDermott et al., 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). It should be noted that the LearnSmart tool is not unique in respect to the testing effect – rather, it could be expected that any form of study aid that provides students with formative feedback in regards to their understanding of core topic knowledge and the opportunity to repeatedly test this understanding would have a positive influence on summative assessment performance. Again, investigating the specific task characteristics that influence the strength of this effect is a potential research direction for future study.

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 ongoing module quizzes and the final exam, even when controlling for known psychological predictors of academic success.

We must always be cautious of invoking causality when interpreting patterns of shared variance in data such as these. Nonetheless, this study is situated in an applied context (undergraduate curriculum design) and the underlying assumption is that, all other things being equal, behaviours such as the extent to which a student makes use of a given study tool can be seen as having a plausibly causal influence on the grade that a student attains – if this were not the case we would not provide them with the tools in the first place.

In conclusion, short of making any strong claims regarding a directly causal relationship between the tool in question and academic performance, the results of this study certainly indicate that if we provide students with access to tools such as this, and they make use of them, then we can expect to see a positive relationship with student academic performance. We therefore strongly advocate: 1. the provision of formative feedback tools such as LearnSmart within undergraduate curricula, and 2. further investigation of the efficacy of these tools and the specific task characteristics that influence academic outcomes.

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