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Exploring adaptive learning, learner-content interaction and student performance in undergraduate economics classes

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ABSTRACT

This study explores the pedagogical use of adaptive learning to foster learner-content interaction, and its subsequent impact on student performance in a large first year Macroeconomics course in an Irish University. To increase student-content interaction, an adaptive learning tool (*Learn-Smart*) is employed to create five weekly adaptive reading assignments, over a six-week period. We include two separate indicators of learner-content interaction (the amount of time spent and number of completed adaptive assignments) in our analysis. Results indicate that student performance is enhanced by the number of completed adaptive assignments, which captures learner-content interaction and adaptive learning. However, the amount of time spent studying was negatively associated with performance. This surprising result comes as a novel contribution, which extends our knowledge of how adaptive learning technology can be potentially used to drive learner-content interaction and student performance. Pedagogically, our findings suggest the need for more intentional design and personalisation of learning activities to enhance student-content interaction and subsequent performance.

1. Introduction

Low student engagement in higher education remains a pressing concern for instructors and institutions due to its perceived significance for student learning, retention and academic success (Bowden, 2022; Collaço, 2017; Kahu, 2013). Given the widespread reliance on blended and online learning approaches for delivery, empirical research has focused on identifying effective teaching and learning strategies for achieving higher levels of student engagement. Indeed, several researchers (e.g. Al Mamun, Lawrie, & Wright, 2022; Bond, Bedenlier, Buntins, Kerres, & Zawacki-Richter, 2020; Picciano, 2017; Riggs, 2020) have recognised the importance of interaction and educational technology in enhancing student engagement.

In the context of undergraduate Economics, factors such as large class sizes, scope of course content, as well as the abstract and mathematical nature of taught concepts, often limit student interaction with content (Goebel & Maistry, 2019; Nepal & Rogerson, 2020). Consequently, many undergraduate Economics courses are characterised by high failure rates, low levels of student attendance and engagement, as well as poor academic performance (Denny, 2014; Ramadan & Hussein, 2017; Stanca, 2006). Undergraduate Economics education is even more problematic for first year students who are often faced with a sudden transition from the directed learning approach adopted in second level education to a more independent learning style (Denny, 2015). Although engaging first-year students in educationally meaningful tasks has been found to be positively associated with academic performance (Kuh, Cruce, Shoup,

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Kinzie, & Gonyea, 2008; Reinke, 2019), research suggests that only a small number of higher education students read recommended texts (Hoeft, 2012; St Clair-Thompson, Graham, & Marsham, 2018).

In this paper, we explore the use of an adaptive learning (defined as the personalisation of learning to suit students' individual learning needs) technology, *LearnSmart*, as a pedagogical tool to foster learner-content interaction, and its subsequent impact on student performance in a large undergraduate Macroeconomics course for first year Business students in an Irish higher education institution. In doing so, our paper contributes to the literature on how adaptive learning can be used to advance students' learning and academic performance.

The rest of the paper is organised as follows: Section 2 presents the conceptual background and Section 3 describes the data and method. The empirical results are discussed in Section 4, whilst Section 5 concludes and offers some implications for further research and practice.

2. Conceptual background

2.1. Learner-content interaction

Previous studies have identified various modes of interactions (i.e. learner-instructor, learner-learner, learner-content and student-learning management system interaction) necessary for effective online teaching (Al Mamun et al., 2022; Davidson-Shivers, 2009; Moore, 1989). These forms of interaction are central to a learner-centred approach which requires more active teaching strategies that encourage students to become active participants in the learning process (Riggs, 2020). Furthermore, these interactions have been acknowledged as critical factors in enhancing student understanding and motivation, as well as improving learning outcomes and collaborative learning (Bernard et al., 2009; Lim, 2023; Sharp & Huett, 2006). Although several studies have examined learner-learner, learner-instructor and student-learning management system interactions (e.g. Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014; Grandzol & Grandzol, 2010; Sharp & Huett, 2006), there remains a dearth of research on learner-content interaction (Kumar, Saxena, & Baber, 2021; Xiao, 2017). Further research on this aspect of the learning process is particularly required in the context of undergraduate Economics, given its potential for promoting student independence and engagement in large cohorts.

Learner-content interaction, that is, time spent with course content such as textbooks and class notes, is pivotal in the educational process and crucial for effective learning outcomes and increased deep learning (Zimmerman, 2012). The definition of learner-content interaction has also been expanded to include learners' access to, and use of content within online learning environments, as well as connections between the learner and learning resources (Ozturk & Kumtepe, 2023; Powell & Leary, 2021). This interaction type is identified as a crucial factor in enhancing student engagement, learning achievements, as well as improving course completion rates and success (Nieuwoudt, 2018; Quadir, Yang, & Chen, 2022; Tang, 2021). This is because learner-content interaction allows for the acquisition and construction of knowledge through direct contact with the subject matter (Malinovski, Lazarova & Trajkovic, 2012). Although access to knowledge is vital, the cognitive processes through which learners deal with that knowledge is more critical (Dunlap, Sobel, & Sands, 2007). Transformations in learners' understanding and cognition occur whilst engaging with the course content (Xiao, 2017). Thus, ensuring ease of access to learning materials by merely uploading these to a learning management system is not enough.

Learning management systems (LMS) are valuable tools which support learners' access to course content, and can provide statistics on time spent accessing material. Nevertheless, their utility to provide information on the quality of student engagement with content is limited because they do not adequately capture the patterns of engagement with content (Dry, Due, Powell, Chur-Hansen, & Bur, 2018; Zimmerman, 2012). As such, the intentional design of learning activities that increase student participation (Bernard et al., 2009; Ozturk & Kumtepe, 2023), and foster student engagement in lower- and higher-level cognitive behaviour is necessary to facilitate deep and meaningful learner-content interactions (Dunlap et al., 2007; Xiao, 2017). The question then arises, how best to increase learner-content interaction in the undergraduate Economics student cohort?

2.2. Adaptive learning as a tool for enhancing learner-content interaction

One response to the identified need for deeper learner-content interaction can be found in adaptive learning (AL), which entails the customisation of learning material to suit individual learning needs (Muñoz et al., 2022; Nguyen & Do, 2008). This personalisation of learning is beneficial to students because their unique characteristics and needs are considered in the design of instructional material and assessments (Li & Wong, 2021; Zhang, Basham, & Yang, 2020).

Using computer algorithms, AL technology encourages deliberate interaction between students and the course material by delivering personalised content to learners based on their responses to set questions or tasks (Wang et al., 2023). Such technology-mediated interaction with content offers the unique opportunity to provide students with immediate feedback and personalised learning, based on their individual strengths and weaknesses (Castro, 2019; Graham, Borup, Pulham, & Larsen, 2019). This, in turn, engenders transformations in students' understanding and cognition (Moore, 1989; Xie, Chu, Hwang, & Wang, 2019).

It is important to note that while the terms *personalised learning* and *adaptive learning* are different, they are often used interchangeably in many studies (Lin, Yeh, Hung, & Chang, 2013; Shemshack & Spector, 2020; Xie et al., 2019; Zhong, 2023). Common elements in their conceptualisation, however, include individualisation, student-centredness and flexible learning environments (Li & Wong, 2021). Nonetheless, adaptive learning delivers several pedagogical benefits including prompt feedback, mastery-oriented learning and interactive learning (Martin, Chen, Moore, & Westine, 2020).

AL has been associated to enhanced knowledge acquisition in several ways: i) ensuring learners' mastery of certain skills and knowledge before progressing to the next learning task; ii) presenting learners with the opportunity to expand their knowledge by exploring the learning material beyond the required level; and iii) facilitating access to learning resources at learners' own pace, with feedback also delivered at the same pace (Martin et al., 2020; Sein-Echaluce, Fidalgo-Blanco, & García-Peñalvo, 2019). It is claimed that AL can, therefore, help to potentially transform learners from passive recipients of knowledge to active participants in the learning process (Kabudi, Pappas & Olsen, 2021).

Despite growing interest, research findings on the application of personalised/adaptive learning in higher education remain divergent due to variations in conceptualisation and implementation (Van Schoors, Raes & Depaepe, 2021; Zhong, 2023). For instance, adaptive learning has been characterised in studies both as a process and technology (Kerr, 2016; Martin et al., 2020). In this paper, the focus is providing insights on the complex interaction between time spent on task, patterns of learner-content interaction mediated by adaptive learning and academic performance.

2.3. Adaptive learning and student performance

As previously detailed, learner-content interaction is crucial for improved student performance and learning achievements. Hence, it is likely that the use of adaptive learning tools which boost learner-content interaction, will be associated with improved student performance. Existing research on the effectiveness of adaptive learning suggests AL has an enhancing effect on student learning and achievement (Alsadoon, 2020; Own, 2010; Wang et al., 2023; Yang, Hwang, & Yang, 2013), learner satisfaction (Li & Wong, 2021; Xie et al., 2019), as well as pass and retention rates in introductory university courses (Daines, Troka, & Santiago, 2016; Johanes & Lagerstrom, 2017). Indeed, Xie et al. (2019) in their systematic review report found that AL had a positive effect on learning achievements in 32 out of 37 studies examined. However, there are also conflicting reports on the impact of AL. For example, Murray and Pérez (2015) using data for an introductory university digital literacy course, found no significant difference in test scores between students enrolled in courses using AL and traditional delivery methods. Similarly, White (2020) finds no relationship between the use of AL technology and students' test scores in comparison against traditional teaching methods in an undergraduate management information course. Indeed, Hardy, Decristan, and Klieme (2019) highlight a lack of consensus on how to assess the impact of successful AL interventions. Consequently, Wang et al. (2023) comment on the need for further research to understand the conditions under which adaptive learning might deliver the largest gains. The contrasting reported results, therefore, necessitate a deeper investigation of the interaction between patterns of engagement mediated by learner-content interaction with AL and subsequent performance.

2.4. Adaptive learning, learner-content interaction and student performance

This study aims to address the identified lacuna by exploring the use of a particular AL technology, *LearnSmart* in relation to student interaction with course content and subsequent performance. *LearnSmart* is an AL tool on McGraw-Hill *Connect* (a web-based assignment and assessment platform), which allows content to be actively tailored to students' needs, providing, in the words of this vendor, a 'personalised learning experience' (McGraw-Hill, 2023). This AL technology aims to enhance learner-content interaction and achievement of learning outcomes by employing questions that are distinct but with related ideas, as well as a healthy mix of question formats such as multiple-choice questions, short answers and fill in the blanks (Miller, Asarta, & Schmidt, 2019). As Garrison and Cleveland-Innes (2005) observe, interaction by itself is not sufficient for cognitive development and deep learning. The use of question prompts to facilitate higher-level engagement with course content, and critical thinking is also vital (Ertmer, Sadaf, & Ertmer, 2011; Le, Tran, Thinh, & Hoang, 2022). An adaptive learning tool such as *LearnSmart* is, therefore, expected to be valuable in addressing these crucial issues.

LearnSmart assesses the student's answers to the practice questions, identifies the topics/concepts they are struggling with and adapts itself accordingly. A reading assignment is, therefore, not marked as completed until the student demonstrates adequate understanding of the selected topic. This is intended to limit rote learning and memorisation, and foster metacognition -i.e. students' ability to identify what they know or do not know about the course content (Qin, Abdourazakou, & Norman, 2017), which, in turn, has been identified as a critical factor in achieving academic success (Kautzmann & Jaques, 2019; Tobias & Everson, 2009).

The effectiveness of *LearnSmart* usage, measured respectively as time spent on task and/or proportion of completed tasks, has been examined in the literature. Some studies (Griff & Matter, 2013; White, 2020) have taken an experimental approach, comparing performance between two student groups, i.e. students who use the *LearnSmart* tool and those who do not. Empirical evidence is, however, mixed. For instance, Griff and Matter (2013) and White (2020) find no significant difference in the performance of *LearnSmart* users and non-users. They also find no relationship between *LearnSmart* usage and student performance. A positive relationship was, however, found in other studies (e.g. Dry et al., 2018; Gurung, 2015; Owens & Moroney, 2015). The current study seeks to investigate the link between AL and performance through the lens of learner-content interaction, an approach that is yet to be examined in the literature. As such, the use of *LearnSmart* adaptive assignments makes it possible to explore how AL may foster learner-content interaction, and what effect emerging patterns of interaction through AL have on student performance in undergraduate Economics classes. We address the following research question, RQ1: Does learner-content engagement with adaptive learning increase student performance?

The research hypothesis is specified thus.

H1. A direct and positive relationship is expected between learner-content engagement with *LearnSmart* adaptive assignments and

student performance.

3. Data and method

3.1. LearnSmart

To explore the link between AL, learner-content interaction and student performance, the study employs *LearnSmart* in teaching introductory Macroeconomics to a large cohort of first year Business students in an Irish University. The adoption of AL technology in the course is primarily driven by the observed low level of student engagement with recommended texts in higher education (St Clair-Thompson et al., 2018), along with the resulting need for instructional design aimed at fostering deep and meaningful learner-content interaction.

The choice of *LearnSmart* as a pedagogical tool for enhancing learner-content interaction is predicated on several important factors. First, it allows for the design of meaningful tasks, which have been identified as essential drivers of academic performance in first year students (Kuh et al., 2008; Reinke, 2019). Second, *LearnSmart* as an AL tool confers ownership on instructors. It offers them the flexibility to develop and deliver content, reflect on its effectiveness and make necessary adjustments to suit students' needs (Muñoz et al., 2022). Furthermore, learning analytics data obtained from *LearnSmart* facilitates i) identification of at-risk students (i.e. students at risk of poor performance in the course), ii) recognition of students' knowledge gaps in real-time and iii) customisation of their learning – which enhances teaching, learning and assessment (Johnson, Becker, & Cummins et al., 2016; Flavin, 2016). Third, this adaptive learning tool is designed to give students agency over their own learning (Li & Wong, 2021). Students receive real-time feedback. They are also presented with the option to review concept resources and rate their level of confidence in the accuracy of their given answers (Fig. 1). All of these features are intended to enable students determine the scope of their own learning on a weekly basis.

3.2. Study design and background

The course examined in this study was split into two sections taught by two different instructors in a traditional face-to face classroom setting. Data for this study comes from the first section of the course taught over a six-week period, covering introductory topics such as national income, unemployment and inflation. Threshold concepts (Meyer & Land, 2005) mastered in the first six weeks of the course form the basis of the taught content in the second section and are critical to enhancing students' understanding of Macroeconomics. This necessitates adoption of a teaching approach which helps to increase student interaction and engagement with the subject matter.

To facilitate increased student interaction with the course content, *LearnSmart* was used to create five weekly reading assignments, each of which had a one-week deadline. As *LearnSmart* offers the instructor flexibility in terms of the selection of topics, depth of coverage and duration of each assignment (Fig. 2), the reading tasks were aimed at helping students gain a deep understanding of these threshold concepts crucial to success in the second half of the course. Readings were assigned from the end of the first week of the academic semester to enable students register their McGraw-Hill *Connect* account and to familiarise themselves with the resource.

Lectures were scheduled to hold twice weekly (Tuesdays and Fridays) - PowerPoint notes were uploaded to the learning management system prior to the first scheduled lecture, while reading tasks were assigned on Fridays. The staggered release of the lecture notes and reading assignments was intended to encourage students to review both the assigned reading and lecture notes in preparation for the first lecture of the week, in a sort of flipped approach to the AL process (Haughton & Kelly, 2015; Yilmaz-Tuzun, 2008). Students could also revise reading assignments after the due date for personal study. In so doing, students could track their own

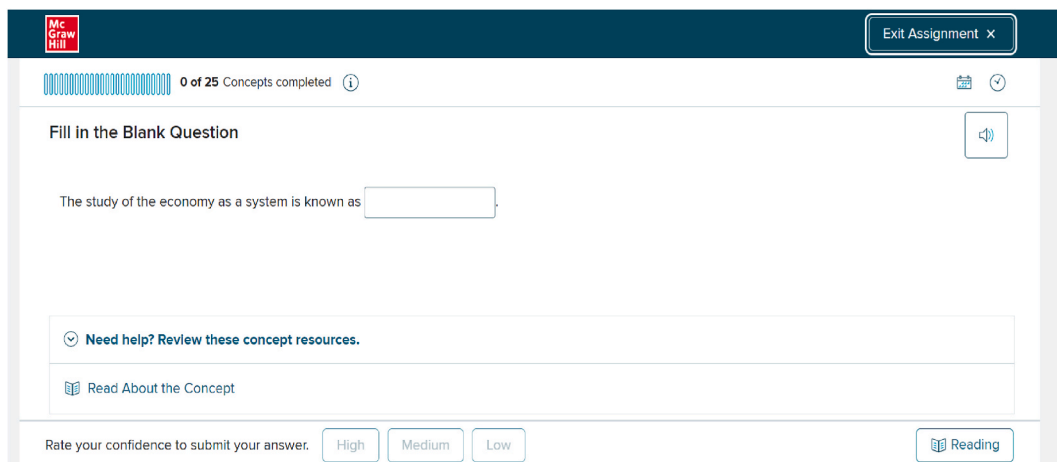


Fig. 1. Student receive immediate feedback and can review concepts (screenshot).

< Select Content ⓘ

Select content to include in your assignment by checking the boxes. Use the [Assignment Scope slider](#) to modify the estimated time and number of concepts.

25 concepts selected

Chapter	Section	Concepts Selected
Chapter 17: Introduction to macroeconomics		25 of 56 concepts selected
17.1: Introduction		3 of 3 concepts selected
17.1: Macroeconomics: The Big Issues		9 of 9 concepts selected
17.2: Some Facts and Economic History		0 of 3 concepts selected
17.3: The Circular Flow		3 of 3 concepts selected
17.4: National Income Accounting		0 of 27 concepts selected
17.5: What GDP Measures		10 of 10 concepts selected

Assignment Scope
30 minutes — 45 minutes
25 concepts selected

25

4

Continue

Fig. 2. Instructor content design dashboard (Screenshot).

learning before and after each lecture.

Each reading assignment was worth 100 points based on the student's response to the questions associated with the assigned reading. Thus, the maximum score for all five adaptive assignments was 500 points. In addition to the reading assignments which examined students' knowledge on a weekly basis, students were given two timed online assessments via the McGraw-Hill *Connect* platform in weeks 4 and 7. Each online test evaluated students' understanding of topics taught in the preceding three weeks. The two online assessments (each worth 100 points) consisted of 20 multiple choice questions created by the instructor. Although the reading assignment scores did not count towards the final grade in the course, students were told that their timed online test scores would be weighted by the number of completed readings. This ensured a higher rate of participation for the adaptive assignments.

LearnSmart's AL technology means that based on their response to practice questions embedded in the adaptive reading assignments, students continue to get questions related to the selected topic, until such a time when they can demonstrate their mastery of the content. Moreover, students can avail of *LearnSmart's* option to review taught concepts on a need-to basis. This enables tracking of their own knowledge in terms of what they know and what they do not know. Therefore, it was anticipated that the design of reading assignments using *LearnSmart* would make students engage more with taught content on a weekly basis, thus increasing their mastery and stimulating deep learning.

3.3. Description of data and variables

The analysis undertaken in this study draws on learning analytics data obtained from McGraw-Hill for a sample of 607 business students who took the first year Macroeconomics course. Learning analytics data enables the tracking of students' progress and real-time adjustments to teaching and learning as required (Flavin, 2016). Ethical issues of confidentiality and data protection were addressed through data anonymisation, with McGraw-Hill Higher Education as the data gatekeeper. Consequently, each student was assigned a unique identifier and all identifiable information such as name and email address were removed from the resulting anonymised dataset. This research study was conducted with ethical approval from the University's Faculty of Business Research Ethics committee. After data cleaning, our analysis is based on a final sample of 600 students who participated in a minimum of one timed test over the period.

In analysing the link between learner-content interaction and student performance, the following equation was estimated using the ordinary least squares regression method:

$$Perf = \beta_0 + \beta_1 (Learner_Content\ Interaction) + \varepsilon_{it}$$

Where student performance (*Perf*) is measured as the sum of the scores obtained from both timed tests. β_1 is the coefficient which captures the effect of learner-content interaction on student performance. ε_{it} is the error term.

Learner-content interaction has been measured in various ways (Powell & Leary, 2021). These include the amount of time spent on quizzes, assignments and other course content (Borup, Graham, & Davies, 2013; Zimmerman, 2012), access to content measured in terms of number and frequency of hits on a LMS or web platform (Biktimirov & Klassen, 2008; Grandzol & Grandzol, 2010) and average logins per week (Choi & Kim, 2018). In addition, time spent on task, and efforts made to engage with learning material have been identified as crucial determinants of students' behavioural and cognitive engagement –critical factors for academic performance (Al Mamun et al., 2022; Ding, Kim, & Orey, 2017; Miller, 2015; Romero & Barbera, 2011).

As such, following Dry et al. (2018) and Griff and Matter (2013), we measure learner-content interaction as i) the total amount of time spent on the *LearnSmart* assignments, and ii) the number of *LearnSmart* adaptive assignments completed. We adopt this approach

because as Korkofingas and Macri (2013, p. 5) note, “it is unlikely that a single measure will adequately capture online participation.” The amount of time spent on AL assignments measures learner-content interaction, while the number of assignments completed by the student captures the use of adaptive learning and learner-content interaction (Dry et al., 2018).

By including both variables in the same analysis, it is possible to explore how AL can be potentially used to enhance student performance through increased interaction with taught content. In doing so, we build on studies such as Owens and Moroney (2015) and Dry et al. (2018), which also include both variables in the same analysis. Grandzol and Grandzol (2010) argue that more interaction (measured as the amount of time) is not always better, such that increased interaction leads to lower performance (defined as completion rates). We, therefore, test for a possible non-linear relation between time spent and student performance by including a squared term of *time spent*.

All statistical analyses were performed using the statistical software package Stata version 15. To correct for heteroskedasticity, robust standard errors are reported. Variable definitions are detailed in Table 1.

4. Results and discussion

4.1. Descriptive statistics

Table 2 presents the summary statistics. The standard deviations indicate significant variation in student performance with a mean test score of 137 out of a possible 200. The average amount of time spent on completing the *LearnSmart* assignments is 107 minutes, 74 per cent of the student cohort completed all 5 assignments, while 3.8 per cent of the sample completed fewer than 3 assignments.

Preliminary analysis of the *LearnSmart* data suggests a high level of engagement and interaction with the content among this cohort of first-year business students. For instance, although the reading assignment scores were not included in their final grade, the completion rate of each individual assignment was over 90 per cent, with an average score of over 95 per cent. Low correlation coefficients and a mean variance inflation factor of 7.03 indicate multicollinearity is not a problem in the regression model.

4.2. Discussion of empirical results

To address our research question of whether learner-content engagement with AL has a direct and positive effect on student performance, we estimate a regression model to examine the separate effects of learner content interaction (amount of time on task), and learner-content engagement with adaptive learning (number of completed assignments). Results are reported in Table 3.

4.2.1. The relationship between learner-content interaction and student performance

The result for student performance (measured by test score) indicates that the predictors of learner-content interaction and adaptive learning explained 12% of the variance ($R^2 = 0.122$, $F(5, 594) = 13.90$, $p = 0.0000 < 0.05$). As can be seen from Table 3, the amount of time spent on completing the reading assignments had a statistically significant negative effect on the timed tests score ($\beta = -0.186$, $p = 0.020 < 0.05$). This result is consistent with Joksimović, Gašević, Loughin, Kovanović, & Hatala (2015) who find a negative association between the amount of time spent on student-content interaction and learning outcome (measured as final grades) in core courses taken as part of a Masters in Information Systems degree programme. The authors suggest their finding may be related to the need for weaker students to study the course content on a repeated basis.

Our results also confirm a non-linear relation between the time spent studying and students' test scores. Specifically, we find that the coefficient of *total time spent squared* is positive and statistically significant ($\beta = 0.000036$, $p = 0.072 < 0.10$). Taken together, the above results suggest that the more time students spend on the reading assignments, the lower their performance in the timed tests. This negative performance effect, however, decreases with time. This latter finding implies that a certain level of time investment is required for students to realise the benefits of using this AL tool.

As detailed in Section 3.3, time spent on task is an indicator of learner-content interaction. Hence, our result appears to support Grandzol and Grandzol's (2010) argument that more interaction is not always better. Time in itself may not necessarily be a sufficient indicator of students' interaction with learning content. This is because students may differ in the amount of time taken to complete the

Table 1
Definition of variables.

Variable	Definition
Dependent variable: Student Performance	
Test Score	Sum of online test scores
Independent variable: Learner-content interaction	
Total time spent	Total amount of time spent on completing assignment (minutes)
Total time spent ²	Square of total amount of time spent on completing assignment
Independent variable: Adaptive learning & Learner-content interaction	
Number of completed LearnSmart assignments:	
Completed assignments_under 3	Completed less than three assignment
Completed assignments_all	Completed all five assignments
Completed assignments_4	Completed four assignments
Completed assignments_3	Completed three assignments

Table 2
Description of variables: Means and standard deviations.

Item	M	SD
<i>Student Performance</i>		
Test Score	137.07	28.72
<i>Learner-content interaction</i>		
Total time spent	106.99	41.31
Total time spent ²	13150.69	12297.43
<i>Adaptive learning & Learner-content interaction</i>		
Completed assignments_under 3	0.04	0.19
Completed assignments_all	0.74	0.43
Completed assignments_4	0.175	0.38
Completed assignments_3	0.04	0.20

Notes: M, mean; SD, standard deviation.

Table 3
Relation between learner-content interaction, adaptive learning and student performance.

	Test Score	
	β	$\beta(\text{SE})$
Total time spent	-0.186**	0.0800
Total time spent ²	0.00036*	0.0002
Completed assignments_3	12.242	9.193
Completed assignments_4	31.936***	8.054
Completed assignments_All	46.419***	7.924
Constant	111.611***	7.032

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; The base category for number of completed assignments is *Completed assignments_under 3* (students with fewer than 3 assignments). Robust standard errors reported.

same task. Moreover, as Dry et al. (2018) note, the “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 ...”. Consequently, the amount of time spent using the AL tool may not necessarily indicate that significant learning has occurred. A disproportionate amount of time may be required by weaker students struggling to master the threshold concepts. Such learners may need to repeat the assignment until mastery is achieved.

Thus, we find that greater learner-content interaction (defined as the amount of time spent) is not associated with increased student performance up to a certain threshold, beyond which performance gains can be observed. The above points to the need for a more detailed examination of patterns of interaction with learning content through the AL tool.

4.2.2. Relationship between adaptive learning, learner-content interaction and student performance

As expected, the number of completed assignments, a proxy for student interaction with the course material and the use of AL, was found to be positively associated with the test score. Specifically, students who completed all five assignments ($\beta = 46.419$, $p = 0.000 < 0.01$) performed better in the timed tests relative to those with fewer than three completed assignments (Table 3). The next best performance was found for students with four completed assignments ($\beta = 31.936$, $p = 0.000 < 0.01$). No statistically significant effect was found in the test score performance of students who had only three completed assignments ($\beta = 12.241$, $p = 0.183 > 0.05$). The above finding is consistent with results from Dry et al. (2018) who find that the usage of *LearnSmart* (measured as proportion of module completion) has a positive effect on the module quiz and final exam scores.

It is important to note that the amount of time spent on *LearnSmart* assignments and the number of completed assignments both signal increased interaction with the course content. The latter, however, also captures the use of AL. The assignment completion rate offers some indication of incremental progress made by students who must demonstrate a required level of understanding in completing adaptive assignments (Dry et al., 2018). Higher task completion rates may be indicative of higher levels of mental effort and persistence, which in turn ensure mastery and can potentially enhance student performance. The number of completed assignments may, therefore, be taken as an indicator of cognitive engagement. The latter relates to the amount of effort students are willing to invest in a task, and is characterised by thoughtfulness and persistence (Boekaerts, 2016; Li, Lajoie, Zheng, Wu, & Cheng, 2021). Therefore, in addressing our research question -does learner-content engagement with adaptive learning increase student performance, we observe that a higher level of engagement with AL (defined as the number of completed adaptive assignments) is associated with increased performance.

Overall, our findings indicate that learner-content interaction (measured in terms of time spent on task) in itself, does not translate to improved student performance. Rather, it is students' engagement with AL through *LearnSmart* adaptive assignments that is associated with increased performance. These results suggest that the quality of engagement is also crucial. AL may enhance student performance directly by providing students with flexible, personalised content through the use of adaptive reading assignments with

embedded question prompts. This stimulates the acquisition and construction of knowledge and increases learning. The indirect effect of AL on performance may occur through stronger learner-content interaction, which fosters deep and meaningful learning. Based on the above, our findings provide support for Hypothesis 1, which states that learner-content engagement with *LearnSmart* adaptive assignments will have a direct and positive effect on student performance.

5. Conclusion and further research

This paper examined patterns of learner-content interaction facilitated through an adaptive learning (AL) technology (*LearnSmart*, licensed and hosted on McGraw-Hill *Connect*, a content management platform). *LearnSmart* was employed as a tool to design weekly reading assignments for a cohort of first-year Business students studying Macroeconomics in an Irish University over a 6-week period. The relationship between AL and the students' performance was explained using the theoretical lens of learner-content interaction. The intentional design of learning activities offers students flexible and personalised learning to suit their individual rhythm and encourages more interaction between learners and taught content. This may, in turn, enable students to become more active participants in the learning process by promoting deep learning which helps to enhance student performance outcomes. Therefore, the study provides much needed empirical evidence using a clearly defined dependent variable and multiple indicators of learner-content interaction. In doing so, we make valuable contributions to the sparse literature on learner-content interaction, while addressing the lack of consensus on the tangible impact of AL. By addressing these gaps, we respond to direct calls for further empirical research on AL by Muñoz et al. (2022). Additionally, by combining the use of online trace data with other dependent variables, we enrich the interpretation of self-regulated learning from various perspectives (Du, Hew, & Liu, 2023).

Our empirical findings appear to support AL as a pedagogical tool for fostering learner-content interaction and improving student performance. On the one hand, the results suggest that student performance, measured in terms of their test scores, is enhanced by the number of completed assignments. On the other hand, the amount of time spent on assignments was found to have a strong non-linear negative effect on the performance of students. Thus, a certain level of time investment is required for performance gains from students' interaction with the AL technology to be realised. We conclude that the amount of time students spend interacting with the AL tool is not sufficient in itself to improve performance. Rather, the quality of study time matters, using a well-conceived instructional design that encourages deep engagement with learning. This result challenges the common identification of more time spent on a task with deeper learning, and the prevailing assumption in the learning analytics literature that more time spent in online environments is generally an indicator of student success.

Our finding implies that AL enhances student performance for most students by providing them with customised learning material which stimulates greater interaction with course content. This interaction is necessary for students' knowledge acquisition and construction, valuable for increased learning and better performance. Pedagogically, our results point to AL as a tool for creating learning activities such as reading assignments, which can potentially help to increase student engagement with taught content. Hence, AL can provide a way to sustain effort and persistence by increasing mastery-oriented feedback and varying demands and resources to optimise challenge, thus meeting some of the recommendations of a Universal Design for Learning (UDL) approach (CAST, 2018). Overall, our findings support AL as a pedagogical approach which entails the deliberate design of learning activities to help students develop cognitive behaviours that foster deep and meaningful interactions with the taught content, while acknowledging that its impact will be modulated by learner diversity.

Generalisability is recognised as a challenge of using online traces to measure self-regulated learning (Du et al., 2023). Other factors which may influence student performance include different sources of student heterogeneity such as previous and current academic performance, socio-economic status, ethnicity, abilities, gender, and age (Hardy et al., 2019; Sclater, Peasgood & Mullen, 2016; Sothan, 2019). A discussion of these factors is beyond the scope of this study and could serve as a fruitful avenue for future research. Moreover, our finding of a non-linear relation between the amount of time spent using the AL tool and student performance merits further investigation, given available data. Furthermore, the mixed empirical evidence on the effectiveness of adaptive learning found to date, has been attributed to several pedagogical choices, such as how closely aligned the course content and assessments are to the AL tasks, and whether usage of the AL tool is optional for students (Griff & Matter, 2013; White, 2020), which warrant further exploration in the context of this study. Additionally, *LearnSmart* assignments were only implemented during the first half of the course over one academic semester. Future research would, therefore, benefit from comparing student performance with and without the *LearnSmart* assignments on the mid-term and end of term assessments over a longer period. Also noteworthy is that, while we can observe whether learner-content interaction and AL usage are positively related to student performance, we cannot infer a direct causal relationship.

Despite these limitations, the paper offers some important insights on whether and to what extent AL can be used to foster learner-content interaction and increase student performance. The findings are particularly relevant in large undergraduate classes, where the need to acknowledge student heterogeneity in the manner in which learners interact with taught content is challenged by large student/staff ratios. The adoption of AL technology in the design of meaningful tasks, which offer students an element of personalised learning and foster learner-content interaction, can be a potentially sustainable and impactful choice to address this need. Also, AL utilised as a pedagogical tool can indirectly serve to provide multiple means of engagement from a UDL approach (CAST, 2018).

Declaration of interest statement

The authors report there are no competing interests to declare.

CRediT authorship contribution statement

Olubunmi Ipinnaie: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Angelica Risquez:** Writing – review & editing, Validation, Supervision.

Data availability

The authors do not have permission to share data.

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