The Impact of Different Teaching Methods, Moodle Access Frequency, and (Mis)matching of Learning Strategies towards Students' Academic Success in Higher Education

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Abstract. This study analyses the impact of learning modes, frequency, and (mis)match of preferred learning strategies on two cohorts of Computer Science students. Using VARK learning strategies, Moodle access data, and grades across learning environments, our finding shows students perform best in offline settings (43.79% achieving first-class grades versus 33.64% in blended and 29.25% in online). Frequent Moodle access correlates with higher performance across all modes. Surprisingly, students with mismatched learning strategies (over 70%) outperformed those with matched strategies. This unexpected result likely stems from the disconnect between lecture-based teaching methods and CS assessments. While lectures align with visual and auditory styles, CS coursework demands kinaesthetic approaches through programming and problem-solving, suggesting adaptability may benefit CS students more than strict adherence to preferred learning styles.

Keywords: Offline, online, and blended learning · VARK learning preferences/strategies · (mis)match of learning strategies

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1 Introduction

The availability of learning materials, learning modes, and students' learning preferences are commonly chosen topics when discussing one's learning process. This section will introduce and compare the different modes of learning, which include offline, online, and blended learning implemented in Higher Education. Next, it discusses how the COVID-19 pandemic has affected education around the world – especially students' learning outcomes, i.e., grades. The second subsection examines the use of Moodle as a Learning Management System (LMS) in students' university lives and how it is affected by different learning modes. Finally, VARK's learning preferences and strategies and how research has indicated that these factors affect students' learning performance are discussed.

1.1 Comparing Offline, Online, and Blended Learning

Traditional or offline learning occurs when students and teachers meet in the same physical space, with instructors leading activities and monitoring behaviour [12]. In contrast, online learning involves students and lecturers interacting entirely through digital platforms, with students demonstrating understanding through various assessments [12]. According to Means et al. [20], online learning can be either "purely online" or "blended" - the latter combining online and traditional teaching methods.

The COVID-19 pandemic forced a dramatic shift from traditional to online learning, accelerating the adoption of digital platforms like Coursera [4]. This transition revealed diverse student experiences and varying performance outcomes across learning modes. Although online learning offers advantages such as flexibility and self-paced study, Huang's [11] survey exposed significant challenges, with 98% of students preferring traditional classrooms due to limited lab experience and teacher interaction. Blended learning emerged as a potential compromise, but its effectiveness remains contested. Some research shows promise - the University of Iowa reported higher achievement in blended versus online learning (95% vs 81%) [3], whilst other researches [7, 13] found no significant impact.

Given these mixed results and the unprecedented nature of the pandemic-driven educational shift, the comparative impact of offline, online, and blended learning requires further investigation. This paper addresses this gap by analysing how these three methods affected student grades.

1.2 The Use of Moodle as Digital Technology

Online learning platforms have become integral to higher education due to their simplicity and practicality [10]. This integration has been facilitated by the growth of digital technologies, particularly Learning Management Systems (LMSs). Among these, Modular Object Oriented Dynamic Learning Environment (Moodle) has emerged as one of the most widely used platforms [10], offering customisable features for tracking student progress, managing assignments, and delivering content. Its global reach now spans 237 countries with over 147,000 sites and 436 million users [21]. The University of Nottingham Ningbo also utilises Moodle as its primary LMS, providing students and instructors with a structured digital learning environment.

While LMSs are widely used in higher education, research into their impact on academic performance remains limited [16, 10, 30]. Li & Tsai [16] found that increased time spent accessing in-class learning materials had no impact on performance but students with infrequent access scored lower academically. Similarly, Wei, Peng, & Chou's [30] study found that engagement metrics (logins, postings, and material access) positively affected academic performance.

1.3 The (Mis)matching of Students' Learning Strategies

Learning preference, or learning style, refers to how learners perceive, interact with, and respond to their learning environment. This concept has been widely discussed in education, leading to various learning style models and instructional approaches [23]. The VARK model, introduced by Fleming and Mills [9], categorises learners into four modalities: Visual (V) learners prefer diagrams and flowcharts over text; Aural (A) learners learn best through listening and speaking; Read/Write (R) learners favour textual information; and Kinesthetic (K) learners benefit most from hands-on experiences. It was widely spread and used in educational research [8, 22, 24] and aligned well with our study of different learning environments.

Learning strategy, distinct from preferences, refers to specific activities students use in practice. Whilst students are encouraged to adopt strategies aligned with their preferences, such as specific note-taking methods and review techniques, their actual strategies may differ [9]. The 2018 VARK Questionnaire [27] assesses learning strategies through 40 questions, revealing that K strategies are most prevalent (79%), followed by A (63%), R (60%), and V (21%). Notably, A and R strategies show higher usage rates compared to stated preferences.

Course materials across different degrees influence learning strategies, often creating mismatches between reported and actual strategies. While some studies suggest a relationship between VARK preference and academic performance [2], most research indicates no significant correlation [26]. Although studies have examined matching teaching and learning styles [2], none have directly investigated how matching or mismatching learning strategies affects performance.

1.4 Present Study (Research Question)

In this research, our objective is to answer the following questions:
1. How do increases in blended learning usage, caused by COVID-19 pandemic affect, students' academic performance, i.e., grades?
2. How does increases in students' frequency of accessing Moodle affect their academic performance?

3. How does a match between students' learning strategies in VARK Strategies questionnaire and in practice affect students' academic performance?

2 Method

2.1 Procedure

The present study included two cohorts of university students majoring in Computer Science. Students were asked to fill out two questionnaires, both adopted from the VARK official website[27] supported by Leite et al. [15].

For the first cohort, the questionnaires were distributed during the offline teaching delivery, while for the second cohort, the questionnaires were distributed during blended teaching. The first questionnaire was the VARK questionnaire, consisting of 16 questions about learning preferences. The other questionnaire was about the learning strategies, which is based on the VARK Strategies Questionnaire. Participation was voluntary with consent obtained from the students themselves.

In this project, learning records were extracted from the university system across three time periods: pre-pandemic (offline learning), during the COVID-19 outbreak (online learning), and during the transition phase when students returned to campus with a mix of in-person and online instruction (blended learning).

2.2 Sampling

Data collection was carried out at the University of Nottingham Ningbo China, involving Year 2 and Year 3 students studying for computer science degrees. The participation rates for both cohorts are 93% and 42% respectively, in which the Year 2 cohort covered 148 students, the Year 3 cohort covered 69 students – making up a total of 217 students participating in this research project. We conducted data collection for all students in both cohorts.

Additionally, we also used Moodle log records data which consists of user and system log records that occur on the Moodle platform. In total, for both cohorts combined, we had eight modules – five modules in the first cohort and three modules in the second cohort shown in Table 1. For the first cohort, two of the modules were held offline, two of the modules were held online, and the last one was held during blended learning. As for the second cohort, all three modules were held during blended learning.

When looking at the results of the VARK learning strategies, we found that in both cohorts (see Fig. 1), kinesthetic is the most common learning style (at 45.33% for the first student cohort and at 40.19% for the second student cohort), followed by aural. Visual takes the third highest portion in the first cohort whilst reading takes the third highest portion in the second cohort. From the 2018 VARK Statistics website [28], we can see that kinesthetic also ranks the first, but followed by reading, aural and visual. Therefore, when comparing our sample

Table 1. Modules teaching semester and delivery of Cohort 1 and 2.

Cohort	Module Name	Teaching Semester	Mode of Teaching Delivery
	Offline Module 1	Autumn Semester 2019	Offline
	Offline Module 2	Autumn Semester 2019	Online
Cohort 1	Online Module 1	Spring Semester 2020	Online
	Online Module 2	Spring Semester 2020	Online
	Blended Module 1	Autumn Semester 2020	Blended
	Module 1	Autumn Semester 2020	Blended
Cohort 2	Module 2	Autumn Semester 2020	Blended
	Module 3	Autumn Semester 2020	Blended

statistics to the statistics shown on the VARK website, we found that only the kinesthetic result in our sample is in line with the statistics shown on the VARK website.

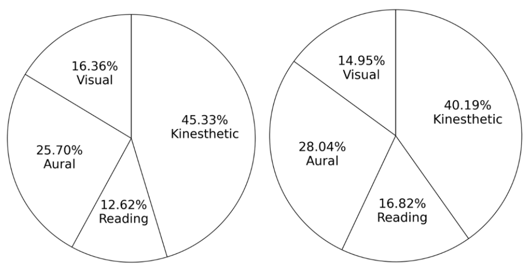

Fig. 1. Learning strategy sample results: cohort 1 (left) and cohort 2 (right)

2.3 Data Preprocessing

For each cohort, aside from the data obtained from the questionnaire results, Moodle logs, and students' individual grades data were used and combined to answer our research questions. The flow chart of the data preprocessing can be found in Fig. 2.

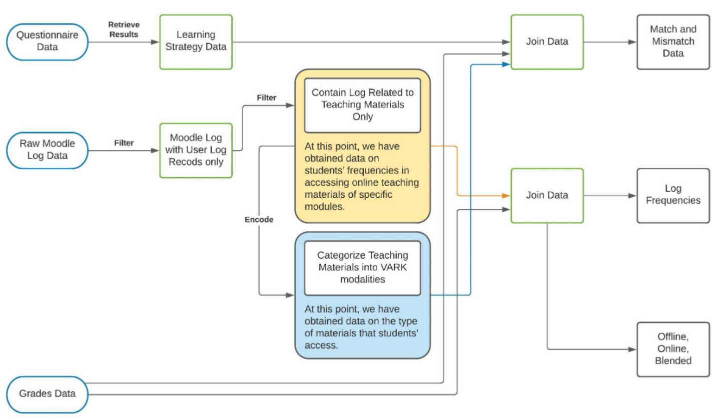

Fig. 2. Flow chart of the data pre-processing that were performed in our research project to answer our research questions.

2.4 Feature Extraction – VARK Modalities and Learning Strategies

Using the questionnaire results, we extracted the students' respective learning strategies using VARK modalities by looking at their responses to questions related to the VARK learning strategies. For the students with multimodal learning strategies, we categorised the students into multiple categories of VARK single modalities – obtaining the sample results shown in Fig. 1.

2.5 Feature Extraction – Moodle Logs

Only Moodle's user log records are used from Moodle logs. The user log records show students' activities on their Moodle, such as accessing teaching materials, posting comments in discussion forums, or checking their grades. We then filtered the log records such that we are left with only records regarding the access of teaching materials – thus, gaining insights on students' frequencies in accessing online teaching materials of specific modules. For future reference, we will refer to this data as the "cleaned Moodle logs" data.

From the cleaned Moodle logs, we categorised the teaching materials into VARK modalities. For example, lecture slides were encoded into type VR, additional reading materials were encoded into type R, and exercise questions into type RK. Finally, the log records were summed up with respect to each student and the most accessed teaching material type was also extracted. For future reference, we will refer to this data as the "in practice learning strategies" data.

2.6 Feature Extraction – Students' Grades Data

Students' grades data were combined with the learning strategies data (from the questionnaire) and the in practice learning strategies data to answer our research question on the (mis)matching of learning strategies (based on the questionnaire results) to the learning strategies that were used in practice.

Students' grades data were also joined with the cleaned Moodle logs data to answer our research questions on the effect of accessing Moodle frequently (based on log records) and how students performed during different teaching modes.

3 Results

3.1 How Students Perform in Offline, Online, and Blended Learning

To compare students' performance in offline, online, and blended learning, we grouped the students based on their degree classifications (see Table 2) and grouped the modules with respect to their teaching modes. An inspection of the distribution of marks suggests there is no significant difference between cohorts, but a high likelihood (t-test p value of 0.006) of online and offline grades being from different distributions.

The grades data were then discretised to find out the relationship between offline, online, and blended learning. Using the data from the first cohort, we

Table 2. Degree Classifications in the British undergraduate degree classifications format.

Numerical average	Degree classification
70%+	I (First Class Honours)
60% - 69%	II-i (Second Class Honours - Upper division)
50% - 59%	II-ii (Second Class Honours - Lower division)
40% - 49%	III (Third Class Honours)
0% - 39%	Fail

categorised students' grades using the degree classifications shown in Table 2 and plotted them in bar graphs to find trends in students' performance during offline, online, and blended learning.

Table 3. Cohort 1 – percentage of students per degree classifications for all modules.

Module	Fail	Third Class	Second Class (Lower Division)	Second Class (Upper Division)	First Class
Online Module 01	10.06	12.58	18.87	24.53	33.96
Online Module 02	16.98	15.72	21.38	21.38	24.53
Offline Module 01	14.29	14.29	14.29	22.98	34.16
Offline Module 02	9.94	4.97	13.66	18.01	53.42
Blended Module 01	8.41	11.21	13.08	33.64	33.64

Based on results as shown in Table 3 and Table 4, we found that the percentage of students achieving a first class grade via offline learning is the highest (at 43.79%) when compared to blended learning (at 33.64%) and online learning (at 29.25%) respectively. Additionally, the percentage of students that fall into the fail, third class, and second class categories (both lower division and upper division) are generally higher during online learning than during offline learning.

Table 4. Cohort 2 – percentage of students per degree classifications for all modes of teaching delivery.

Mode of Teaching	Fail	Third Class	Second Class (Lower Division)	Second Class (Upper Division)	First Class
Offline	12.11	9.63	13.98	20.50	43.79
Online	13.52	14.15	20.13	22.96	29.25
Blended	8.41	11.21	13.08	33.64	33.64

3.2 The Effect of Frequent Moodle Log Access to Students' Performances

Using the data from the first and second cohort, we grouped the students based on their frequency in accessing online teaching materials by percentile rankings. There are 10 groups in total – ranging from 1-100th percentile, in which each group consists of 10 percentile rankings (e.g., 1-10, 11-20).

Based on our findings as shown in Table 5 and 6, we found that in both cohorts, students are more likely to perform better when they have a higher log records – which possibly indicates more learning activities.

Table 5. Cohort 1 – Average Grades per Log Percentiles for All Modules

Percentile	Online 1	Offline 1	Offline 2	Online 2	Blended 1
10th	48.07	56.20	49.80	62.73	54.08
20th	59.73	66.20	55.00	64.00	60.50
30th	63.07	57.73	53.07	62.83	63.60
40th	63.86	61.60	66.13	74.80	63.86
50th	61.87	60.93	60.31	64.56	66.00
60th	69.93	55.07	57.54	74.23	57.38
70th	68.50	63.60	62.39	70.07	61.58
80th	67.93	67.79	65.55	71.47	64.38
90th	61.40	66.53	59.31	73.59	67.00
100th	68.07	69.07	60.57	66.54	70.90

Table 6. Cohort 2 – Average Grades per Log Percentiles for All Modules

Percentiles	Module 01	Module 02	Module 03
10th	57.86	50.88	67.29
20th	59.71	71.50	66.43
30th	63.00	62.00	72.50
40th	56.43	69.75	78.00
50th	69.86	82.71	65.50
60th	72.29	65.80	71.00
70th	77.00	81.43	74.86
80th	69.63	69.57	66.00
90th	75.83	69.43	75.14
100th	68.29	71.00	64.71

3.3 The Effect of (Mis)matching of Students' Learning Strategies

Using the data from the first and second cohort, we grouped the students based on their (mis)matching of most accessed teaching material type to their learning strategy type. The matching occurs when students have their learning strategy type to be equivalent to their most accessed material type and vice versa.

Our findings revealed that there is a significant difference in terms of the student's proportion in the "match" and "mismatch" category. We found that generally, there are over 70% of students that fall into the mismatch category. Additionally, in terms of average grades, we found that generally, students who fall under the mismatch category perform better than those who have a match in their learning strategies and in practice learning strategies.

4 Discussion

4.1 Students' Performance During Offline, Online, and Blended Learning

Results indicate that offline learning yields better student performance compared to online and blended approaches. This trend supports studies by Artino Jr and Lee [6, 14], which emphasised the importance of instructional interaction and teachers' instant feedback in student satisfaction. Artino Jr further documented that online training caused significant student boredom and frustration [5]. According to Lizzio, Wilson, & Simons [18], higher student satisfaction typically leads to better performance. In Maqableh & Alia's study of 853 students, 52.6% disagreed with the shift to online learning [19], primarily due to institutional and personal unpreparedness. During online and blended delivery, reduced teacher feedback and student interactions likely contributed to lower satisfaction levels and decreased performance.

The pandemic-imposed transition to online learning, rather than by voluntary choice, further impacted performance. Studies from Hurlbut demonstrate that students who willingly choose online courses benefited most from this format [12]. Lin et al. establishes that lack of motivation correlated with reduced learning behaviour [17]. Additional factors such as poor internet connectivity, improper learning environments, and unsupportive parents also affected learning outcomes [17].

4.2 Students' Performance with Respect to Moodle Log Frequency

Analysis of Moodle usage patterns reveals that students who frequently access online materials demonstrate better performance outcomes. Tang and Chaw's research establishes a correlation between student motivation and frequency of online material access [25], suggesting that motivated students engage more actively with learning materials. A limitation of this analysis is the inability to determine whether students meaningfully engage with downloaded materials or access them multiple times.

4.3 Students' Performance with Respect to the (Mis)matching of Learning Strategies

Our findings indicate that students in the mismatch category for their learning strategy perform better than those in the match category. This implies that a student's preferred learning strategy may not be the most efficient for specific subjects.

This finding challenges conventional educational wisdom that emphasizes aligning teaching with preferred learning styles. Instead, exposure to diverse learning approaches may develop more robust skills particularly valuable in computer science, where theoretical understanding must translate to practical implementation. The cognitive flexibility gained from navigating between conceptual lectures and hands-on programming may develop transferable meta-learning skills that benefit students across different contexts. Studies support this learning adaptability: Vorhaus showed that higher education students often change their learning strategies for different purposes [29], and AlKhasawneh documented significant modifications in VARK strategies to achieve course objectives [1].

In terms of student distribution, the mismatch category significantly outnumbers the match category. This disparity stems from the university's lecture-based teaching and slide-format materials, which promote visual and reading channels despite the majority being kinesthetic learners – resulting in a match to mismatch ratio of roughly 3:7 or 2:8.

The programming module (offline module 1 for cohort 1 and module 2 for cohort 2) showed a contrasting trend, where matched students outperformed mismatched ones. This exception can be attributed to two factors: biweekly programming assessments that enhanced retention and increased practice motivation, and the module's emphasis on hands-on coding practice that aligned with the predominantly kinesthetic learners (see Fig. 1). The provision of more practical exercises, categorised as RK materials, led to a higher proportion of matching learning strategies.

4.4 Limitations

A key limitation is the small sample size, restricted to only CS students in higher education. Future studies should include larger samples across different education levels and disciplines for broader generalisability.

Another limitation is that the study lacked a questionnaire on students' experiences with different learning modes. Such insights could help identify behavioural changes and impact of students' willingness to adopt online learning.

Additionally, the study did not employ a balanced strategy for the Modules Teaching Semester and Delivery for Cohort 1 and 2 students due to differences in response rates. Furthermore, while the modules were all from Professor Prapa's courses and had similar difficulty levels, they were not identical, which may have introduced variability in the results. Future research should consider balancing strategies and account for module complexity to improve comparability.

5 Conclusions

This paper examines three aspects of academic performance using data from two cohorts of Computer Science students at the University of Nottingham Ningbo China. By analysing grades, Moodle usage, and VARK learning strategies across offline, online, and blended learning modes during the COVID-19 pandemic, we identified several key patterns in student performance.

Results showed that students performed better in offline learning compared to blended or online modes, primarily due to reduced student-teacher interactions and lower motivation in remote settings. Further analysis revealed that higher Moodle access frequency correlated with better academic performance, suggesting active engagement with online resources benefits learning outcomes. In terms of learning strategies, students with mismatched VARK types generally performed better, as the university's lecture-based teaching (type VR) differed from students' predominant learning strategy (type K). However, programming modules presented an exception, where teaching methods (type RK) aligned with learning strategies, resulting in higher grades for matched students.

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