

Article

Efficacy of an Adaptive Learning System on Course Scores

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Abstract: Adaptive learning systems have gained popularity within higher education, given the affordances that claim to enhance student learning outcomes by providing personalised learning trajectories that allow students to interact with course content at their own pace. Nonetheless, studies investigating the impact of such systems on learning outcomes such as course scores have been mixed, in part due to the research approaches applied, as found by the review undertaken in this study. Yet, for purposes of accountability, it remains critical to investigate the efficacy of adaptive learning systems, at least for its relation to course scores when assessment stakes are involved. This study reports the efficacy of an in-house adaptive learning system used within an institution in terms of its impact on course scores, based upon propensity score analysis, a quasi-experimental approach considered as a feasible alternative to randomised controlled trials. Results of this study reported a difference in course scores, suggesting merit in using the in-house adaptive learning system, though the difference did not present statistically significant differences at the 95% confidence level. Directions for future research are also discussed.

Keywords: higher education; course evaluation; efficacy; adaptive learning

1. Introduction

One of the primary objectives of general and higher education is to create an effective and efficient learning environment for students. However, the classic learning context revolves around an environment in which a learner is provided with the same information, structure, and interface [1]. Yet, to improve diverse students' learning, educational researchers point out that students learn more effectively when instructional materials are individualised to meet their needs [2]. This is particularly important for students who have been working for some years prior to pursuing academic studies due to job and family responsibilities, and may have limited time to complete academic work related to their coursework [3]. Further, students with diverse levels of knowledge and skills could pose more challenges for faculty members to teach or integrate fundamental concepts into the curriculum.

To enhance students' competencies and success in multiple programs, alternative teaching and learning approaches are crucial, including the use of technology in instruction that had been emphasised during the recent COVID-19 pandemic [4]. As an example, given the complexity of mathematics [5], sufficient prior knowledge and personalised supports for individual students are important to the enhancement of students' mathematics learning outcomes [6]. To foster learners' problem-solving competence, researchers have developed various learning strategies and technological tools to enhance students' learning outcomes [7]. In particular, adaptive learning platforms have been gaining popularity in higher education settings. A study by [8] suggested that the core elements of adaptiveness contribute to incremental learning, regular assessment, and the availability of many paths to a final destination. In this regard, adaptive learning transforms the learning environment from a fixed to flexible setting.

In addition to making a difference to teaching and learning processes, the adaptive learning approach changes another high priority factor—time. As mentioned, students in



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the workforce (e.g., part-time students) have limited time due to multiple responsibilities. Yet, for mastery to occur during learning, some students need more time than others. Incidentally, adaptive learning platforms provide a solution to this, by providing students an opportunity to navigate their learning trajectories at a self-determined pace when completing course content within the scheduled deadline [9]. For these reasons, adaptive learning platforms provide flexible context, content, and an opportunity for students in the workforce to complete required pre-requisite assignments at their own pace.

While adaptive learning systems provide some affordances to enhance learning and teaching, efficacy studies of such systems have yielded inconclusive findings, some due to less robust research approaches (e.g., studies without control groups), as identified by the literature review undertaken in this study. Some have reported learning gains in terms of course scores, while others reported otherwise. Nonetheless, it remains critical to establish whether an adaptive learning system impacts learning outcomes, at least in terms of course scores particularly where stakes are higher; in the least desirable situation, an adaptive learning system should not be detrimental to student course scores as they engage with it. To this end, this study seeks to contribute to scholarship by reporting the efficacy of an in-house adaptive learning system used within an institution (i.e., AdLeS) in terms of its impact on course scores, based upon a quasi-experimental approach considered as a feasible alternative to randomised controlled trials.

2. The Potential of Adaptive Learning: Improving Educational Performance

In part to scaffold students' current levels of understanding and identify knowledge gaps, research studies have also indicated that adaptive learning systems have the potential to improve learners' performance [10]. However, due to the evolving states of adaptive learning within higher education, research findings on adaptive learning systems have been mixed [11]. In particular, the review undertaken here of some studies published since 2015 found some that showed no statistically significant difference on student learning outcomes and others that demonstrated significant learning outcomes (see Table 1). As an example, to investigate the efficacy of adaptive systems, ref. [1] examined the use of two instructional methods to compare students' scores and completion rates. The first method employed an adaptive learning approach in which instruction and tasks were adapted in real time. The second method engaged a more traditional approach using a set of quizzes supplied by the textbook publisher. Finding that neither the first nor the second method provided a learning advantage to students' learning, ref. [1] concluded that both instructional delivery approaches did not vary significantly during the course of learning.

In the same vein, having implemented an adaptive learning system with the aim to examine performance differences between the pre-test and post-test of students who completed the adaptive learning versus those who did not participate, ref. [2] found that the adaptive learning intervention significantly increased students' knowledge of chemistry content but not for other subjects. It is noteworthy, however, that [2] explained that the differences between pre- and post-test scores in biology, mathematics, and information literacy were greater for students who completed the adaptive system compared to those who did not, though the difference in scores were not statistically significant following the intervention.

Table 1. Efficacy studies of adaptive learning systems.

Author(s)	Participants	Methods	Findings	Remarks
[12] Arsovic, B., & Stefanovic, N. (2020)	Total number of first and second years of undergraduate students; number was not indicated	<i>t</i> -test, ANOVA, & multivariate linear regression	Students who attended the adaptive course obtained higher marks, and the pass rate was higher.	Comparability of students who attended the traditional or adaptive course was not observed. This could suggest that the finding (of students who attended the adaptive course attained higher scores) could be influenced by confounding variables.
[13] Daines, J.B., Troka, T., & Santiago, JM. (2016)	27 students from Calculus I course, 19 from Trigonometry and Pre-calculus prerequisite courses	Descriptive statistics	Results show that average pass rates in Trigonometry, Pre-calculus and Calculus I increased from 76% to 94%, 66% to 94%, and 69% to 86%, respectively.	As no control group was observed, the findings could possibly be confounded by single-group threats (e.g., maturation).
[14] Foshee, C.M., Elliott, S.N., & Atkinson, R.K. (2016)	2880 college students	Pre-test and post-test, paired sample <i>t</i> -test, two-way ANOVA	Results show statistically significant improvements in students' learning and math efficacy suggesting that the adaptive system led to successful remediation.	The authors indicated that it was deemed unethical to use a control group for first-year students. However, without a control group, the outcome could have been influenced by other confounding variables.
[2] Liu, M., McKelroy, E., Corliss, S.B., & Carrigan, J. (2017)	128 first year undergraduate students (74 participated in Biology module; 52 in Chemistry; 62 in Math; 50 in Information Literacy) 3422 college students.	ANCOVA, <i>t</i> -test, Pearson correlation, linear regression	The adaptive learning intervention significantly increased students' knowledge of Chemistry but not other subjects.	No control group was observed. The effects of the adaptive system could have been influenced by other confounding variables.
[15] Mojarad, S., Essa, A., Mojarad, S., & Baker, R. (2018)	Non-ALEKS-section consisted of 706 students; ALEKS-section consisted of 417 students who participated	Logistic regression to calculate propensity score matching	Five comparisons were statistically significant in favour of ALEKS, with a boost of 6 to 19 points in pass rates.	The study had a large sample size and applied propensity score analyses that supported the findings.
[16] Mojarad, S., Baker, R.S., Essa, A., & Stalzer, S. (2021)	2072 community college students	Matched comparisons using the inverse proportion of treatment weights and chi square	This replication study obtained an effect size of 0.36, which was higher than that of a similar previous study which was 0.22. Results indicated that adaptive and deep learning were more targeted at students' learning in areas of difficulty and accuracy than traditional teaching modes.	The study was observed to have a large sample size and comparable control groups to validate findings of the prior research.
[17] Mou, C., Tian, Y., Zhang, F., & Zhu, C. (2022)	3426 college students	Deep neural networks	Results indicated that neither the adaptive learning nor the traditional approaches provided a definitive learning advantage. The algorithm sequencing system helped learners recognise 21.4% more (and recall 21% more) questions than a traditional flashcard learning tool.	The study recommended that future research should account for students' characteristics (e.g., matching students from each of the modes of teaching).
[1] Murray, M.C., & Pérez, J. (2015)	218 university students	Correlation, and <i>t</i> -test	The researchers concluded that more similar research studies are needed. Further, evidence related to the comparability of the control group was not observed. Academic performance in terms of quiz scores were not studied. However, the researchers suggested that further studies are necessary to understand long-term usage behaviours and attitudes.	The researchers concluded that more similar research studies are needed. Further, evidence related to the comparability of the control group was not observed. Academic performance in terms of quiz scores were not studied. However, the researchers suggested that further studies are necessary to understand long-term usage behaviours and attitudes.
[18] Ruan, S., Jiang, L., Xu, J., Tham, B.J.K., Qiu, Z.N., Zhu, Y., Murnane, E.L., Brunskill, E., Landay, J.A. (2019)	76 students from 12 different universities over 20 majors including Mathematics, Computer Science, Biology, History, Communication, Psychology, and others	Descriptive statistics, pre- and post-test, two sample <i>t</i> -test	The algorithm sequencing system helped learners recognise 21.4% more (and recall 21% more) questions than a traditional flashcard learning tool.	The researchers concluded that more similar research studies are needed. Further, evidence related to the comparability of the control group was not observed. Academic performance in terms of quiz scores were not studied. However, the researchers suggested that further studies are necessary to understand long-term usage behaviours and attitudes.
[19] Shelle, G., Earnesty, D., Pilkenton, A, Powell, E. (2018)	85 undergraduate students competed the pre-test and 50 attempted post-test, 75 completed the questionnaire	Descriptive statistics, pre- and post-test, <i>t</i> -test; qualitative approach with open, axial, and selective data analysis	There was a significant difference between the pre- and post-test average scores suggesting the effectiveness of the tool	No control group was observed. The effects of the adaptive system could have been influenced by other confounding variables.

Further, to examine the efficacy of an adaptive platform, ref. [12] compared college students who adopted an adaptive learning system (i.e., ALEKS) with those who chose not to use it. They collected data from four courses including pre-algebra, elementary algebra, intermediate algebra, and college mathematics. The comparisons showed that students using ALEKS had significantly higher pass rates than non-users. Mojard and colleagues pointed out that all comparisons were statistically significant in support of the adaptive learning system, which enhanced pass rates by 6 to 19 points between users and non-users. Subsequently, ref. [13] conducted a follow-up study to investigate: (1) if usage of the adaptive platform had increased and, (2) whether users had the same improvements in terms of learning outcomes as demonstrated in the previous study. Similarly, this follow-up study compared students using ALEKS with non-users by adding a new analysis approach that was not applied in the original research. The results showed that all comparisons between users and non-users were again statistically significant in support of the adaptive learning system. The pass rates for the original research achieved a boost of 6 to 19 points between users and non-users. In comparison, the pass rates for the follow-up study achieved a boost of 13 to 20 points. With these, ref. [13] concluded that ALEKS was likely to be beneficial for learners within the same educational context.

The findings of the research studies discussed are consistent with those of [11], indicating that the efficacy of adaptive learning systems within higher education yielded mixed results. Although adaptive learning has been adopted across different higher education contexts and various disciplines to influence student performance, it remains unclear how it could be efficacious. Given these inconclusive results, the efficacies of different adaptive learning approaches and their learning outcomes need to be further investigated in various educational settings. Specifically, the continued investigation of the efficacy of adaptive learning systems remains critical as it would provide information useful for instructors and institutions to decide whether to implement adaptive learning and if yes, what would work better for their students.

Adaptive Learning in the Institution in This Study

The institution in this study comprises mainly adult learners with diverse academic and demographic backgrounds along with varied work experiences. About 80% of enrolled undergraduate learners read their studies while working. To ensure all learners are given the best possible opportunity to achieve their optimal performance, learning and teaching instruction cannot be one-size-fits all, but one that is personalised to the level of individual prior knowledge and learning behaviour. To this end, adopting personalised learning as part of innovating for diverse learners is a key instructional strategy adopted by the institution in this study.

One form of personalised learning is via technology-enabled adaptive systems where the digital platform adapts both components of content and assessment based on individual learners' prior knowledge. The adaptive learning system used in this study (i.e., AdLeS) also caters to personalised learning behaviours as it intends for learners to have flexibility when they learn online within a stipulated period, depending on the progress they make in the learning process. Based on these characteristics, AdLeS aims to enable learners to level up their prior knowledge, which is varied and uneven, such that they are able to engage with the tertiary level content more meaningfully. Further, the outputs from AdLeS would reflect analytics of learners' learning gains and gaps, thereby enabling instructors to perform more targeted instruction to address these gains, and in particular, the learning gaps.

3. Methodology

Based on the gaps of the efficacy studies identified in Table 1, it was determined that propensity score analysis [20], the Student's *t*-test [21], and Cohen's *d* [22] would be appropriate for this study. Data between July 2020 and January 2022 was first curated from two main sources (i.e., student demographics from the data information office, and student course examination results from the school) as AdLeS was piloted only from July

2021. Subsequently, the data was processed such that students with missing covariates (e.g., General Certificate of Education Ordinary [GCEO] Level English or Mathematics grades) were deleted before data from both sources were merged, for the purpose of computing propensity scores. In order to minimise unaccounted hidden bias [23,24], all available and relevant covariates were considered with the exception of the concomitant variable (i.e., end-of-course examination score [TOA]). These included the: (1) student unique identifier (2) course code (i.e., course A7 or course B8; both are level one Calculus courses in the tertiary institution) (3) academic semester that the student read and completed the course (4) age when student read and completed the course (age) (5) gender (6) post-secondary institution that the student was from prior to matriculating with the current tertiary institution (7) GCEO Level English grade (ELGRnum) (8) GCEO Level Mathematics grade (MAGRnum) (9) course computer-marked assignment score (CMA), and (10) mid-of-course tutor-marked assignment score (TMA).

Propensity Score Analysis

While randomised controlled trials are considered the gold standard for efficacy research studies of educational programmes or interventions, practical issues remain. For example, artificially establishing control and treated groups within the same semester of study may disadvantage either, particularly if the stakes are high, and calls into question the issue of research ethics [25]. In this regard, quasi-experimental methods could be used and one such approach is propensity score analysis [26]. Propensity score analysis via SAS (9.4) was used in this study as it was not possible to randomise both control (students who did not interact with AdLeS across the July 2020 and January 2021 semesters; $N = 162$ for course A7 and $N = 76$ for course B8) and treated (students who interacted with AdLeS across the July 2021 and January 2022 semesters; $N = 98$ for course A7 and $N = 56$ for course B8) groups, on the basis of research ethics and that AdLeS was introduced only in the July 2021 semester.

Of the three common methods within propensity score analysis (i.e., weighting, stratification and matching), matching (i.e., propensity score matching [PSM]) was used in this study as the aim was to establish whether the treated group benefited from their interaction with AdLeS in terms of their TOA). PSM matches each individual in the treated group with one in the control group who is similar on one of more covariates, based upon the definition of a propensity score, that is, the conditional probability estimates of a subject receiving treatment given observed covariates [20] (see Equation (1)).

$$e_i \equiv e(X_i) \equiv P(W_i = 1 | X_i = x_i) \quad (1)$$

where e_i is the propensity score, X_i is a scalar summary of a vector of the covariates, $P(W_i = 1 | X_i = x_i)$ is the probability of treatment (i.e., 0 means non-treatment and 1 means treatment) given a vector of the covariates x_i .

Matching this way allows a between-groups comparison thereby providing an estimate of the effect of a treatment on a non-randomised control group. For this study, propensity scores for each subject in both the control and treatment groups were first estimated by fitting a binary logistic regression model [20] before matching subjects based on this score [27]. In fitting the regression model, all covariates, other than the concomitant variable that may be impacted by the treatment [28], were included to minimise the occurrence of unaccounted hidden bias, as opposed to selecting covariates to maximise the predictive power of the logistic regression, which is not the focus in propensity score analyses [23,24].

To achieve optimal matching with the highest number of matches, three matching methods (i.e., greedy nearest neighbour matching, optimal matching, and matching with replacement) were considered. In addition, the caliper value (i.e., the upper limit of the difference in propensity score between each pair of matched subjects) and different regions of support were applied and iteratively adjusted [29]. Three approaches were then used for balance assessment: (1) standardised mean difference of covariates (2) treated-to-control variance ratio of propensity scores between both treatment and control groups,

and (3) percent bias reduction of propensity scores. Following the balance assessment, Student's *t*-test was applied along with the computation of Cohen's *d* to determine if TOA scores were influenced by students' interaction with AdLeS.

4. Results

Of the three types of matching, greedy nearest neighbour matching was found to be optimal based on the iterative matching procedure discussed. Greedy matching was also deemed more appropriate for this study as the number of students who interacted with AdLeS for both courses was smaller than those who did not interact with AdLeS; [30] specified that greedy matching works well in such instances. Despite the importance of a caliper specification to improve matching quality and enforce a common support region [30], this specification had to be lifted for optimal matching in this study to run successfully, contrary to caliper width recommendations by [31,32] (i.e., 0.20 to 0.25). Similarly, matching with replacement was deemed as less ideal as individuals in the control group (i.e., students who did not interact with AdLeS) would have to be re-used; this would decrease precision owing to increased reliance on just a few individuals, and may impact effect sizes [33].

With greedy nearest neighbour matching, 55 and 43 matched pairs were found for course A7 and course B8, respectively. Figures 1 and 2 illustrate that the standardised mean differences for the matched pairs of course A7 and course B8 were acceptable based on the 0.25 threshold for covariate balance recommended by [34]. Further, Table 2 shows that the treated-to-control variance ratios of propensity scores between both treatment and control groups for both course A7 and course B8 were 0.99 and 1.21, respectively, well within the thresholds for optimal balance by [34] (i.e., between 0.5 and 2). The percent bias reduction of propensity scores for both course A7 and course B8 were also considered adequate given their values of 87.16% and 79.86%, respectively [35].

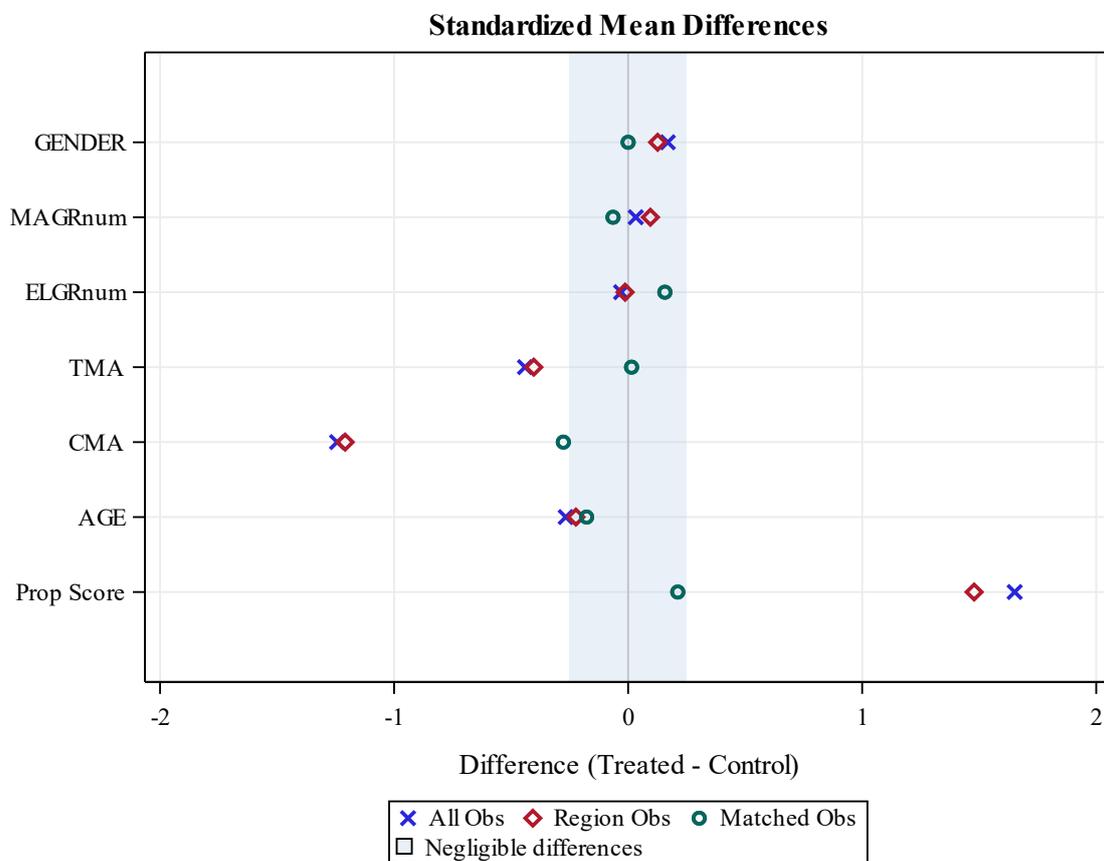


Figure 1. Standardised Mean Differences of Matched Pairs for Course A7.

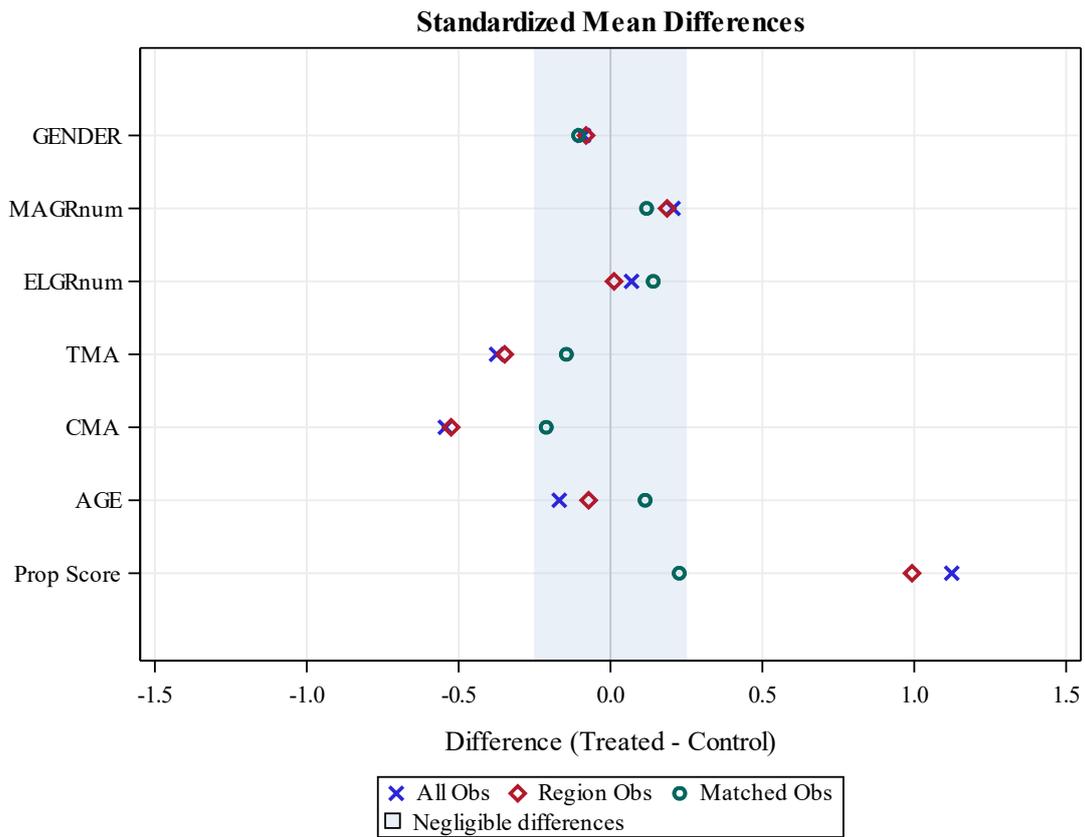


Figure 2. Standardised Mean Differences of Matched Pairs for Course B8.

Table 2. Treated-to-control Variance Ratio and Percent Bias Reduction for Course A7 and Course B8 Propensity Scores.

Propensity Score	Course A7	Course B8
Treated-to-control variance ratio	0.99	1.21
Percent bias reduction (%)	87.16	79.86

Figures 3 and 4, which illustrate the propensity score distributions for individuals in the treated and control groups, further indicate that the distributions are well-balanced for the matched observations.

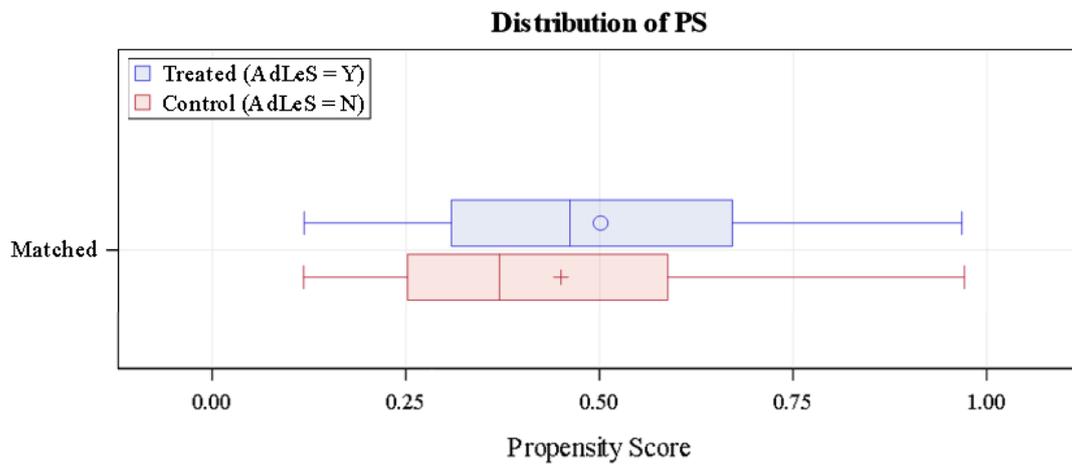


Figure 3. Propensity Score Distributions for Course A7.

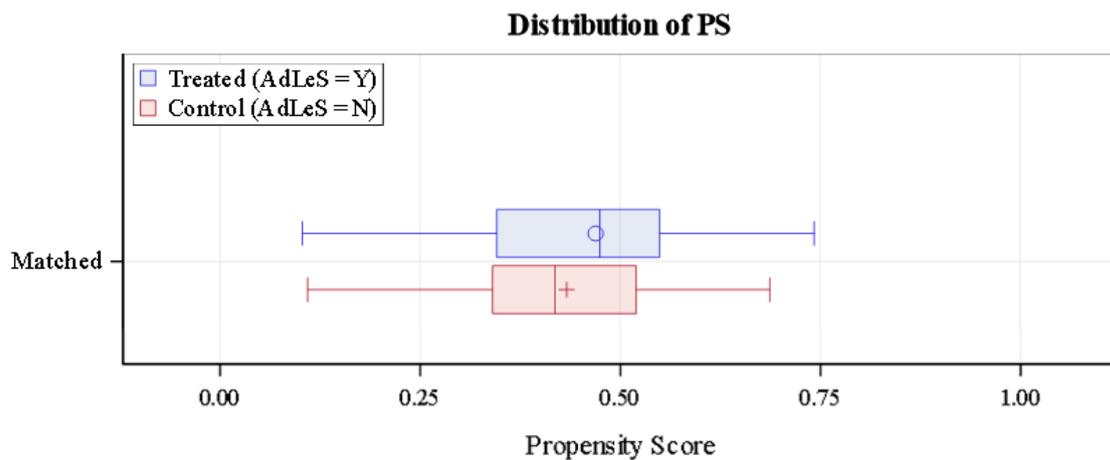


Figure 4. Propensity Score Distributions for Course B8.

Given the acceptable findings upon the balance assessment, Student's *t*-tests were conducted on the matched pairs, as well as prior to the matching to establish the worth of PSM in this study. Table 3 presents the *t*-test results.

Table 3. Comparison of TOA Scores.

Course	Comparison of TOA Scores	N	Equality of Variances <i>p</i> Values	<i>t</i> Value	<i>p</i> Value	95% CI	Cohen's <i>d</i>
A7	Students who interacted AdLeS with students who did not interact with AdLeS, without PSM	162 (without AdLeS); 98 (with AdLeS)	0.47	−0.25	0.80	[−0.21, 0.28]	0.03
A7	Students who interacted AdLeS with students who did not interact with AdLeS, with PSM	55	0.48	−1.75	0.08	[−0.05, 0.71]	0.33
B8	Students who interacted AdLeS with students who did not interact with AdLeS, without PSM	76 (without AdLeS); 56 (with AdLeS)	0.79	−1.48	0.14	[−0.08, 0.61]	0.26
B8	Students who interacted AdLeS with students who did not interact with AdLeS, with PSM	43	0.39	−1.73	0.09	[−0.06, 0.80]	0.37

5. Discussion

Results in Table 3 demonstrate that the TOA scores did not present statistically significant differences at the 95% confidence level between students who interacted with AdLeS and those who did not, regardless of whether PSM was applied. However, relying solely on statistical significance is inadequate as it only suggests whether the findings are likely to be due to chance; whether interacting with AdLeS impacts TOA scores, and to what extent, remains unknown. In this regard, it is worthwhile considering effect size as it quantifies the magnitude of differences found [36]. For this study, the effect size would indicate whether AdLeS impacted the TOA scores and to what extent.

Without PSM, based on recommendations by [37], the effect size of AdLeS on course A7 and course B8 would be considered negligible and small, respectively. Nonetheless, it is noteworthy that [31] effect size benchmarks (i.e., 0.2 suggests a small effect, 0.5 suggests a medium effect, and 0.8 suggests a large effect) should not be interpreted strictly [38]. On the contrary, applying the recommendations of [39] for effect sizes of educational interventions (i.e., less than 0.05 indicates a small effect, 0.05 to less than 0.20 indicates a medium effect, and 0.20 or greater indicates a large effect) would render the effect size of AdLeS on course A7 and course B8 as small and large, respectively. With PSM and based on the recommendations from [39], however, the effect sizes for both course A7 and course B8 would be considered large and, hence, more consistent. Particularly for course

A7, the effect size suggests practical significance [40,41] in that students who interacted with AdLeS yielded higher TOA scores than those who did not.

While PSM overcomes issues such as research ethics and presented AdLeS as having a large effect size on both courses in this study, there are limitations to this approach. The identification and availability of relevant covariates are dependent on the data information office, and pertinent covariates could have been omitted resulting in propensity score estimation bias. It is undeniable that the computation of propensity scores is limited by observable variables afforded by access granted for this study, and does not account for hidden bias due to other unknown variables. It is also noteworthy that propensity score analyses works best when sample sizes are large, and those within this study might not be considered as such.

6. Conclusions and Practical Implications

This study sought to determine whether students' TOA scores would be impacted if they interacted with AdLeS. While the results indicate non-statistical significance at the 95% confidence level, the effect sizes suggest that there is merit in having students use AdLeS within a course. This finding, consistent with what was gleaned the literature, indicated that while there is some merit to using an adaptive learning system, more work is needed to thoroughly unpack specific learning benefits. In particular, we envisage how instructors act on the analytics produced by the adaptive learning system and what specific teaching strategies they adopt will influence the eventual performance in the TOA scores. These conditions constitute an indication of the direction of future research on using adaptive learning systems for personalised learning.

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