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Navigating the Terrain:

Emerging Frontiers in Learning Spaces, Pedagogies, and Technologies

Combining self-reported and clickstream data to understand university students' learning experiences and outcomes in flipped classrooms

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This study examined the relationships between students' self-reported perceptions of learning environment, students' course marks, learning strategy and online study duration measured by clickstream data in an undergraduate flipped classroom course amongst a cohort of Australian first-year university students. The clickstream data identified two groups of students using two distinct learning strategies focusing either on completing the assessments in the course or on the learning activities preparing for the face-to-face learning. Students' perceptions of learning environment were measured by a self-reported questionnaire. Using cluster analysis, students were grouped as either having positive or negative perceptions. Of the students who adopted a learning strategy focusing on assessments, a significantly higher proportion of them hold negative perceptions of learning environment. In contrast, amongst students who used a learning strategy focusing on completing the preparation activities, a significantly lower proportion of them had negative perceptions. Furthermore, students who hold negative perceptions were also found to study less hours than their classmates who had positive perceptions. The multiple regression analyses showed that self-reported perceptions could explain only 4.8% of variance in students' course marks, whereas learning strategy and online study duration measured by clickstream data predicted around 17.2% of variance in students' course marks.

Keywords: learning environment perceptions, learning strategies, online study duration, clickstream data, flipped classrooms

Introduction

Over the past few decades, higher education has experienced significant changes, including the redesign of traditional lecture-based courses through the implementation of flipped classrooms (Cho et al., 2021; McLean & Attardi, 2023). Flipped classrooms, a specific form of blended learning, primarily use in-class time to deepen students' understanding of the course material, clarify key concepts, and contextualize knowledge through interactive activities like group work or team projects (Algarni & Karanicolas, 2023). These classrooms create complex learning experiences, as students must navigate both in-person and online environments. In addition to interacting with instructors and peers, students also spend considerable time engaging with digital learning tools such as blogs, wikis, discussion forums, podcasts, and videos (Fenwick, 2015; Ellis, 2022).

Given the complexity of this learning environment, it is crucial to understand how students learn—such as the learning strategies they employ, the amount of time and effort they dedicate, and their perceptions of learning environment—to improve their experiences in flipped classrooms. Research has shown that flipped classrooms do not always lead to high student satisfaction (Turan, 2023) or favorable course outcomes (Cevikbas & Kaiser, 2023; Shen & Chang, 2023). While some studies in higher education have explored the relationships between students' learning strategies, study duration, learning environment perceptions, and course outcomes in traditional face-to-face settings (Guo et al., 2022), these relationships have rarely been studied in the context of flipped classrooms. Therefore, this study aims to explore these relationships in flipped classrooms to develop targeted strategies that can enhance students' learning experiences.

Additionally, much of the previous research has relied on self-reported data to measure students' learning strategies (e.g., Asikainen et al., 2023) and study duration (e.g., Fostervold et al., 2022; Valadas et al., 2017). Self-reported data are often criticised for their subjectivity, susceptibility to careless responses, and inability to fully capture the complexity of students' learning behaviors (Hitt et al., 2018; Matcha et al., 2020; Zhou & Winne, 2012).

To overcome these limitations, researchers have increasingly turned to clickstream data, which are digital traces extracted from learning management systems (LMS) used in technology-enhanced learning. Clickstream data offer a more objective view of students' online learning activities and can capture the dynamic and nuanced ways in which students engage with the material (Liao & Hu, 2023; Richardson, 2017). However, relying solely on clickstream data without considering meaningful context or theoretical frameworks may lead to misleading conclusions (Han, 2022; Reimann et al., 2014).

In recent years, researchers have begun combining self-reported data with clickstream data to gain deeper insights into students' learning experiences in contemporary university settings (e.g., Gašević et al., 2017; Ye & Pennisi, 2022). This combined approach offers complementary perspectives and allows for triangulation of findings (Han et al., 2022). Therefore, this study will integrate both self-reported and clickstream data to better understand students' learning experiences and outcomes in flipped classrooms.

Literature review

Learning strategies and study duration measured by clickstream data

The recent growth of the emerging field of learning analytics has led to a surge in studies that gather rich and detailed clickstream data, tracking students' online learning as they interact with various digital resources and activities. Clickstream data has been applied in multiple areas of higher education, such as guiding students in their career choices (e.g., Kew & Tasir, 2022), improving retention by identifying at-risk students early (e.g., Li et al., 2022), offering personalised feedback (e.g., Zheng et al., 2022), supporting collaborative learning (e.g., Kaliisa et al., 2022), monitoring students' emotional engagement (e.g., Joksimović et al., 2022), and uncovering patterns of learning strategies (e.g., Saavedra et al., 2022).

Earlier research in learning analytics primarily relied on clickstream data measuring total frequency or duration of students' online learning activities to describe their learning behaviour. More recent studies, however, have advanced by collecting more detailed descriptors of students' online activities with timestamps. These data are then analysed using data mining techniques, such as Hidden Markov Models, agglomerative sequence clustering, and process mining algorithms, to identify different learning strategies (e.g., Jovanović et al., 2017; Matcha et al., 2019). Several studies have employed a two-step approach to analyse students online online learning sequences (e.g., Fincham et al., 2019; Matcha et al., 2020). The first step identifies common learning behaviours shared across all students using a Hidden Markov Model, which groups sequences of activities into a limited number of types based on similar patterns. The second step applies agglomerative sequence clustering to categorise students into sub-groups based on the type and frequency of online learning sequences identified in the first step. Each sub-group exhibits distinct learning strategies, differentiated by both the type and number of online learning sequences they employ.

For example, using this two-step method, Jovanović et al. (2017) identified five distinct online learning strategies among 290 computer science undergraduates:

- "Intensive strategy": Characterised by a broad range of online learning activities and the highest number of online learning sequences.

- "Strategic strategy": Focused on summative and formative assessment tasks, generating the second-highest number of online learning sequences.
- "Highly strategic strategy": Emphasised summative assessment tasks and reading activities, with the third-highest number of online learning sequences.
- "Selective strategy": Primarily concentrated on summative assessment tasks with limited reading activities, resulting in the second-lowest number of online learning sequences.
- "Highly selective strategy": Engaged solely with summative assessment tasks, producing the fewest online learning sequences.

Jovanović et al. (2017) also examined the relationship between students' learning strategies and their students' course marks. Their findings revealed that students who employed the "intensive," "strategic," and "highly strategic" strategies achieved higher marks on both mid-term and final exams compared to those who used the "selective" and "highly selective" strategies.

However, Jovanović et al.'s (2017) study, as well as similar studies using this method (e.g., Fincham et al., 2019; Matcha et al., 2020), had a key limitation: both the type and the number of learning sequences were used together in the cluster analysis. Since the number of online learning sequences is closely linked to online study duration (though not an exact measure of it), this approach mixed learning strategies with online study duration. Consequently, it remained unclear whether the differences in students' course marks between student clusters were due to learning strategies, online study duration, or a combination of both.

To overcome this limitation, Han et al. (2022) used the proportions of different types of online learning activities to define students' learning strategies. This study identified two main learning strategies: a learning strategy prioritising learning the content in the course and a learning strategy prioritising completing the assessment activities in the course. The study also examined the relationship between students' learning strategies and their online learning sessions and found that students who followed the learning strategy prioritising learning the content not only had more online learning sessions but also achieved better students' course marks compared to those who adopted the learning strategy prioritising completing the assessment activities. The study further identified a logical relationship between learning strategies and students' perceptions of learning environment. Specifically, students with more positive perceptions were more likely to adopt the learning strategy prioritising learning the content, while those with poorer perceptions tended to adopt the learning strategy prioritising completing the assessment activities. Despite the improvements in methodology, this study faced a major limitation. The number of learning sessions was not an accurate measurement of online study duration. The present research will address this limitation by using the actual duration of online learning.

The present research

The present research aimed to understand students' learning experiences and outcomes in flipped classrooms by combining self-reported data (i.e., perceptions of learning environment) and clickstream data (i.e., learning strategies and online study duration). It sought to answer two research questions:

1. To what extent do students' learning strategies, online study duration, and students' course marks differ by their perceptions of learning environment in flipped classrooms?

2. How do students' perceptions of learning environment, learning strategies, and online study duration, contribute to students' students' course marks in flipped classrooms?

Method

Participants and recruitment

The study involved a cohort of first-year students who were recruited from a large, research-intensive university in Australia. These students were enrolled in a course on computer system introduction. The recruitment process adhered strictly to the ethical guidelines set by the researcher's institution. One week prior to data collection, each student in the course received a Participant Information Statement and a Participant Consent Form, which outlined that participation in the study was entirely voluntary. Only students signed a Participant Consent Form were allowed to participate in the study.

The flipped classroom course

The face-to-face part of the flipped classroom course included a weekly lecture, tutorial, and laboratory practice. The lectures focused on explaining challenging concepts and providing examples of how these concepts could be applied to real problems. In the tutorials, students had the opportunity to undertake learning activities that required them to solve real problems. The laboratory practice was designed to give students practical experience in computer system design.

The online learning part of the flipped classroom course required mandatory participation both before and after each week's lecture, tutorial, and laboratory. These activities served as preparation for and a review of the content covered in the face-to-face sessions. The online learning consisted of five types of activities, all hosted on the LMS: online readings, online videos, two types of online quizzes both before and after the lectures, and a dashboard. Students were required to complete the online readings, videos, and the before-lecture quizzes prior to take part in the face-to-face sessions.

Data and instruments

Self-reported data

Perceptions of learning environment were collected through two self-reported scales, each with 5-point ratings (1=strongly disagree, 5=strongly agree). These scales have been utilised and validated in prior research to explore students' learning experiences in blended and flipped classroom settings (Ellis & Bliuc, 2019; Han et al., 2020). The *Perceptions of the Integrated Learning Environment* scale had seven items and evaluated students' views on the integration of online and in-person learning components. The *Perceptions of Online Contributions* scale had six items and measured how valuable students found online contributions to the course was.

Clickstream data

The learning management system (LMS) collected data including students' identification numbers and time-stamped records of online activities. This data included the type of activities, along with the date and time (down to seconds). The online activities were categorized into five types: pre-lecture readings, pre-lecture videos, pre-lecture quizzes, post-lecture quizzes, and dashboard interactions.

The duration of all the time-stamped online learning activities was aggregated to derive the total online study time. The average weekly online study time was then calculated by dividing the total online study time by 13 weeks.

Data analysis

To address the first research question—how learning strategies, online study duration, and students' course marks differ based on students' perceptions of learning environment, the first step in the data analysis was to identify learning strategies using the clickstream data. A hierarchical cluster analysis was performed using the proportions of the frequencies of the five types of online learning activities. Following identification of the learning strategies, the second step was to group students according to their levels of perceptions of learning environment by using the self-reported questionnaire data. This was done by conducting a hierarchical cluster analysis using the mean scores of the two perception scales (*perceptions of the integrated learning environment* scale and *perceptions of online contributions* scale). Then the clusters varied by students' perceptions of learning environment were used as a between-subjects variable to examine how students' learning strategies, study duration, and their course marks might differ using either chi-square tests one-way ANOVAs. The chi-square tests were used to compare the proportions of students adopting different learning strategies, whereas the one-way ANOVAs were used to compare the mean values of the online study duration and students' course marks.

To address the second research question—how perceptions of learning environment, learning strategies, and online study duration contribute to students' course marks—we conducted two multiple regression analyses with students' course marks as the dependent variable. The first multiple regression analysis used the mean scores of *perceptions of the integrated learning environment* scale and *perceptions of online contributions* scale as the two independent variables. The second multiple regression analysis expanded on the first model by adding the clickstream data of the learning strategies and online study duration as two additional independent variables.

Results

Students' learning strategies

Table 1
Identified Two Learning strategies

	Learning strategy focusing on assessments		Learning strategy focusing on preparation		F	p	η^2
	M	SD	M	SD			
Online readings	122.622	59.981	240.54	94.681	149.751	.000	.358
Online videos	162.000	144.073	291.96	175.732	44.283	.000	.141
Online quizzes before the lectures	405.022	733.979	777.494	766.177	20.918	.000	.072
Online quizzes after the lectures	554.400	214.731	627.66	208.095	8.135	.005	.029
Dashboard	32.163	31.205	51.90	46.164	16.984	.000	.059

The hierarchical cluster analysis identified two groups of the students adopting distinct learning strategies. The results of one-way ANOVAs in Table 1 shows that the two groups of students differed significantly on the frequencies of all the five online learning activities: online readings (F (1, 269) = 149.751, p < .001, η^2 = .358), online videos (F (1, 269) = 44.284, p < .001, η^2 = .141), online quizzes before the lectures (F (1, 269) = 20.918, p < .001, η^2 = .072), online quizzes after the lectures (F (1, 269) = 8.135, p< .010, η^2 = .029), and dashboard (F (1, 269) =16.984, p < .001, η^2 = .059).

In terms of the frequencies, group 2 students had higher frequencies of all the five online learning activities than group 1 students. In terms of the proportions, group 2 students had higher proportions of online readings, online videos, and online quizzes before the lectures than group 1 students. But group1 students had a higher proportion of online quizzes after the lectures. Proportionally speaking, group 1 students adopted a learning strategy focusing more on completing the assessment tasks in the course; whereas group 2 students used a learning strategy emphasising more on the completing preparation activities before the face-to-face lectures in the course.

Results for research question 1 – students' learning strategies, online study duration, and students' course marks by perceptions of learning environment

The results of learning strategies, online study duration, and students' course marks between students holding positive and negative perceptions of learning environment are presented in Table 2. The results of the chi-square test showed that two groups of students differed significantly on the learning strategies they adopted (χ^2 (1) = 5.953, *p* = .015, ϕ = .148). Specifically, we found that of the students who adopted a learning strategy focusing on assessments, a significantly higher proportion of them hold negative perceptions the flipped classroom learning environment (n = 113, 53.8%). In contrast, amongst students who used a learning strategy focusing on completing the preparation activities, a significantly lower proportion of them had negative perceptions (n = 22, 36.1%). Furthermore, the results of one-way ANOVAs found that the two groups of students also differed significantly in terms of how long spent to study online in this flipped classroom course (F (1, 269) = 25.265, $p < .001$, $\eta^2 = .089$). Students who reported negative perceptions were found to study less hours than their classmates who reported positive perceptions. However, the two groups of students did not differ on their course marks (F (1, 269) = 2.685, $p = .102$, $\eta^2 = .010$).

Table 2
Students' Learning strategies, Online Study Duration, and Students' Course Marks by Perceptions of Learning Environment

	Negative perceptions		Positive perceptions				
Learning strategies	n	%	n	%	χ^2	*p*	ϕ
Learning strategy focusing on assessments	113	53.8%	97	46.2%	5.953	**.015**	.148
Learning strategy focusing on preparation	22	36.1%	39	63.9%	5.953	**.015**	.148
	M	*SD*	*M*	*SD*	*F*	*p*	η^2
Online study duration	3.617	1.449	4.767	1.842	25.265	**.000**	.089
	M	*SD*	*M*	*SD*	*F*	*p*	η^2
Students' course marks	66.315	14.304	69.659	13.029	2.685	.102	.010

Results for research question 2 – contributions of perceptions of learning environment, learning strategies, and online study duration to students' course marks

Table 3
Results of Multiple Regression Analyses

Variables	B	SE	B	T	Adjusted R^2	P	F^2
Model 1					.048	**.000**	.050
Perceptions of integration	5.217	1.321	.262	3.949		**.001**	
Perceptions of online contributions	-1.725	1.016	-.113	-1.698		.091	
Model 2					.220	**.000**	.282
Perceptions of integration	3.513	1.273	.172	2.759		**.006**	
Perceptions of online contributions	-2.995	0.940	-.197	-3.188		**.002**	
Learning strategy focusing on preparation	7.709	1.818	.277	4.241		**.000**	
Online study duration	1.935	0.568	.225	3.406		**.000**	

The results of the multiple regression analyses are displayed in Table 3. Model one reveals that of the two perceptions of learning environment scales, only perceptions of integration between face-to-face and online learning ($\beta = .262$, $p < .001$) significantly and positively predicted students' students' course marks: F (2, 268) = 7.800, $p < .001$, $f^2 = .050$; accounting for 4.8% of the variance in the students' course marks. In Model two, all the four independent variables (Perceptions of integration between face-to-face and online learning ($\beta = .172$, $p < .010$), perceptions of online contributions ($\beta = -.197$, $p < .010$), learning strategies ($\beta = .277$, $p < .001$) and online study duration ($\beta = .225$, $p < .001$) were significant predictors of students' course marks: F (4, 266) =

19.356, $p < .001$, $f^2 = .282$. Altogether the four variables explained about 22% of the variance in students' course marks. While the two self-reported variables accounted made small contributions to students' course marks, the two clickstream variables made much substantial contributions, accounting for approximately 17.2% of the variance in students' course marks.

Discussion

In general, the results of our study regarding the relations between students' learning strategies, students' course marks, and perceptions of learning environment were consistent with previous studies using self-reported questionnaire to measure students' learning strategies (e.g., Ellis & Bliuc, 2019; Guo, 2018). However, our study extended previous research as we examined possible differences of students' study duration by their perceptions of learning environment. We found that students holding positive perceptions of flipped classroom learning environment had longer study duration online. Viewed together, these results seemed to suggest that students when students perceived the face-to-face and the online part of the learning environment were well integrated and when they viewed the online contributions were important in their learning in the flipped classroom courses, they were not only more strategic in terms of learning strategies they selected, but were also more committed to learning and were willing to devote more time. At the same time, students with positive perceptions also obtained higher course marks in flipped classroom learning.

Furthermore, our study showed that the contributions of both learning strategies and online study duration to students' course marks were significant. These findings were in line with the results of Cho and Yoo (2017), who used clickstream data to measure online study duration and found that the more time students spent on online learning, the better learning outcomes they achieved. Existing research which examined relationships between self-reported study duration and students' learning outcomes produced conflicting results. A closer examination of these studies found that most of these studies had students from diverse academic disciplines (e.g., Nonis & Hudson, 2010; Valadas et al., 2017). One possible reason could be that there might be disciplinary variations concerning the relationships between study duration and students' course marks.

Our results that the significant contributions from both learning strategies and study duration corroborated the results by Kember et al. (1995). In this study, Kember et al. used questionnaire to measure students' learning strategies and also asked students to use diaries to record their study duration. Theu used students Grade Point Averages (GPAs) to represent their learning outcomes. The results showed that both learning strategies and study duration were significantly and positively related to students' GPAs. They further showed that even when students reported using a deep learning strategy but if they spent little time on studying, they could not achieve good GPAs. Likewise, even when students spent longer duration to study but if they adopted a surface learning strategy, their GPAs were also low. While the research context in Kember et al. was, Our study not only extended Kember et al.'s investigation from the traditional classroom learning to the flipped classroom learning, we also used a more objective type of data—the clickstream data to measure students' learning strategies and study duration.

Limitations of the study and future research

Despite some interesting findings, the limitations of the study should be noted and may be addressed in the future research. First, the study outcomes might be influenced by the possibility of presenting the Hawthorne effect (Sedgwick & Greenwood, 2015), as the participants had known that their interactions with online learning would be recorded by the LMS for the research purpose before the study through reading the statements in the Participant Information Statement and the Consent Form. Students might have logged into the LMS more frequently to show that they actively participated in the online learning of this course. Furthermore, neither the self-reported nor clickstream data used in this study reflected changes of students' learning strategies and study time in the course. Future research may consider measuring students' learning strategies and time multiple times during the semester in order to capture possible fluctuations and changes of learning strategies and time. The longitudinal type of design will help reveal dynamic relations between perceptions of learning environment, students' learning strategies, study duration, and their course marks.

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