APPLICATION OF KNOWLEDGE SPACE THEORY-BASED ADAPTIVE LEARNING PLATFORM (ALEKS) FOR IMPROVING THE STUDENTS' MATHEMATICAL PROFICIENCY (THE CASE OF STAMFORD INTERNATIONAL UNIVERSITY)

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Abstract

This research addresses the value of Knowledge Space Theory (KST) based on the teaching of computational subjects to business students. The research is a quasi-experiment involving an action implemented at Stamford International University, Thailand. A KST-based adaptive learning platform (ALEKS) was introduced in teaching mathematics at undergraduate level of business education. This paper seeks to answer the question of the new platform's efficiency in preparing students for subsequent computational courses, and especially whether this relationship is strong for underperforming students. The action thus held at Stamford International University involved a sample of 340 students studying mathematics in the academic year 2018-2019, three trimesters in total, who either took a Pre-college Algebra course powered by ALEKS (treatment group) or did mandatory revision/preparatory tests (control group), which were not based on KST-tools. We analyzed their further grades and pass-fail rates in the subsequently taken subject of College Algebra. We find the action to be successful, the application of KST-based learning in mathematics significantly improves all students' performance in subsequent computational subjects, but this relationship proves to be stronger for underperforming students. The work connects with the stream of literature on the efficiency of the use of KST-based tools in teaching and learning computational subjects at the college level.

Keywords: Knowledge Space Theory, Computational Skills, KST-based Adaptive Learning Platform, Mathematics

Introduction

Business education is becoming more and more popular every year with millions of students over the world enrolled in various business programs. Business education includes a wide array of majors ranging from marketing and management to finance and logistics. Naturally, various business majors require different sets of skills and knowledge, however, the overarching umbrella of business

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administration commands the business graduates to possess the necessary skills of teamwork, problem-solving, communication, planning and time management, and the ability to obtain and process information (Kaiser, 2019), as well as computational skills (Hodge & Lear, 2011; Chadi, 2017). In this research, we would like to describe the role of a new concept of Knowledge Space Theory (KST) in improving the computational skills of undergraduate business students.

Knowledge Space Theory was first introduced by Doignon and Falmagne (1985), who described the state of knowledge as a specified set of problems or questions an individual can solve; these states are organized in families which are distributions of all possible knowledge states, such families, in turn, are termed knowledge spaces (Doignon & Falmagne, 1985; Doignon et al., 1999). Heller et al. (2006) specify that the probability of some problems in the space being solved is conditional on the solution of a pre-requisite problem, thus problems can be mutually dependent, or comprehensive (Albert & Hockemeyer, 1997). Such a relationship was termed prerequisite or precedence (Albert et al., 2011). Under KST, the collection of knowledge states corresponding to a prerequisite relation is called a knowledge structure (Craig et al., 2011). The current knowledge state of a learner can be thus measured by adaptive assessment and the path to knowledge mastery can be achieved through learning sequences adaptively picked by the software.

ALEKS, the Assessment, and Learning in Knowledge Spaces (ALEKS), is an online adaptive learning platform with artificial intelligence components based on Bayesian networks to select the next skill or problem for a student to work on (Doignon et al., 1999; Craig et al., 2011). ALEKS was designed in 1997 containing two modules: teaching and assessment, where teaching is self-guided and assessment is comprehensive, covering the set of all possible questions of the topic or subject domain (Doignon et al., 1999). Competence-based KST is used to develop activity-based learning to facilitate the teaching and learning process (Marte et al. 2008; Steiner et al., 2009), and leading to the development of computational skill.

This research is a quasi-experiment, measuring the effect of the application of knowledge space theory in education, namely on the mathematical proficiency of business students with the view to improve their computational skills. The project is based on an action implemented at Stamford International University (STIU) - the launch of ALEKS platform, which is using a knowledge spaces theory as the baseline concept and is an intelligent tutoring system able to identify students' weaknesses and address them with relevant assignments. The platform has the purpose of improving the students' computational skills which, measured by the average grade in mathematical courses such as MAT101 or together with MAT102, demonstrated low value over the past years, and created concern in instructors of subsequent computational and business subjects about the problem-solving capacity of students. We noted that mathematical proficiency is extremely important for business students due to its high relevance in developing problem-solving capacity in students and general CT (Wing, 2006; Voskoglou & Buckley, 2012).

Based on the presented theory we have formulated the following overarching hypothesis-application of knowledge space theory-based tools, like ALEKS, is associated with improvement of students' mathematical proficiency, proxied by the academic performance in subsequent computational courses. H1a: Students' exposure to KST-based tools is associated with a higher probability of passing the subsequent mathematics course.

H1b: Students' exposure to KST-based tools is associated with a higher grade in the subsequent mathematics course.

Additionally, we will also explore the link between KST-based tools exposure and the mathematics performance for low-performing students:

H2a: Exposure of low-performing students to KST-based tools improves their probability of passing the subsequent mathematics course.

H2b: Exposure of low-performing students to KST-based tools is associated with a higher grade in the subsequent mathematics course.

Overall, we expect the mathematic performance of students previously exposed to KST-based tools, namely ALEKS platform to be significantly higher than those of students not exposed to ALEKS before taking the mathematics course.

The project is of exploratory and evaluative nature and is highly pragmatic with the main objective of enhancement of the quality of education and addressing the needs of the market. We are using a deductive approach based on the premise of the effect of knowledge space theory on student performance. The chosen methodological tool is quantitative methods with data derived from secondary sources available from the university registrar, to evaluate the effect of computational skill of the overall performance of business students, and a quasi-experiment. An experimental group of students were the first to start using ALEKS platform in 2018 is to be compared in its ultimate outcome with a control group of students who did not use the ALEKS platform in the same year, the outcome studied is the students' performance in the subsequently taken course of college algebra.

Objectives

The purpose of this research is to discover the link between the application of KST and the mathematical proficiency of business students (based on the case of Stamford International University, Thailand). Namely, two objectives are to be met:

1. To examine the relationship between exposure to KST-based tools and academic success in further studies of mathematics.

2. To explore the role of previous academic performance in the relationship between KST-based tool exposure and success in further mathematics courses.

Literature Review

Computational skills refer to the broad area of Computational Thinking (CT), a concept that gained popularity in the recent decade after being defined by Wing in 2006. Wing (2006, 2008) was the first to unite mathematical and programming skills in one concept. Snalune (2015) finds that CT-skills are essential for modern day business students, as they represent students' ability to analyze and solve problems. Sanford and Naidu (2016) refer to CT as the core ability every student must possess.

At the same time, pedagogical science has been on the lookout for new practical approaches to find new learning pathways, and one of the most promising ones has been found to be the Competency-Based Learning (CBL) approach (Bechtel et al., 1999; Voorhees, 2001; Henry et al., 2017).

Within the CBL domain a new approach, the Knowledge Space Theory (KST), was developed in the late 1980s. It was pioneered by Doignon and Falmagne (1985, 2016), Doignon et al. (1999) and later developed further by multiple education researchers (Albert et al., 2007; Heller et al., 2013; Hockemeyer et al., 1997; Dowling & Hockemeyer, 2001; Hockemeyer, 1997; Heller et al., 2015; Conlan et al., 2006; Ünlü et al., 2013; Heller et al., 2013; Ganter et al., 2017; Reimann et al., 2013; Kickmeier-Rust & Albert, 2015; Sitthisak et al., 2013), and which bases teaching and learning on activity and student-centered perspective on learning outcomes (Marte et al., 2008). KST is applied in multiple areas of knowledge and its generally considered that KST is universal and is not constrained by subject areas (Heller et al., 2006; Steiner et al., 2009; Albert et al., 2011; Albert et al., 2007; Heller et al., 2013). In this study, we will apply the KST approach in teaching computational subjects, so necessary to achieve higher CT skills by students.

The purpose of knowledge space theory is an efficient assessment of a learner's mastery of a subject domain (Hockemeyer et al.,1997) and has been not only widely used in teaching and learning on different levels of education (Rienties et al., 2006; Steiner et al., 2009; Craig et al., 2011) and different subject areas (Albert & Hockemeyer, 1997; Taagepera & Noori, 2000; LaVergne, 2007; Albert et al., 2011), but also inspired the creation of the ALEKS platform, weaknesses and address them with the relevant assignment. Since its appearance, ALEKS has attracted some scholarly attention as an application of KST, namely a positive effect was discovered between the application of ALEKS in teaching mathematical subjects at school (LaVergne, 2007; Khazanchi, 2021), at the after-school level (Craig et al., 2011; Craig et al., 2013), at the college level (Stillson & Aslup, 2003; Hagerty & Smith, 2005; Heller et al., 2006; Mills, 2021), and in general tutoring (Pappas & Driggas, 2016). This research seeks to connect with the works of Hagerty and Smith (2005) and Heller et al. (2006) but in a more contemporary setting and the context of a diverse sample of business students, for whom computational skills are critical.

Methodology

Our research is based on collections of student data from Stamford International University. The student data covers a period of two years, between 2018 and 2019. The sample size is 340 and consists of undergraduate business students who completed the course MAT101, Basic Mathematics between 2018 and 2019. Some students who attempted MAT101 during that period had to also do a short Pre-Algebra course which was taught using the KST-based ALEKS platform. The course was included in the curricula in 2019, thus, student who took MAT101 in the previous term of the year 2018 did not have to do the Pre-Algebra course, and students who took MAT101 in 2019 had to take MAT100 already (Figure 1). So our sample is divided into treatment group of students who did take the MAT100 course, in total we had 134 students in that group; and the control group of 206 students, which includes students, who didn't take MAT100, but took prep tests before taking the course of MAT101 in subsequent semesters. For the purposes of our research MAT100 is a quasi-experiment and has the following timeline:

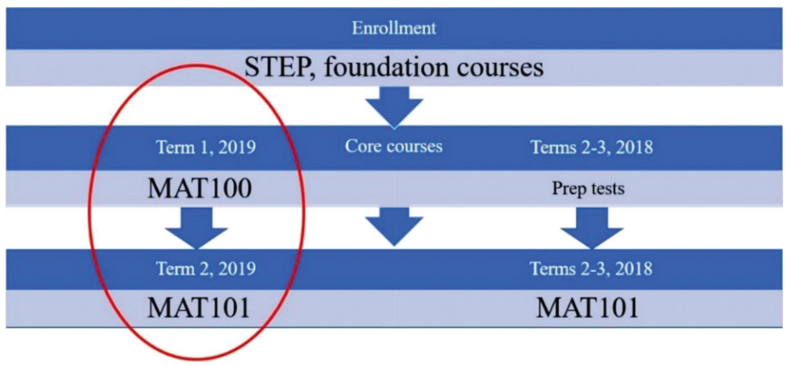

Figure 1 Quasi-experiment design

MAT100 is a self-paced course, where students have to do assignments on their own, the assignments are suggested by the platform based on students' current problems which the system identifies and addresses. The course can be completed between 3 and 12 weeks, this varies depending on the students' capabilities.

More specifically the research design utilized is the nonequivalent group posttest-only quasi-experimental design, commonly used to evaluate the effects of certain interventions (Gibbons & Herman, 1996). To ensure the validity of our research design, and to control for a possible endogeneity bias, we made sure students' mean GPA between groups (GPA recorded before the quasi-experiment) do not differ significantly (mean 2.22, Table 1), the p-value for the two-sample t-test of the group means is 0.1388. And to ensure the effect comes from ALEKS specifically and not from the revision of mathematics material we made sure all students in the control group were pre-treated with mandatory revision/preparatory tests, which were not based on KST tools.

Variables

1. Dependent Variables

Dependent variables are variables indicating mathematical proficiency, the choice of which is suggested by Schoenfeld (2007) as not perfectly assessing all aspects but very informative and highly correlated with the directly measured proficiency scores. The same approach is suggested in Topphol (2018), and Burkhardt equates mathematical proficiency with mathematics performance (Burkhardt, 2007). Moreover, the final scores for MAT101 are a result of a comprehensive assessment of the course outcomes through examinations, weekly homework assessments, tests, and project presentations.

The second variable denoting mathematical proficiency is the pass rate on MAT101 course. The pass rate is set at the threshold of 60 out of 100 points on the final grade, which we will see as the proficiency threshold for the purposes of this research.

MAT101gi-quantitative variable, a numeric grade in the MAT101 course the students earned, varies between 0 and 100;

MAT101pi-binary variable, equal to “1” if the student passed the MAT101 course, and “0” if failed;

2. Independent Variables

Independent variables are the variables describing the essence of the experiment and the conditions. The main factor and the object of this study is the fact of taking the ALEKS-powered course before the main mathematics course. However, we are also interested in seeing the differences in MAT100 effect for students with different academic aptitude level. The overall academic aptitude is proxied by the grade point average (Lei et al., 2001; Grove et al., 2006; Rudakov & Roshchin, 2019). To stand for low or high proficiency we select a threshold of the mean GPA. To see if the effect if different for students with different academic aptitude we create an interaction term.

MAT100i-is a binary variable, “1” if the student has taken the ALEKS MAT100 course and “0”-if no;

GPA-to account for differences in students’ capabilities, we use a 4-scale GPA measure;

gpaLo-is a binary variable equal to “1” if the student’s GPA is lower than the mean, and “0” if higher;

MAT100*gpaLo-interaction term for students who have low performance and have taken the ALEKS course.

3. Control Variables

Control variables include nationality (to account for differences in previous schooling), gender, program of studies, track (national or international), and students’ age.

We ensure all regression assumptions are met by data.

To test hypotheses 1a and 2a we are using the method of logistic regression in the following model specifications:

Model 1: $MAT101pi = \alpha 0 + \alpha 1MAT100i + \alpha 2 \sum controls + \alpha i,$ (1)

Model 2: $MAT101gi = \alpha 0 + \alpha 1MAT100i + \alpha 2 \sum controls + \alpha i,$ (2)

To test hypotheses 1b and 2b we are using the CLMR approach in the following model specifications:

Model 3: $MAT101pi = \alpha 0 + \alpha 1MAT100i*gpaLo + \alpha 2 \sum controls + \alpha i,$ (3)

Model 4: $MAT101gi = \alpha 0 + \alpha 1MAT100i*gpaLo + \alpha 2 \sum controls + \alpha i,$ (4)

Additionally, to test H1b and ensure no bias we are using the two-sample t-tests.

The analysis is done on Statistical software "The R" and SAS Enterprise Guide. The data is collected from STIU database of academic service division.

Results

Summary statistics of all variables under study are presented in Table 1 and Table 2 (Appendix A) and already reveal the differences between the groups of students who had taken MAT100 and, those who did not.

Table 1 reports descriptive statistics of the quantitative variables on the sample, a 4-scale grade point average as of the term before the quasi-experiment measurement (beginning of term 3, 2018), which is a proxy for academic proficiency; and grades on the subject MAT101, which is a proxy for mathematical proficiency, the grade is on the subject taken in.

Table 1 Descriptive statistics for quantitative variables

Quantitative variables	Full Sample (N = 340)		MAT100 (N = 134)		No MAT100 (N = 206)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
MAT101 grade	71.93	23.61	81.85	16.04	65.49	25.48
GPA	2.22	0.97	2.61	0.94	2.48	0.89
Age	18.53	0.25	18.60	0.24	18.47	0.21

The two groups are of nonequivalent sizes which is acceptable for quasi-experimental design (Jhangiani et al., 2015), actually up two double difference in sizes is acceptable if other statistics are equivalent. The mean GPA for the sample is 2.22 with the minimum of zero and the maximum of 4.0, the variable is normally distributed and has a standard deviation of 0.97, meaning that most values are clustered between 1.25 and 3.19.

All of the assumptions of CLMR are observed for all variables, namely the dependent variable is normally distributed, the relationship is liner, there is no evidence of heteroscedasticity and there are no significant outliers. Variance Inflation Factors (VIFs) do not exceed 2.0.

Table 2 Regression results

Regression results	Dependent Variable			
	MAT101-grade (Estimate)		MAT101-pass (Estimate)	
	Model 2	Model 4	Model 1	Model 3
MAT100	9.212***	3.885*	0.104*	-0.018*
gpaLo		-6.701*		-0.133**
MAT100*gpaLo		13.172**		0.302***
Controls	(Yes)***	(Yes) ***	(Yes) ***	(Yes) ***
Adj R^2/AUC	0.450	0.4636	0.887	0.891

In the first part of Table 2 we present the results of regression models 1-4.

Stepwise regression model filtered out non-significant controls that do not add predictive power to the model, these are "track", "program", "gender", and "age", the remaining controls are "nationality" and "overall academic aptitude" proxied by GPA. Model 1 (1) results indicate that the MAT100 factor is significant in its relationship with dependent variable, meaning the likelihood of passing the subsequent MAT101 course is higher for students, exposed to KST-based tools. The ROC curve for model 1 is presented in Fig. 2, it indicates the model performs well in accuracy, area under the curve is 0.887. ANOVA analysis (Table 3) supports the results of logistic regression on Model 1 and we accept hypothesis 1a.

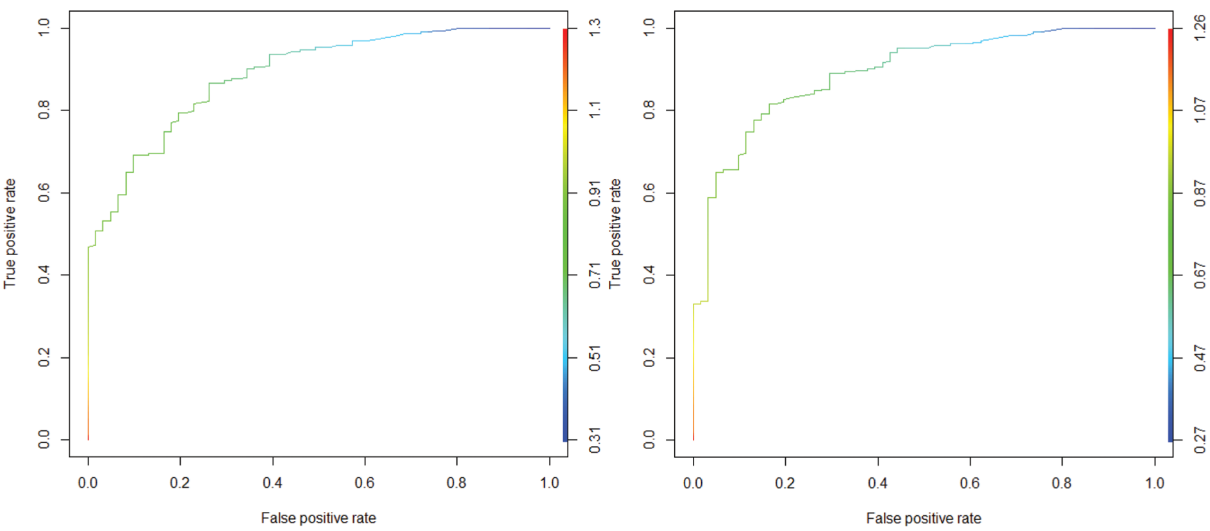

Figure 2 Receiver operating characteristic curves for models 1 and 3

Regression on Model 3 (3) (Table 1) also demonstrates a highly significant relationship between the interaction term (low proficiency students who completed the MAT100 course before attempting MAT101) and the probability of passing the MAT101 course, model accuracy is 0.981 (AUC) and it is higher than for Model 1, which means the effect is higher for low GPA students, than for the overall sample. ROC curve is presented in Fig. 2, showing the high accuracy of the model. Table 3, ANOVA results also support Hypothesis 2b.

Results of Model 2 (2) are satisfactory to support hypothesis 1a (H2a). The model explains almost half of the MAT101 grade variance (Adj R^2 = 0.450) with MAT100 factor being significant and having a positive relationship with the dependent variable; according to the model, participation in ALEKS course increases the subsequent MAT101 grade by 9.12 points (t-value of 4.52).

Table 3 ANOVA Analysis for Models 1 and 3

ANOVA Results	Model 1		Model 3	
	F-value	p-value	F-value	p-value
MAT100	46.682	7.58e-09***	46.682	3.641e-09***
GPAlo			39.922	< 2.2e-16***
MAT100*GPAlo			33.491	9.336e-05***
Controls	(Yes)	***	(Yes)	***

Model 4 (4) shows the effect of interaction term, MAT100 and low GPA, this interaction term filters out the effect of MAT100 for students with GPA below the sample mean. Results indicate that in absence of MAT100 low GPA students are more likely to have lower grades in MAT101, but ALEKS-powered MAT100 course reverses that effect, evidence is that low performing students, who have participated in MAT100 course tend to have 13.2 points higher MAT101 scores (t-value of 3.002, significant at 0.01). This result supports hypothesis H2a.

Discussion

Results show a strong relationship between the exposure to KST-based tools, proxied by participation in MAT100 course and the computational skill, proxied by the successful passing and the grade in MAT101 course. The effect is evidenced by the statistically significant coefficients of MAT100 variable in all models.

This effect is stronger for students with GPA below the mean, namely the negative and significant t-value for the factor gpaLo indicates that these students are 13% more likely to fail MAT101 course (Model 4) and to have lower MAT101 grade (6.7 points lower), however previous exposure to KST-powered MAT100 course (ALEKS) reverts this effect. Regression results indicate that low GPA students who took MAT100 have 13 points higher grades in MAT101 and 30% higher probability to pass MAT101.

ANOVA results for logistic models 1 and 3 support our conclusions and indicate statistically significant relationship between MAT100 factor and the probability to pass MAT101 for all students and even higher for low proficiency students.

As results of all models hypotheses 1 and 2 are fully sustained.

We can also illustrate results graphically, Fig. 3. Shows box-plot for H2a, the effect of MAT100 exposure on MAT101 grade, we see that the means are different, the red box has a mean below 80 points and the yellow box (MAT100 TRUE).

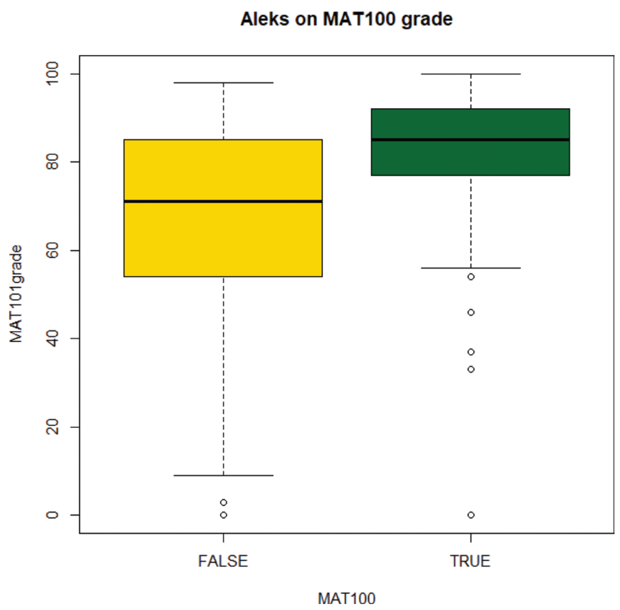

Figure 3 Boxplot for Hypothesis 2a (full sample)

Mean MAT101 score for control group is 65.5 and the mean score for the test group is 81.9, simple two-sample t-test shows that this difference is significant at 0.01 level, thus, we conclude that taking MAT100, which is an ALEKS-powered course is beneficial. This finding connects with Hagerty and Smith (2005), Stillson and Aslup (2003), and Nwaogu (2012).

The difference of the effect of KST-based tool on MAT101 performance between low and high-performing students is seen from Figure 3, where the yellow and the green boxes represent the students with GPA above the mean, and the red and blue boxes represent students with GPAs below the mean.

The low performing group who took MAT100 (the blue box) has the mean much higher than those who did not take MAT100 (the blue box) and the difference between their means is larger than the difference between the means of those who had not taken MAT100. We also see that the red box students were more likely to fail the course not having reached the pass threshold, the mean of that group is hardly far above 60 points. This finding partially connects with Mills (2021) in the way that KST-tools application predicts progress in further studies of mathematics for struggling students.

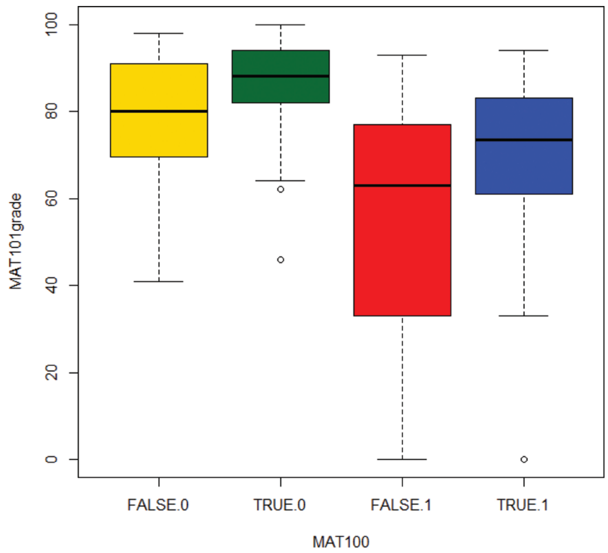

Figure 4 Boxplot for Hypothesis 2b

This course introduces the knowledge space theory-based learning and facilitates further success in mathematical subjects and computational skill in general.

Our results also connect with Doignon et al. (1999), Marte et al. (2008), Steiner (2009), and Rahayu and Osman (2019) in the way that demonstrates efficiency of KST-based tools on mathematic proficiency.

Conclusion

We find evidence to the positive effect of KST-based online learning (ALEKS) in the sample of business students on the results of a mathematics subject taken after the KST- treatment. An especially important outcome is that this effect is stronger for students with lower academic aptitude.

To deepen our understanding of the role Computational Thinking plays in the academic performance, employability, and other aspects of student life, we suggest a qualitative study should be conducted that would isolate the specific elements of mathematical proficiency that KST targets.

Overall, we conclude that KST-based ALEKS platform is beneficial for improving student's performance in college mathematics, the subject notoriously feared and avoided by all students who have it on their curricula, but essential for business students as it is a pillar domain of computational thinking, an integral skill area for future managers, also required by the industry.

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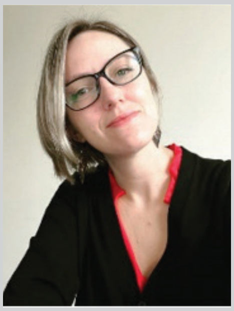

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