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# The relations between study approach, study time, and academic performance in flipped classrooms by questionnaire and clickstream data: To what extent are they consistent?

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## Abstract

This study used both questionnaire and clickstream data to examine the relations between study approach, study time, and academic performance in low-stake and high-stake assessments in flipped classrooms. The questionnaire data identified two clusters of students reporting deep and surface study approaches. Students who reported a deep study approach performed better than those who reported a surface study approach on both low-stake and high-stake assessments. The clickstream data detected two clusters of students using either preparation-oriented or assessment-oriented approaches. Students who adopted preparation-oriented approach achieved higher on both low-stake and high-stake assessments. Students' study time measured by both questionnaire data and clickstream data consistently contributed to both low-stake and high-stake assessments. However, the contributions of study approach to academic performance were not consistent across the two types of data, as self-reported study approach was only a significant predictor of high-stake but not low-stake assessment, suggesting that study approach measured by questionnaire data might not be sufficiently sensitive to detect variations in study approaches in flipped classrooms. Pedagogically, the results suggest that raising students' awareness of the importance of pre-lecture learning and aligning assessments and learning activities may foster quality flipped classroom learning. Methodologically, the study demonstrates the advantages of combining questionnaire and clickstream data to understand students' experiences of learning in flipped classrooms.


**Keywords** Study approach · Study time · Questionnaire data · Clickstream data · Low-stake and high-stake assessments · Flipped classrooms

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## Introduction

Over the last few decades, learning in higher education has undergone significant transformation, such as re-designing large lecture-focused courses by adopting flipped classrooms (Cho et al., 2021). As a special type of blended learning designs, flipped classrooms mainly use classroom time to enhance understanding of learning materials, to clarify key concepts, and to contextualise knowledge via applications (Algarni & Lortie-Forgues, 2023). While research has shown that multiple benefits of flipped classrooms, such as promoting active learning (Huang et al., 2023), increasing opportunities of teacher-student and student–student interactions in the in-class time (Yañez et al., 2023); flipped classrooms not always lead to desirable learning outcomes (Cevikbas & Kaiser, 2023; Shen & Chang, 2023). Thus, it is important to understand how learning outcomes in flipped classrooms are associated with various aspects in learning, such as how students learn (study approach) and how much time they devote to learning (study time), so that targeted strategies can be developed to improve students' learning in flipped classrooms.

Existing research on students' experiences of learning in flipped classrooms have focused on either the association between students' study approach and academic performance (Han, 2023; Fincham et al., 2019; Gašević et al., 2017; Jovanović et al., 2017) or study time and academic performance (Cho & Yoo, 2017). The present study will include these variables in a single study by investigating the relational patterns between study approach, study time, and academic performance in flipped classrooms. This helps educators and researchers to understand whether being more strategic, investing more time, or both are important for students to achieve good learning outcomes in flipped learning.

Furthermore, research in traditional face-to-face learning context has shown inconsistent results between study time and academic performance (Fostervold et al., 2022), as positive relations (Kember et al., 1995, 1996), negative relations (Ackerman & Gross, 2003; Krohn & O' Connor, 2005), and no relations (Nonis & Hudson, 2010; Valadas et al., 2017) have all been reported. These studies predominantly adopted self-reported measures (e.g., questionnaires or learning diaries) to measure study time. However, self-reported measures are often criticized for: (1) their subjective nature and being affected by students' careless answering and item nonresponse (Hitt et al., 2016; Zamarro et al., 2018); and (2) their inability to represent the complexity of students' learning in reality (Han et al., 2022; Matcha et al., 2020; Zhou & Winne, 2012). Hence, using more objective measures, such as clickstream data (i.e., the digital traces extracted from the learning management systems (LMS) in technology-mediated learning) may help clarify previous inconsistencies regarding how study time is associated with academic performance. Suggestions have been made to combine questionnaire and clickstream data to improve our understandings of university students' experiences of learning in contemporary learning designs (e.g., flipped learning), as the two types of data are able to provide complementary information and serve a purpose of triangulation (Han et al., 2022; Gašević et al., 2017; Ye & Pennisi, 2022). Therefore, the present study will use both questionnaire and clickstream data to measure study approach and time, and to examine the extent to which the relational patterns between study approach, study time, and academic performance are consistent by the two types of data.

Moreover, previous research has indicated that students' learning engagement is differently related with their academic performance on low-stake and high-stake assessments (Ober et al., 2021). It is unknown if students' academic performance on low-stake and high-stake assessments are also differently associated with study approach and time in flipped classrooms. This is an additional research gap to be addressed in the present study.

Specifically, the present study will address four research questions:

1. To what extent do students' study time and academic performance on low-stake and high-stake assessments differ by their study approach measured by questionnaire data in flipped classrooms?
2. To what extent do students' study time and academic performance on low-stake and high-stake assessments differ by their study approach measured by clickstream data in flipped classrooms?
3. How do students' study approach and time (measured by questionnaire and clickstream data) contribute to students' academic performance on low-stake assessment in flipped classrooms?
4. How do students' study approach and time (measured by questionnaire and clickstream data) contribute to students' academic performance on high-stake assessments in flipped classrooms?

## Literature review

### Relations between academic performance, study approach, and study time by questionnaire data

Study approach is defined as "context-specific ways of tackling learning tasks", which is "relatively consistent preferences … irrespective of the task or problem presented" (Entwistle & Peterson, 2004, p. 537). This definition suggests that study approach is not a stable psychological trait of learners but is simultaneously shaped by the learner and the learner' experienced learning context (Hua & Wang, 2023). Existing research has predominantly used self-reported methods, such as interviews or questionnaires, to measure study approach. Across a variety of learning tasks and in a range of academic disciplines, past studies have consistently identified two broad categories of study approach—deep and surface (Trigwell & Prosser, 2020). Students who report a deep approach learn in proactive, reflective, and engaging ways; whereas students who report a surface approach learn in mechanistic ways, such as through rote memorization (Zakariya et al., 2022). Deep and surface approaches have also been reported in the use of online learning technologies. A deep approach to using online learning technologies uses technologies in a meaningful way to facilitate learning, such as to broaden views and deepen conceptual understanding; whereas a surface approach applies technologies in learning in simplistic ways to merely fulfil practical purposes, like downloading documents, completing assignments, or satisfying course requirements (Ellis & Bliuc, 2019).

Research has shown relatively consistent relations between study approach and academic performance: students who report a deep approach often obtain better academic results whereas a surface approach tends to be associated with poorer learning outcomes (Guo et al., 2022). As mentioned, previous research using self-reported methods to examine the relations between study time and academic performance have found mixed and inconclusive results (Fostervold et al., 2022), with positive relations (Kember et al., 1995, 1996), negative relations (Ackerman & Gross, 2003; Krohn & O' Connor, 2005), and no relations (Nonis & Hudson, 2010; Valadas et al., 2017) have all been reported. Clearly further research is required in this area. Using both questionnaire and clickstream data to measure study time will strengthen analytic power and may help clarify these inconclusive results.

## Relations between academic performance, study approach, and study time by clickstream data

The recent development of learning analytics has made it possible to collect rich and detailed clickstream data of students' learning when they interact with a variety of online learning resources and activities. The large volume of clickstream data processed by educational data mining and machine learning algorithms have been useful in a variety of domains in higher education, such as to advising students' career choice (Kew & Tasir, 2022), to improve retention by detecting at risk students early on (Li et al., 2022), to provide personalised feedback (Zheng et al., 2022), to facilitate collaborative learning (Kaliisa et al., 2022), to monitor students' affect in learning (Joksimović et al., 2022), and to identify patterns of study approach (Saavedra et al., 2022).

Using data mining techniques, such as Hidden Markov Model, agglomerative sequence clustering, and process mining algorithms to analyse sequences of online learning events recorded by LMSs, a number of studies have identified study approaches used by students in flipped classrooms or online courses (Han, 2023; Fincham et al., 2019; Jovanović et al., 2017; Matcha et al., 2019).

For instance, in an engineering flipped classroom course, Han (2023) identified four study approaches differed on variations of the frequencies of online learning activities. Students adopting four approaches also showed significant differences on their course marks. Those who were involved in "extensive pre-lecture videos watching, moderate pre-lecture quizzes, and few post-lecture quizzes" scored highest; followed by students who were involved in "extensive pre-lecture videos watching, moderate pre-lecture quizzes, and moderate post-lecture quizzes". Students used an approach involving "moderate pre-lecture videos watching, few pre-lecture quizzes, and moderate post-lecture quizzes" were ranked the third in terms of their course marks. Those employed an approach with "few pre-lecture videos watching, few pre-lecture quizzes, and extensive post-lecture quizzes" scored the lowest in the course. The study results seemed to indicate the importance of pre-lecture activities in flipped classroom learning, as those participating in few pre-lecture online learning had the poorest academic performance. This study, however, did not have information on study time, hence, how study approach and study time contribute to academic performance is unknown.

A number of studies used the information of both type and number of time-stamped learning sequences to identify students' study approach in flipped classrooms. Jovanović et al. (2017) found five types of online study approach in an undergraduate flipped classroom course:

- "intensive approach": which was characterized by a variety of online learning activities with the most learning sessions;
- "strategic approach": which prioritized summative and formative assessment tasks and generated the second most learning sessions;
- "highly strategic approach": which emphasized summative assessment task and reading activities and had the third most learning sessions;
- "selective approach": which predominantly focused on summative assessment task with few reading activities and generated the second least learning sessions;
- "highly selective approach": which only performed summative assessment task and generated the least learning sessions.

Jovanović et al. (2017) also compared students' academic performance based on their study approaches. The results showed that students who adopted "intensive approach", "strategic approach", and "highly strategic approach" obtained higher marks than their peers who employed "selective approach" and "highly selective approach" on both mid-term and final examinations.

Jovanović et al.'s (2017) study and studies adopting a similar method (Fincham et al., 2019; Matcha et al., 2020) suffered from a major limitation, as they used the criteria of both types of learning sequences and the number of learning sessions (According to Jovanović et al. (2017), learning sessions are defined as continuous online learning events with a break less than 30 min) to identify study approach. As a result, the study approach was mixed with study time as more learning sessions might indicate longer study time. Consequently, it was unclear as to whether the differences in academic performance were primarily influenced by the types of learning activities they were engaged with, or the varying learning sessions, or a combination of both.

To separate study approach and study time, Han et al. (2022) used the proportions of different types of online learning activities to identify students' study approach and found a content-oriented and an assessment-oriented study approach in a blended course. The study further showed that students who adopted a content-oriented approach had significant more learning sessions and better academic performance than their peers who used assessment-oriented study approach. However, learning sessions were not an accurate measurement of study time, as the duration of each learning session varied. This limitation will be addressed in the present study by using the exact duration of study time recorded in the LMS. Moreover, Han et al.'s (2022) study only used clickstream data to examine the relations between study approach and academic performance in blended learning. The present study will extend the investigation from blended learning into the flipped classroom context and will use both questionnaire and clickstream data to measure study approach and time, which will allow us to examine the extent to which the relations between study approach, study time, and academic performance are consistent across the two types of data.

## Material and method

### Participants

The participants were 271 undergraduates aged between 18 and 31 years old ($M = 19.75$, $SD = 2.12$) in a metropolitan research-intensive university in Australia. They were enrolled in a first-year introductory course in computing system. Data collection strictly followed the ethical requirements of the researcher's institution to ensure voluntary participation and to obtain written consent. One week before the data collection, each student was given a Participant Information Statement, which explained that participation in the study was voluntary, their identity would not be revealed in the publications resulted from the study, and their decision to participate or not would not have any consequences. All the participating students provided a written consent.

### The flipped classroom course

The flipped classroom course lasted for 13 weeks. Before the weekly face-to-face lecture, students were required to go through the pre-lecture readings, watch pre-lecture videos, and complete pre-lecture quizzes in a custom-designed LMS, which was designed to meet the needs of the teaching team of the course. The face-to-face lectures then expanded the theoretical concepts in the pre-lecture videos, explained the difficult points, and provided examples of applying theories to solving practical problems. These concepts and applications were further strengthened and practiced in the face-to-face tutorials and labs via problem-solving tasks, mini case studies, and hand-on exercises. After face-to-face sessions, students were also required to complete post-lecture quizzes. Hence, the online learning functioned as both preparing and reviewing the face-to-face learning. However, the online learning activities were not graded and counted as part of students' course marks. There were five online learning activities, namely pre-lecture readings, pre-lecture videos, pre-lecture quizzes, post-lecture quizzes, and interactive dashboard (see Table 1 for a detailed explanation).

### Data and instruments

#### Study approach and study time measured by a questionnaire

Study approach was assessed by two scales with 5-point anchors (from 1-strongly disagree to 5-strongly agree). The scales had good reliability and were used in

**Table 1** Details of the clickstream data

| Events | Content | Function | Frequency | Duration |
|---|---|---|---|---|
| Pre-lecture readings | Compulsory and supplementary reading Materials, links to webpages, and preparation requirements | Preparing students for lectures, tutorials, and laboratory practice in the coming week | ✓ | ✓ |
| Pre-lecture videos | Videos clips of pre-recorded lectures | Explaining key concepts and examples of tasks lectures, tutorials, and laboratory practice in the coming week | ✓ | ✓ |
| Pre-lecture quizzes | Multiple-choice-questions and short answer questions | Evaluating students' understanding of important theoretical concepts to be covered in the face-to-face lectures in the coming week | ✓ | ✓ |
| Post-lecture quizzes | Problem-solving sequences and mini case studies | Assessing students' abilities to apply theories to tackling practical issues | ✓ | ✓ |
| Interactive dashboard | Learning analytics data | Providing students visualization on their online learning progress, learning patterns, and performance in relation to the class average | ✓ | ✓ |

previous studies to investigate students' learning experiences in blended and flipped classroom courses (Han et al., 2022; Ellis & Bliuc, 2019).

- *the deep approach to using online learning technologies* (6 items, $\alpha = 0.74$): uses online learning technologies in meaningful ways to facilitate learning, such as to deepen understanding of the concepts in the course or to facilitate learning through inquiry process in the course (e.g., *I spend time using the online learning technologies in this course to connect key ideas to real contexts*).
- *the surface approach to using online learning technologies* (5 items, $\alpha = 0.76$): uses online learning technologies in formulaic and mechanistic ways, such as to download documents or to fulfil course requirements (e.g., *I use online learning technologies in this course mainly to download files*).

Students' average weekly online study time was measured by a dichotomous item, which asked students to select whether their average weekly online study time in the course was more or less than 4 h (i.e., *In general, the average weekly time you spent studying online in this course was □ less than 4 h □ more than 4 h*). The determination of 4 h was based on the course requirement.

### Online learning events measured by clickstream data

The online learning events captured by the clickstream data are displayed in Table 1. There were five types of online learning events, namely pre-lecture readings, pre-lecture videos, pre-lecture quizzes, post-lecture quizzes, and interactive dashboard. Both the frequency and duration of the online learning events were recorded. As the study time measured by the questionnaire was the average weekly online study time, similar measurement was also derived using the clickstream data. The duration of all the online learning events was aggregated and then divided by the number of weeks in the course (13 weeks). The clickstream data measured the duration of the online learning events in seconds, which was transferred into hours in order to match the hours used in the questionnaire data.

### Academic performance on low-stake and high-stake assessments

Students' academic performance in the course was measured by two types of assessments differing on the stake, with both assessments had an equal 50% weights in the course marks. The low-stake assessment was the highest 10 scores of students' performance on problem-solving tasks in tutorials, with the maximum score of each tutorial was 5. The high-stake assessment was the end-of-semester close-book examination. The examination had 20 multiple-choice questions (1.5 each, the maximum score was 30), which assessed students' understanding of theoretical concepts in the course; and four mini case studies (5 each, the maximum score was 20), which examined students' abilities to apply theories to solving practical problems.

**Table 2** Students' study time and academic performance by study approach using questionnaire data

| Clusters | More deep Less surface ($n=71$) | | Less deep More surface ($n=199$) | | | | |
|---|---|---|---|---|---|---|---|
| *Study approach by questionnaire data* | *M* | *SD* | *M* | *SD* | *F* | *p* | $\eta^2$ |
| Deep study approach | 4.18 | 0.36 | 3.40 | 0.57 | 117.38 | $<.001^{***}$ | .31 |
| Surface study approach | 1.88 | 0.48 | 2.96 | 0.7 | 141.01 | $<.001^{***}$ | .34 |
| *Study time by questionnaire data* | n | % | n | % | $\chi^2$ | *p* | φ |
| Below 4 h | 24 | 33.8% | 87 | 43.5% | 2.04 | .09 | .09 |
| Above 4 h | 47 | 66.2% | 113 | 56.5% | 2.04 | .09 | .09 |
| *Academic performance* | *M* | *SD* | *M* | *SD* | *F* | *p* | $\eta^2$ |
| Low-stake assessment | 34.91 | 3.68 | 32.89 | 5.35 | 8.63 | $.004^{**}$ | .03 |
| High-stake assessment | 37.14 | 11.46 | 32.41 | 11.61 | 8.77 | $.003^{**}$ | .03 |

$^{***}p<.001$, $^{**}p<.01$, $^{*}p<.05$

## Data analysis and results

### Data analysis and results of research question 1—study time and academic performance by study approach using questionnaire data

#### Data analysis methods

To answer research question 1, we first conducted a hierarchical clustering analysis using the *Mean* of the six items in the Deep Approaches to Using Online Learning Technologies scale and the *Mean* of the five items in the Surface approaches to Using Online Learning Technologies scale. We then compared if the proportions of students who reported studying below or above 4 h/week differed between clusters using a chi-square test and if the low-stake and high-stake assessment scores differed by cluster using one-way ANOVAs.

Using the increasing values of the squared Euclidean distance between the clusters based on the *Mean* scores of deep and surface approaches to using online learning technologies, the hierarchical cluster analysis retained two clusters shown in Table 2. One-way ANOVAs found that students in the two clusters differed significantly on the deep ($F(1, 269)=117.38$, $p<0.001$, $\eta^2=0.31$) and surface approaches ($F(1, 269)=141.01$, $p<0.001$, $\eta^2=0.34$). One cluster had 71 students, who reported using more deep but less surface approaches; whereas another cluster had 199 students, who reported using less deep but more surface approaches. However, the proportions of students who reported studying less and more than 4 h differ significantly between the two clusters ($\chi^2(1)=2.04$, $p=0.09$, $\varphi=0.09$). In terms of academic performance, the two clusters differed significantly on both low-stake ($F(1, 269)=8.63$, $p=0.004$, $\eta^2=0.03$) and high-stake ($F(1, 269)=8.77$, $p=0.003$, $\eta^2=0.03$) assessments. Students who reported more deep but less surface approaches performed significantly better than those reporting less deep but more surface approaches on both low-stake and high-stake assessments.

**Table 3** Students' study time and academic performance by study approach by clickstream data

| Study approach by clickstream data | Preparation-oriented approach ($n=136$) | | Assessment-oriented approach ($n=135$) | | $F$ | $p$ | $\eta^2$ |
|---|---|---|---|---|---|---|---|
| | $M$ | $SD$ | $M$ | $SD$ | | | |
| Proportion of pre-lecture readings | 13.06 | 5.00 | 11.16 | 5.78 | 8.42 | .004** | .03 |
| Proportion of pre-lecture videos | 14.90 | 7.33 | 12.51 | 8.52 | 6.13 | .014* | .02 |
| Proportion of pre-lecture quizzes | 34.47 | 17.93 | 23.66 | 18.27 | 24.14 | <.001*** | .08 |
| Proportion of post-lecture quizzes | 34.83 | 12.69 | 49.82 | 18.05 | 62.63 | <.001*** | .19 |
| Proportion of interactive dashboard | 2.74 | 2.37 | 2.85 | 2.64 | 0.13 | .716 | .00 |
| Study time by clickstream data (hour) | 4.72 | 1.62 | 3.00 | 1.09 | 103.75 | <.001*** | .29 |
| Low-stake assessment | 35.16 | 3.94 | 31.67 | 5.42 | 36.75 | <.001*** | .11 |
| High-stake assessment | 37.54 | 11.39 | 29.72 | 10.77 | 33.76 | <.001*** | .12 |

***$p<.001$, **$p<.01$, *$p<.05$

## Data analysis and results of research question 2—study time and academic performance by study approach by clickstream data

To answer research question 2, we first identified types of the observed study approach by: (1) calculating proportions of the frequencies of the five online learning events to the total frequencies of online learning events; and (2) applying a hierarchical cluster analysis using the five proportions. The reason for using proportions in the cluster analysis rather than the raw frequencies was due to wide variations in the raw frequencies of different types of online learning events among the participants. We then conducted one-way ANOVAs to compare if the observed weekly study hours and students' scores on low-stake and high-stake assessments using the study approach as a between-subjects independent variable.

Table 3 displays the results of cluster analysis, which show that the two clusters had 136 and 131 students respectively. One-way ANOVAs revealed that of the proportions of five types of the online learning events, the two clusters differed significantly on pre-lecture readings ($F(1, 269)=8.42$, $p=0.001$, $\eta^2=0.03$), pre-lecture videos ($F(1, 269)=6.14$, $p=0.014$, $\eta^2=0.14$), pre-lecture quizzes ($F(1, 269)=24.14$, $p<0.001$, $\eta^2=0.08$), and post-lecture quizzes ($F(1, 269)=62.63$, $p<0.001$, $\eta^2=0.19$). However, the two clusters did not differ on the proportions of interactive dashboard events ($F(1, 269)=0.13$, $p=0.716$, $\eta^2=0.00$). Students in cluster 1 had higher proportions of pre-lecture readings, pre-lecture videos, and pre-lecture quizzes than cluster 2 students. But cluster 2 students had a higher proportion of post-lecture quizzes than cluster 1 students.

The proportional distribution of the online learning events (Fig. 1) suggested that cluster 1 learners prioritized their learning by focusing more on the online learning activities designed to prepare for the face-to-face component in the flipped course. As shown in Fig. 1, the preparation learning activities (i.e., pre-lecture readings, pre-lecture videos, and pre-lecture quizzes) used by cluster 1 students accounted

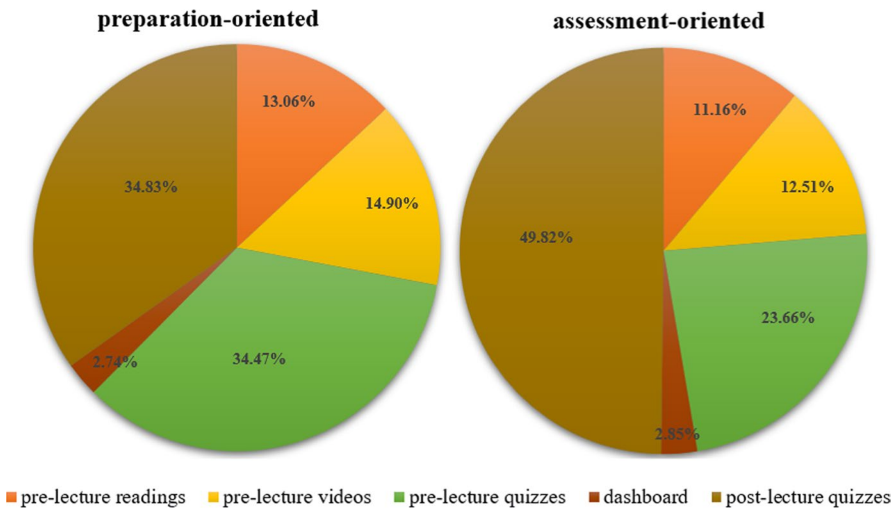


**Fig. 1** The preparation-oriented and assessment-oriented study approaches

for almost two thirds (62.43%) of all the online learning activities. In contrast, the preparation activities of cluster 2 learners formed less than 50% (47.33%) of all the online learning activities. Instead, cluster 2 learners focused more on the assessment activities in learning, which took up almost 50% (49.82%) of all the activities. These results seemed to suggest that cluster 1 students adopted a preparation-oriented approach, whereas cluster 2 students used an assessment-oriented study approach.

With regard to study time and academic performance, one-way ANOVAs showed that students who adopted the preparation-oriented approach spent significantly more hours studying online than those who employed the preparation-oriented approach ($F(1, 269) = 103.75$, $p < 0.001$, $\eta^2 = 0.29$). Students with the assessment-oriented approach also scored more highly on both low-stake ($F(1, 269) = 36.75$, $p < 0.001$, $\eta^2 = 0.11$) and high-stake assessments ($F(1, 269) = 33.76$, $p < 0.001$, $\eta^2 = 0.12$) than their peers with the assessment-oriented approach.

## Data analysis and results of research question 3—contributions of students' study approach and time to academic performance on the low-stake assessment

To answer research question 3, we conducted multiple regression analyses using low-stake assessment scores as the dependent variable. We constructed the initial multiple regression models using only the study approach (*M* scores of the approach scales) and time (the categorical variable of the weekly study time) by questionnaire data as the independent variables. We then constructed the subsequent models using the study approach and time by clickstream data as the predictors. To ensure the linear relationship between the predictors and dependent variables in the multiple regression analyses, we performed correlation analyses first. Based on the correlation analyses results, we only entered predictors which were significantly correlated with the assessment scores into the regression equations.

**Table 4** Results of correlation analyses

| Variables | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|
| 1 Low-stake assessment | .30*** | .15* | −.03 | .20** | .35*** | .35*** |
| 2 High-stake assessment | – | .04 | −.20** | .17** | .33*** | .30*** |
| 3 Deep study approach | – | – | −.27 | .18** | .19** | .17** |
| 4 Surface study approach | – | – | – | −.01 | −.09 | −.15* |
| 5 Self-reported study time above 4 h[a] | – | – | – | – | .25** | .17** |
| 6 Observed preparation-oriented approach[a] | – | – | – | – | – | .54*** |
| 7 Observed study time | – | – | – | – | –- | – |

[a]As self-reported study time and observed study approach were categorical variables, point biserial correlations were calculated

***$p<.001$, **$p<.01$, *$p<.05$

Two dummy variables were created for the study approach by clickstream data (1 represented the preparation-oriented study approach and 0 represented the assessment-oriented study approach) and study time by questionnaire data (1 was weekly online study time above 4 h, 0 was weekly online study time below 4 h) as they were categorical variables.

The correlation analyses are presented in Table 4, which shows that the low-stake assessment score was significantly and positively correlated with deep study approach ($r=0.15$, $p<0.05$), self-reported study time above 4 h ($r=0.20$, $p=0.001$), observed preparation-oriented approach ($r=0.35$, $p<0.001$), and observed study time ($r=0.35$, $p<0.001$). The high-stake assessment score was significantly and negatively correlated with surface study approach ($r=-0.20$, $p=0.001$); but positively associated with self-reported study time ($r=0.17$, $p=0.006$), preparation-oriented approach ($r=0.33$, $p<0.001$), and observed study time ($r=0.30$, $p<0.001$). The variables which significantly correlated with the low-stake and high-stake assessments were entered in the multiple regression equations.

The results of multiple regression analyses using the low-stake assessment score as the dependent variable are presented in Table 5. It shows that when the low-stake assessment was regressed on study approach and time by questionnaire data (model 1a), only weekly study time above 4 h ($\beta=0.17$, $p=0.007$) was a significant predictor, explaining about 5% of the variance in the low-stake assessment score ($F(2, 268)=6.84$, $p=0.001$, $f^2=0.05$).

When the low-stake assessment was regressed on the study approach and time by clickstream data (model 1b), both preparation-oriented approach ($\beta=0.21$, $p=0.003$) and study time ($\beta=0.24$, $p<0.001$) were significant and positive predictors, explaining approximately 15% of the variance in the low-stake assessment score ($F(2, 268)=23.19$, $p<0.001$, $f^2=0.18$).

**Table 5** Multiple regression analyses using the low-stake assessment score as the dependent variable

| Variables | B | SE | $\beta$ | $t$ | Adjusted $R^2$ | $p$ | $f^2$ |
|---|---|---|---|---|---|---|---|
| *Model 1a* (study approach and time by questionnaire data as predictors) | | | | | .05 | | 0.05 |
| Deep study approach | 0.95 | .48 | .12 | 1.96 | | .051 | |
| Study time by questionnaire | 1.67 | .61 | .17 | 2.72 | | .007** | |
| *Model 1b* (study approach and time by clickstream data as predictors) | | | | | .15 | | 0.18 |
| Preparation-oriented approach | 2.08 | 0.68 | .21 | 3.05 | | .003** | |
| Study time by clickstream | 0.74 | 0.21 | .24 | 3.52 | | < .001*** | |

***$p < .001$, **$p < .01$, *$p < .05$

**Table 6** Multiple regression analyses using the high-stake assessment score as the dependent variable

| Variables | B | SE | $\beta$ | $t$ | Adjusted $R^2$ | $p$ | $f^2$ |
|---|---|---|---|---|---|---|---|
| *Model 2a* (study approach and time by questionnaire data as predictors) | | | | | .07 | | 0.08 |
| Surface study approach | −2.82 | 0.85 | −.20 | −3.31 | | .001** | |
| Study time by questionnaire data | 4.00 | 1.41 | .17 | 2.84 | | .005** | |
| *Model 2b* (study approach and time by clickstream as predictors) | | | | | .13 | | 0.15 |
| Preparation-oriented approach | 5.66 | 1.60 | .24 | 3.55 | | <.001** | |
| Study time by clickstream data | 1.18 | 0.49 | .16 | 2.39 | | .018* | |

***$p<.001$, **$p<.01$, *$p<.05$

### Data analysis and results of research question 4—contributions of students' study approach and time to academic performance on the high-stake assessment

The procedure of the data analysis for research question 4 was the same as that for research question 3, except the high-stake assessment was used as the dependent variable for the regression model. The results of are displayed in Table 6. The results demonstrate that when using the study approach and time by questionnaire data to predict students' performance on the high-stake assessment (model 2a), both surface study approach ($\beta = -0.20$, $p = 0.001$) and study time ($\beta = 0.17$, $p = 0.005$) were significant predictors. Altogether the two predictors explained approximately 7% of the variance in the high-stake assessment score ($F(2, 268) = 9.48$, $p < 0.001$, $f^2 = 0.08$). While students' self-reported study time positively contributed to the high-stake assessment score, surface study approach negatively predicted high-stake assessment score.

When using the study approach and time by clickstream data to predict students' performance on the high-stake assessment (model 2b), both preparation-oriented approach ($\beta = 0.24$, $p < 0.001$) and observed study time ($\beta = 0.16$, $p = 0.018$) were significant and positive predictors, explaining approximately 13% of the variance in the high-stake assessment score ($F(2, 268) = 19.17$, $p < 0.001$, $f^2 = 0.15$).

To evaluate the predictive performance of the linear regression model used, we compared it with the other three machine learning models, namely support vector regression (SVR) (Smola & Schölkopf, 2004), tree regression (Loh, 2011), and XGBoost (Chen & Guestrin, 2016).

The analyses used low-stake assessment and high-stake assessment scores as the two dependent variables and five independent variables: deep and study approaches measured by questionnaire, study approach by clickstream data (dummy variable), study time by questionnaire (dummy variable), and study time by clickstream data. To ensure robust evaluation, the analyses adopted a leave-one-out cross-validation approach (James et al., 2013), where each observation was used once as the test case, while the remaining data was used for training. This process was repeated for all samples in the dataset to assess the models' ability to generalise to unseen data.

The implementation was conducted using the following R packages. The metrics package calculated error metrics. The e1071 package enabled the implementation of SVR (Dimitriadou et al., 2008). The rpart package supported tree

**Table 7** Results of the four machine learning models

| Model | Dependent variable | RMSE | MAE | MAPE |
|---|---|---|---|---|
| Linear regression | Low-stake assessment score | 3.54 | 3.54 | 12.4% |
| SVR | Low-stake assessment score | 3.52 | 3.52 | 12.6% |
| Tree regression | Low-stake assessment score | 3.60 | 3.60 | 12.6% |
| XGBoost | Low-stake assessment score | 3.88 | 3.88 | 13.2% |
| Linear regression | High-stake assessment score | 9.09 | 9.09 | 33.8% |
| SVR | High-stake assessment score | 9.19 | 9.19 | 33.1% |
| Tree regression | High-stake assessment score | 9.42 | 9.42 | 34.0% |
| XGBoost | High-stake assessment score | 9.76 | 9.76 | 35.0% |

regression (Therneau et al., 2015), and the xgboost package facilitated gradient-boosted modeling (Chen et al., 2019). Default parameter settings were used for linear regression and tree regression, while SVR employed a radial basis function kernel with a gamma value of 0.50. For XGBoost, 100 boosting rounds were configured with an objective function to minimize squared error.

Model performance was assessed using three metrics: Root Mean Squared Error (RMSE), which emphasizes larger errors, Mean Absolute Error (MAE), which reflects the average magnitude of prediction errors, and Mean Absolute Percentage Error (MAPE), which measures relative accuracy as a percentage of actual values. The results of the models are summarized in Table 7.

For the low-stake assessment score, linear regression and SVR demonstrated similar performance, with RMSE and MAE values of approximately 3.54 and 3.52 respectively, and MAPE around 12.5%. Tree regression showed slightly higher errors with RMSE of 3.60, while XGBoost had the highest error rates, with RMSE of 3.88 and MAPE of 13.2%. These results indicate that simpler models, such as linear regression, effectively captured the relations in this dataset, while the increased complexity of XGBoost may result in overfitting.

For the high-stake assessment score, linear regression again outperformed the other models with the lowest RMSE of 9.09 and MAPE of 33.8%. SVR closely followed, with an RMSE of 9.19 and a MAPE of 33.1%, indicating its capability to model slightly more complex relationships. However, tree regression and XGBoost struggled with higher error rates, as reflected by their RMSE values of 9.42 and 9.76 respectively. These findings highlight that more complex models may not generalize well in this dataset with limited size or linear characteristics.

To sum up, linear regression appeared to be the most effective model of the four models, outperforming more complex approaches such as XGBoost and tree regression. Its strong performance was likely to be attributed to the dataset's relatively small size and the linear tendency between the predictors and the dependent variables. On the other hand, the added complexity of models like XGBoost did not translate into better results, possibly due to overfitting or insufficient data for such advanced techniques.

## Discussion

The present study investigated the relations between students' study approach, study time, and academic performance on low-stake and high-stake assessments in flipped classrooms using both questionnaire and clickstream data.

### Study time and academic performance by study approach

Both the questionnaire and clickstream data identified two groups of students who approached learning in flipped classrooms distinctively, even though with different features. As shown by clickstream data, approximately 50% of the population sample adopted a study approach focusing more on the three online learning activities prior to the face-to-face learning and teaching. The rest of 50% of the participants adopted the approach with an emphasis on the post-lecture assessment activities. In flipped classrooms, preparation before attending face-to-face learning and teaching is highly important as students are supposed to familiarize themselves with fundamental concepts through the preparation in order to actively interact and deeply engage with learning tasks during the classroom time (Cho et al., 2021; Förster et al., 2022). Thus, the preparation-oriented study approach is considered being more strategic and favourable than the assessment-oriented study approach in flipped classrooms. This was supported by the results that students who adopted the preparation-oriented study approach performed significantly better than their peers who used assessment-oriented study approach on both low-stake and high-stake assessments. Similar results were also reported in a previous study (Han, 2023). Of the four study approaches identified in Han (2023), students who actively participated in the pre-lecture online learning activities obtained the highest marks, whereas those involved with few pre-lecture online learning activities scored the lowest in the course.

Even though the preparation activities are important in flipped classrooms, our study showed that approximately half of the students in this course approached learning by prioritizing the leaning activities related to assessments. Some of the existing studies also found a high proportion of students focused on assessment-related tasks (Fincham et al., 2019; Jovanović et al., 2017). For instance, Jovanović et al. (2017) found that as high as two thirds of their participants in a flipped engineering course approached learning by predominantly undertaking summative assessment tasks. In another study, Fincham et al. (2019) reported that more than 40% of their participants adopted either assessment-oriented study approach or highly assessment-oriented study approach.

One possible reason for a high proportion of our participants using the assessment-oriented study approach could be related to the assessment tasks used in the course and the design of the in-class learning activities. The online post-lecture quizzes, which evaluated student' abilities to applying theories in tackling practical issues, had a similar format as the problem-solving tasks in the low-stake assessment and the mini case studies in the high-stake assessment. The low-stake assessment solely used the problem-solving tasks, and the mini case studies also accounted for

40% of the total scores of the high-stake assessment. Research has suggested that students tend to adjust their learning to the incentives of obtaining higher grades (Rotellar & Cain, 2016). Hence, our participants might consider focusing on the post-lecture quizzes would help them gain better marks in the course.

Moreover, out of the three types of in-person sessions (lectures, tutorials, and labs), the activities in the tutorials were largely structured on practicing problem-solving tasks, which might also lead students to perceive the importance of the post-lecture quizzes. If the design of the assessment tasks and the learning activities in course place more weights on the preparation component (e.g., the pre-lecture activities are graded), the number of students who favour the assessment-oriented study approach may not be as high as in the current study. This also suggests that the results of the study may only be generalisable to other flipped courses which share similar learning and assessment designs.

In terms of the academic performance by study approach, the results of the two types of data were consistent. When students reported more deep but less surface approaches, they obtained significantly higher marks on low-stake and high-stake assessments than those who reported less deep but more surface approaches. These results were consistent with previous studies using questionnaires to measure study approaches in flipped classrooms (Han, 2023).

Furthermore, we found logic and consistent results between the observed study approach and academic performance across the low-stake and high-stake assessments. When students were observed adopting the preparation-oriented approach, they achieved significantly better results on both low-stake and high-stake assessments than those who adopted the assessment-oriented approach. A number of previous studies have also reported that when students adopted a strategic study approach in flipped classrooms, their course marks were higher (Han, 2023; Fincham et al., 2019; Gašević et al., 2017; Jovanović et al., 2017). However, previous studies used either questionnaire or clickstream data to measure study approach, which prevented them from examining the extent to which the relational patterns obtained by the two types of data were consistent. By using the two types of data, our study triangulated the results obtained from the two types of data and demonstrated the logic and consistent relations between the study approach and academic performance across the two types of data.

With regard to the relations between study time and study approach, however, the findings were not consistent across the two types of data. Students' study time by clickstream data showed significant differences between those adopting preparation-oriented and assessment-oriented approaches. Those who used the preparation-oriented approach on average spent more than 1.7 h per week than their peers who employed the assessment-oriented approach. This finding seems to suggest that strategic learners are also diligent learners as they tend to spend more time and effort in learning (Han et al., 2022). However, such pattern was not replicated by using the questionnaire data as we did not find significant differences on the proportions of students who reported studying more or less than 4 h by their reported study approach. One possible reason for the non-significant difference of the self-reported study time could be the insensitivity of the dichotomous item used in the questionnaire.

### Contributions of study approach and time to low-stake and high-stake assessments

Our study showed that the contributions of study approach to academic performance were not consistent across the two types of data, as the study approach measured by the questionnaire was only a significant predictor of students' performance on high-stake assessment. In contrast, the study time, whether being measured by questionnaire or clickstream data, consistently contributed to both low-stake and high-stake assessments. These findings were in line with the results of previous studies which used either clickstream or self-reported data. For instance, using clickstream data to measure students' online study time in a flipped engineering course, Cho and Yoo (2017) found that the more time students spent online, the higher their course marks were. Using self-reported diaries, Kember et al., (1995, 1996) found positive relations between study time recorded in students' diaries and Grade Point Averages (GPAs) among Hong Kong mechanical engineering students.

Kember et al., (1995, 1996) further demonstrated that both study approach and time had an impact on students' GPAs. They found that of students who reported using a deep study approach, those spending little study time were not able to obtain good GPAs. On the other hand, students who spent a long time studying but reported a surface approach did not attain good grades either. These findings were consistent with our results of the significant contributions of both study approach and time to high-stake assessment.

A possible reason for the inconsistent contributions made by the self-reported study approaches to low-stake and high-stake assessments could be that the study approaches measured by the questionnaire were only sensitive to the high-stake assessments, which were more complex in nature than the low-stake assessments. Similar findings were reported in Davidson's (2002) study, which showed that students' reported study approaches only significantly predicted their performance on the complex examination questions but not on simple examination questions.

Gašević et al. (2017) also argue that clickstream data is more sensitive than questionnaire data to detect variations in study approaches in flipped classrooms. This concurred with the results of our study. We found that unlike the questionnaire data, the clickstream data showed nuanced distinctions between different approaches by capturing important features in students' online learning, such as different proportional distributions of students' activities before and after face-to-face learning. This might also offer an explanation as to why the observed study approach was a consistent predictor of students' performance on both low-stake and high-stake assessments in flipped classrooms.

### Pedagogical and methodological implications

The results of the study are useful for improving learning and teaching in flipped classrooms. As our study showed that both observed study approach and time contributed to students' academic performance in flipped classrooms, teachers can use different strategies to improve these two aspects, which may enhance students' learning experiences and outcomes in flipped classrooms (Bamoallem & Altarteer, 2022).

Consistent with the literature in flipped learning, which emphasizes the preparation before the classroom time (Cho et al., 2021; Förster et al., 2022), our studies also showed that the preparation before attending face-to-face learning and teaching is highly important in flipped classrooms, as we found that students who adopted the preparation-oriented study approach achieved better performance in the course. To encourage students to adopt the preparation-oriented approach, at the beginning of the course teachers should explain the principles of flipped classrooms and emphasize the importance of pre-lecture preparations via various online learning activities, especially when the majority of the enrolled students do not have much experience in this type of learning and teaching (Aidoo et al., 2022; Jiang et al., 2022). Moreover, aligning the learning activities with assessment tasks (Biggs et al., 2022) may also help students focus more on the preparation before the in-class sessions in flipped learning. For instance, teachers may give some weights for the preparation activities in students' course marks, and/or design some in-class learning activities centered on preparation (Gross et al., 2015). For instance, 5–10% of course marks can be devoted to students' timely completion (before the lectures) of pre-lecture videos and pre-lecture quizzes. Or students are invited to raise the difficult points or challenging tasks in the first five minutes of the lectures or tutorials. To increase students' online participation time in flipped classrooms, teachers may improve social presence and establish online learning communities via discussion boards or instant messaging chat groups to foster students' online engagement (Divjak et al., 2022; Jia et al., 2021). Gamification elements can also be embedded in various online learning activities in order to stimulate students' learning motivation and interests to study online (Ekici, 2021).

The study also provides some important methodological implications. An important one was the advantages of combining questionnaire and clickstream data to understand contemporary students' experiences of learning, such as their study approach and study time (Ober et al., 2021; Ye & Pennisi, 2022). The use of multiple data sources not only provides complementary information and richer description of patterns of students' learning than using only a single data source, but also strengthens the analytic power and enables the findings from two types of data to be triangulated.

## Conclusion

The study used both questionnaire and clickstream data to measure study approach and time, and examined their relations with students' academic performance on low-stake and high-stake assessments in flipped classroom learning. One contribution made by the study was how the study approaches were identified using the clickstream data. Our strategy separated study time from types of learning activities, which were not clearly distinguished in previous research using clickstream data to classify study approaches (Fincham et al., 2019; Gašević et al., 2017; Jovanović et al., 2017). Our approach allowed a more nuanced examination of whether differences in students' academic performance were influenced by the types of learning activities they engaged with or duration of learning they devoted to. We found that both study approach and study time measured by clickstream data consistently contributed to low-stake and high-stake assessments. This finding clarified previous inconsistent results of self-reported studies on the relations between study approach, time, and academic performance (Ackerman & Gross, 2003; Kember et al., 1995, 1996; Krohn & O' Connor, 2005; Nonis & Hudson, 2010; Valadas et al., 2017), suggesting that both being strategic and spending sufficient time in learning are important to achieve good learning outcomes.

Despite these interesting findings, the limitations of the study are noted and should be addressed in the future research. First, neither the questionnaire nor clickstream data used in this study reflected changes of students' study approach and study time in the course. Future research may consider measuring students' study approach and time multiple times during the semester to capture possible fluctuations of these variables. The longitudinal design will help reveal dynamic relations between study approach, time, and academic performance. Furthermore, our study only used the study approach and study time as predictors to explain academic performance. Future research should include other variables in the experiences of students' learning as predictors and use more complex machine learning models to identify their relations with academic performance. Moreover, the design of the assessment tasks and the learning activities in the course (e.g., the online learning activities were not graded, the online post-lecture quizzes largely resembled in-class learning activities) might affect students' decision of the study approaches they chose. Future studies can explicitly examine the influence of different types of assessments and learning activities on students' choice of study approach in flipped classroom learning.

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## Declarations

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