On multi-device use: Using technological modality profiles to explain differences in students' learning

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ABSTRACT

With increasing abundance and ubiquity of mobile phones, desktop PCs, and tablets in the last decade, we are seeing students intermixing these modalities to learn and regulate their learning. However, the role of these modalities in educational settings is still largely under-researched. Similarly, little attention has been paid to the research on the extension of learning analytics to analyze the learning processes of students adopting various modalities during a learning activity. Traditionally, research on how modalities affect the way in which activities are completed has mainly relied upon self-reported data or mere counts of access from each modality. We explore the use of technological modalities in regulating learning via learning management systems (LMS) in the context of blended courses. We used data mining techniques to analyze patterns in sequences of actions performed by learners (n = 120) across different modalities in order to identify technological modality profiles of sequences. These profiles were used to detect the technological modality strategies adopted by students. We found a moderate effect size ($\epsilon^2 = 0.12$) of students' adopted strategies on the final course grade. Furthermore, when looking specifically at online discussion engagement and performance, students' adopted technological modality strategies explained a large amount of variance ($\eta^2 = 0.68$) in their engagement and quality of contributions. The result implications and further research are discussed.

CCS CONCEPTS

• Information systems → Data mining; **• Human-centered computing → Mobile devices**; **• Applied computing → Education**;

KEYWORDS

Mobile Learning, Trace Analysis, Multi-device use, Blended learning, Online discussions, Learning analytics

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1 INTRODUCTION

The education sector has witnessed modernization of aspects of learning with advancements in technological modalities brought about by the digital era. With the influx of prevalent, popular and affordable modalities (such as mobile phones and tablets), the multi-device use to access course materials is becoming more prominent and has yielded promising affordances to support formal learning. According to the 2017 ECAR study[1] [39], student device ownership has steadily increased compared to previous years (97% of students owned smartphones, 95% owned laptops and 53% owned tablets) with over three-quarter (78%) of the students connected to two or more devices simultaneously. However, the mere access to and use of these modalities are insufficient for guaranteeing effective learning. That is to say, although students use various modalities extensively, the use is 'widespread but not deep' [9]; that is, the use of many of these modalities have not yet achieved their full potential for academic purposes. The challenge for educators and designers, thus, is one of understanding and exploring the impact, if any, of students' patterns of usage of these modalities on their learning and overall academic performance.

Existing research in learning analytics has identified differences in patterns of tool-use by students [22, 29, 33] and has shown significant relationships of those patterns with academic performance [27, 35, 36]. However, the modality of tool access has rarely been studied within the learning analytics research. Typically, scores of counts and time spent online extracted from the log files are accumulated across all device modalities, and the consequences of the adopted modalities on the result interpretation, if any, are not analyzed. This is particularly problematic given that there is a critical paucity of student-facing learning analytics dashboards or recommender systems that are specifically created for the use on mobile or tablet devices [47] in comparison to their wide-spread desktop counterparts. That is, challenges may emerge if students predominately use mobile and tablet modalities for their studying. Additionally, learning activities are often completed by students using multiple modalities, used either sequentially or simultaneously [31, 43], and so, identifying patterns of the use can help examine the changes in the study habits of students.

Despite the many benefits of studying the impact of the adopted technological modalities in learning, determining the patterns of use itself is a complex and challenging task. Most of the existing studies that compare different modalities have relied on count data [46, 49], self-reports and questionnaires [1, 31], or in some cases, mere assumptions [38], to make statements about modality-use patterns. Thus, the aim of this paper is to bridge several of the previously discussed gaps and explore the *sequential* patterns in

[1] The findings were developed using a representative sample of students from 124 U.S. colleges and universities.

use of technological modalities in an educational context. We focus on using data mining techniques and learning analytics methods to analyze students' learning sequences and provide insights into how students learn and regulate their learning using different technological modalities. We further demonstrate how understanding differences in adopted modality-use patterns can be used to explain variance in the performance in asynchronous online discussions (AODs). Thus, the two main research questions for this study are:

(1) **RQ1**: Can we detect patterns in students' use of multiple modalities that are indicative of their adopted technological modality strategy when using an LMS tool? If so, what kind of strategies emerge?
(2) **RQ2**: Is there an association of the identified strategies with students' performance in AODs and overall academic performance?

The study is based on the Multi-Device Learning Framework proposed by [31] which considers how different devices can be used together. The framework suggests that patterns of use differ considerably between modalities based on three major aspects – multiple devices, learning activity, and contextual environment (location). Combined and complimentary use of modalities, say fixed desktop technologies and mobile technologies, serve different functions in supporting the learning process; for instance, mobile phones 'to check', tablets 'to immerse' and desktop 'to manage' ([20], as cited in [2]). A survey conducted by ECAR [1] found that students prefer accessing academic progress information and course material via their mobile devices. For viewing course videos, Wong [49] found mobile phones were preferred over desktop computers. Nakahara et al. [38] posited that desktops are favored for browsing and posting activities, considering the mobile phone's limited bandwidth, small screen and awkward text input functions. Tabuenca et al. [46] found push notifications work better on a mobile phone app than on a desktop web-version of the app. The results of the Stockwell [43] study revealed that learners typically use different modalities depending on the time of a day; mobile phone usage takes place mostly across the morning or very late at night, most typically at home, and no usage at all in the afternoon or in the evening. In contrast, when using PCs, learners tend to focus their usage in blocks in the afternoon or after midnight, working primarily at home at night and at the university during the afternoon. Looking specifically at rate of mobile use for learning activities, Stockwell [42] revealed that a significant number of learners did not use the mobile phone at all and a majority used a combination of both mobile and desktop computers for completing vocabulary activities. Even though their scores did not differ much, the amount of time spent by mobile phone users for completing each activity was longer by at least 1.4 minutes.

The variety in usage, based on the above factors, confirms that certain devices may be used more often than others for study depending on the type of activities and time of day. As a result, access to multiple modalities can lead to change in study patterns and potentially influence the overall learning experience. This is exactly what we explore in this paper.

2 METHODS

2.1 Study Context

In this study, we analyzed the data produced by the second and third year undergraduate students in two programming-oriented courses at a Canadian university. The data were collected over two semesters (Fall 2017 and Spring 2018). Each course lasted 13 weeks and had a combined enrollment of 121 students (83+38). The courses used blended delivery, utilizing the university's learning management system (LMS) to support learning activities and students' overall schoolwork. The students were experienced in using the LMS as they used it on a day-to-day basis in prior courses. The LMS hosted access to reading material, posted lecture slides, tutorial materials, general course information, weekly or bi-weekly course assignments, assignment submission, grades, and allowed participation in online discussion activities. In addition to the web-browser versions of the LMS (desktop/laptop/mobile), students had access to the mobile app version provided by the LMS vendor. Upon comparison of the features and functionalities offered by the two versions, no apparent differences were revealed.

Both courses were similar in structure, having a 2-hour face-to-face lecture per week, a 2-hour in-lab tutorial per week, tutorial participation contributed 10% towards the final grade, assignments 40% of the grade, quizzes and exams in 2nd year course 50% and in the 3rd year course 35%, and the 3rd year course had three online discussions 5% each for a total of 15%. Assignments, four in each course, were all individual, comprising of programming tasks, developed in the programming environment outside of the LMS. The assignment specifications were posted in the LMS, students submitted assignments via the LMS, and received feedback and grades as comments in the LMS. The discussion activities were 10-14 days long, in small groups of 6-8 students, conducting research and developing a shared statement to an open ended question. A minimum of four posts was required for a student to get the full mark, which considered content, collaboration and quality of the group final statement. The grades for discussions were posted in the LMS as well. Students could plan their studying using LMS calendar where deadlines for all learning activities were posted.

2.2 Learning traces and study sessions

The study used the interaction trace data from students' engagement with the LMS. Students self-regulated their participation in the course activities, guided by the course requirements and deadlines. The use of technological modalities was a choice of each student. Each student action in the LMS was logged with the following data: student id, course id, type of learning action, action URL, session number, start time, end time, and user-agent.

The study sessions were extracted from the events data in two subsequent steps. In the first step, the study sessions representing continuous sequences of events where any two events were within 30 minutes of one another were identified. Since there does not exist a unified time-on-task estimation method within the learning analytics community [28], the 30-minute threshold was chosen as in previous studies [13, 24, 29]. Given that the LMS serves mainly as a content-providing host, i.e. tracking, reporting, and delivering the educational material, a closer analysis showed that 80th percentile of the continuous time spent on activities was 11.6 minutes, which seemed insufficiently short, while 85th percentile was 48.9 minutes, which seemed overly long.

Analyses of the sessions extracted in the preliminary step revealed that a majority of them (95%) were composed of a single modality use (*absolute* sessions). Two kinds of mixed-use behavior was observed in the remaining 5% of sessions with two or more modality-use (*mixed* sessions): (a) *actual* mixed-use where students simultaneously and/or alternatively used two or more modalities to access the LMS, and (b) *chanced* mixed-use wherein student's two or more *seemingly* detached activities (as evident from a large time-gap separation, say 22 minutes) occurred from two *different* modalities and ended up in the same session mainly due to our chosen 30-minute threshold. Hence, in the second step, the mixed sessions were further split based on a 20-minute delimiter with the overall aim of having either absolute sessions or actual mixed-sessions but fewer chanced mixed-sessions. This delimiter was selected after observing the distribution of *switch times*[2] for all mixed sessions.

The two-step process resulted in 26,935 study sessions across 121 unique students for the 13 active weeks of the two courses. To gain an insight into the general pattern of study sessions we removed outliers following a similar process as reported in [13, 24]. Specifically, study sessions comprising of a single event were removed along with students with excessive study session counts (one student registered 506 sessions, compared to a median of 206). Removing these outliers resulted in 18,895 study sessions across 120 students.

2.3 Data Analysis Techniques

2.3.1 Pre-processing data. Four main steps were involved in the pre-processing of the logged data consisting of all possible clicks.

First, the modality of access associated with each event in the log data was determined from the examination of the user-agent field, and resulted in four broad categories: Desktop, Mobile, Tablet, and Unknown (for all unclear modalities). The Desktop category included access from a web browser running on desktop computers or laptops. The Mobile category included both LMS versions that could be possibly used on cellphones (see Section 2.1), i.e. web browser or dedicated LMS application. The Tablet category included access from tablets. The Unknown category included all other modalities, which we could not categorize with certainty. In terms of access to technological modality, the majority of students (86%) used a combination of Mobiles and Desktops, the most common device ownership combination [5], for at least one learning sequence. 8% used all three major modalities (Desktop, Tablets, Mobiles), and 6% used Desktop only.

Secondly, the count measures were extracted based on the number of times each learning action was performed by each student. Table 1 contains the types and total counts of learning actions, categorized into activities, captured by LMS.

Thirdly, the time-on-task variable (time spent on activity) was calculated using the difference between the start times of two logged events. This is a common technique used previously in many studies [29, 34, 37], with the underlying assumption that the entirety of the time between two logged events was spent on a particular learning activity. Such assumptions are widespread and inevitable for time-on-task estimations in learning analytics.

[2]Switch time refers to the difference between start times of two subsequent actions which are performed on different modalities.

Table 1: Breakdown of activities and access (in terms of number of actions) from different modalities

Activity	Desktop	Mobile	Tablet	Unknown
Course Planning and Management	37,535	43,527	453	4,453
Assignments	20,999	5,814	34	0
Course Content	20,419	4,486	31	1
Discussions	3,791	509	3	0
Grades	2,938	467	0	0
Quizzes	1,993	196	4	0

Fourthly, the word count for the messages was obtained by counting the total number of words in the message and the quality of the messages (scaled to a value between 0 and 100) in the discussions was calculated using the Coh-Metrix framework. It is a well-established computational linguistics facility for analyzing discussion texts over several measures of cohesion, language and readability [18]. Out of the several possible measures, we look at five main measures - Narrativity, Deep Cohesion, Referential Cohesion, Syntactic Simplicity and Concreteness. These measures were chosen since these account for almost 50% of the variance in a text [17] and are shown as strong indicators of social knowledge construction [23, 30].

Table 2 shows the extracted variables, divided into four groups: counts, time spent, word counts and quality. We have three variables related to the counts and three variables related to time spent on the three main actions in a discussion activity (posting, reading and replying), along with two variables for word counts and ten variables (5 measures x 2 message types) related to quality of the messages.

2.3.2 Technological-modality sequence analysis. In order to examine the presence of patterns in students use of several technological modalities, we relied on the analyses of their learning sessions by following an approach similar to the approach proposed for detection of learning strategies from trace data [24]. Each session was encoded as a sequence of modalities using a representation format of the TraMineR R package [14]. Fig 1 presents few examples of learning sequences. As the example indicates, the sequences could be composed of either *absolute* (sequence 1, 3 and 4) or *mixed* sessions (sequence 2), thereby explaining the diversity in their composition. Additionally, the varying lengths of sequences (sequence 1 vs. sequence 3) are reflective of the differences in density of activities in a session. These sequences were used later for clustering to obtain students' technological-modality profiles.

2.3.3 Clustering. Following the proposals by previous researchers [13, 24, 29], we used agglomerative clustering based on Ward's method for two kinds of clustering. First, the modality sequences (N = 18,895) were clustered to detect patterns in students' modality-use behaviours (i.e. *technological-modality profiles*). The computation of the distance (similarity) between sequences, required for the clustering algorithm, was based on the optimal matching distance metric

Table 2: Extracted features: Dependent variables examined in the study

Type	Name	Description
Count	count_PostDiscussion	Total number of the discussion board messages posted by the student
	count_ViewDiscussion	Total number of times student opened one of the course's online discussions
	count_ReplyDiscussion	Total number of the times student replied on discussion board messages posted by another student
Time Spent	time_PostDiscussion	Total time spent on posting discussion board messages
	time_ViewDiscussion	Total time spent on reading course's online discussions
	time_ReplyDiscussion	Total time spent on replying to a existing thread in online discussions
Word count	post_wc	Average number of words for all the posts made to the discussion board
	reply_wc	Average number of words for all the replies made to the discussion board
Quality	q_Post	$q \in$ { five principal components of Coh-Metrix* } Average measure of q for all posts
	q_Reply	$q \in$ { five principal components of Coh-Metrix* } Average measure of q for all replies

* Five principal components of Coh-Metrix include Narrativity, Deep Cohesion, Referential Cohesion, Syntactic Simplicity and Concreteness

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  Sequence
1 Mobile-Mobile-Mobile
2 Mobile-Mobile-Desktop-Desktop-Desktop-Desktop
3 Mobile-Mobile-Mobile-Mobile-Mobile-Mobile-Mobile-Mobile-Mobile
4 Tablet-Tablet-Tablet-Tablet
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Figure 1: Examples of technological modality sequences encoded in the TraMineR format

[14]. According to this metric, the distance between two sequences of states is the minimal cost, in terms of insertions, deletions, and/or state substitutions required to transform one sequence into another. Since any substitution cost can be replaced with a combination of insertion and deletions, the cost of insertion/deletion in our analyses was set at a half the maximum substitution cost, a widely used cost setting [21], to avoid pseudo-substitutions. These computed distances were then normalized, to account for differences in sequence lengths, by dividing the distance by the length of the longer sequence.

The optimal number of sequence clusters were obtained from (a) inspection of the resulting dendrogram, and (b) calculating the "dunn index" proposed by Dunn [10], and computed using the clValid R package [4]. The Dunn Index is the ratio between the smallest distance between observations not in the same cluster to the largest intra-cluster distance. It has a value between 0 and infinity and should be maximized.

The sequence clustering algorithm produced four clusters, i.e. technological-modality profiles. Next, for each student we computed four corresponding variables $seq.clust_i$, $i = 1{:}4$, where $seq.clust_i$ is the number of sequences in cluster i for a particular student. These four variables plus the variable *seq.total*, representing the total number of learning sequences for the student, were used in the second cluster analysis to group students (N = 120) (i.e. *technological-modality strategies*). All five variables were normalized; the Euclidean metric was used to compute the distance between vectors. After the clusters of students were computed, each cluster was summarized by calculating its *centroid*, which represented the mean value of all cluster members across all clustering variables. The student cluster assignments (representative of their technological-modality strategies) enabled us to group students and identify whether different strategies relate to differences in overall academic performance, and participation and performance in online discussions.

The optimal number of student clusters was obtained from (a) inspection of the resulting dendrogram, and (b) using the "silhouette statistic" proposed by Rousseeuw [25, 40] and computed using the clValid R package. The Silhouette value measures the degree of confidence in a particular clustering assignment and lies in the interval [-1,1], with well-clustered observations having values near 1 and poorly clustered observations having values near -1.

2.3.4 Statistical Analyses. To examine if there was a significant difference between the identified student groups, we performed a multivariate analysis of variance (MANOVA). The student cluster assignment was treated as the single, independent variable along with the dependent variables described in Table 2: three measures of counts, three measures of time-spent, two measures of word counts and ten measures of quality.

Assumptions: Before running the MANOVA, we checked the homogeneity of covariance assumption using Box's M test and the homogeneity of variance using Levene's test. The Shapiro-Wilk test was performed to check for multivariate normality. To protect from the violations of the test assumptions, we log-transformed the data and used the Pillai's trace statistic which is considered to be a robust against assumption violations. [3].

Main effect test: In case of a significant MANOVA result, a follow-up univariate one-way analyses of variance (ANOVA) were conducted on each dependent variable that produced non-significant Levene's test result. To prevent the inflation of type I error rates due to the multiple ANOVA comparisons, the Bonferroni correction was adopted. In case of significant Levene's test (i.e., the homogeneity of variance assumption was violated), the non-parametric Kruskal-Wallis test was used. Finally, the measures of eta-squared (η^2) and epsilon-squared (ϵ^2) were used to report the effect sizes for ANOVAs and Kruskal-Wallis tests, respectively and interpretations were done using Cohen's [7] primer, the most commonly used primer for effect size interpretation.

Post-hoc test: The significant Kruskal-Wallis tests were followed up by Dunn test for multiple comparisons (also using Bonferroni corrections). This is an appropriate test for comparing groups with unequal numbers of observations [50]. After significant ANOVAs, Tukey's honest significant difference (HSD) test was used to check for the differences among the individual pairs of clusters.

3 RESULTS

3.1 Clustering of sequences as manifestations of students' technological-modality profiles (TMP)

The inspection of the dendrogram and Dunn indices led to the conclusion that a four cluster solution was optimal. The resulting clusters indicate the four different kinds of technological-modality profiles that students tended to use when studying and self-regulating their studies through the LMS.

Table 3 provides descriptive statistics for the sequence lengths in each profile cluster. Additionally, Fig 2 presents sequence frequency plots for each of the four profiles. These represent the ten most frequent sequences in each profile. The bar widths are proportional to the frequencies of occurrence. Thus, the y-axis indicates the cumulative percentage of the top 10 sequences. The bar lengths along the x-axis is the number of actions in the sequence. For instance, the most frequent sequence in the TMP3 cluster is a sequence of two actions on Desktop. It accounts for almost 38.72% of 9,571 sequences in TMP3. The second most frequent sequence consists of three actions on Desktop (26.76% of 9,571 sequences), is indeed very similar to the previous one. It is interesting to note that for this cluster (similar to clusters 1 and 4), the 10 most frequent sequences account for about 99.6% of all the sequences, which reflects a small diversity, i.e., a small number of different patterns than those plotted. However, the 10 most frequent sequences in TMP2 cluster account for only about 45.3% of all the sequences, which reflects a high diversity. Upon inspection, it was revealed that a majority of the remaining sequences were also similar in composition (actions completed on Mobile) to the ones plotted, but were even longer.

Table 3: Characteristics of sequences (in terms of lengths i.e. action count) in the technological-modality profiles

Cluster	N	Mean	Median(Q1,Q3)	Min	Max
TMP1	1498 (7%)	6.45	3(2,5)	2	127
TMP2	2684 (14.2%)	19.42	16(11,24)	2	233
TMP3	9571 (50.65%)	3.13	3(2,4)	2	22
TMP4	5142 (27.21%)	10.88	9(7,12)	6	108

Drawing from Table 3 and Fig 2, the four clusters can be characterized as follows:

- TMP1 Cluster - *Diverse* (N = 1,498, 7.0%): This cluster constituted the smallest number of sequences. The grouping comprised learning sequences composed of actions from a wide range of modalities (desktops, mobiles, tablets, and unknown). This strategy cluster contained relatively short learning sequences (median = 3 actions in one learning session).
- TMP2 Cluster - *Mobile Oriented* (N = 2,684, 14.2%): This cluster was twice as large as the *Diverse* strategy cluster. Mobile constituted the most dominant modality for majority of actions in the sequences belonging to this cluster. Actions from other modalities were present but not frequent. This profile contained the longest number of learning actions in a session (median = 16 actions in one learning session).
- TMP3 Cluster - *Short-Desktop Oriented* (N = 9,571, 50.6%): This cluster was predominantly focused on actions from the Desktop modality. It was the biggest of all the four TMP clusters containing almost half of all learning sequences. The learning sessions (and, thus sequences) in this cluster tended to be short (median = 3 actions in one learning session) with the longest session composed of 22 actions only.
- TMP4 Cluster - *Desktop Oriented* (N = 5,142, 27.2%): This cluster was also predominantly focused on actions performed using the Desktop modality. However, unlike TMP3, this cluster contained relatively longer learning sessions (median = 9 actions in one learning session).

3.2 Clusters of students based on the adopted technological-modality profiles

The student clustering was performed based on the vectors of five values for each student as described in the method section, i.e. four counts of students' learning sequences in each identified TMP clusters and students' total number of learning sequences *seq.total*. After examining the different ways of cutting the tree structure (i.e., different numbers of clusters), using both dendogram and silhouette methods, we chose the solution with 3 clusters as the optimal one.

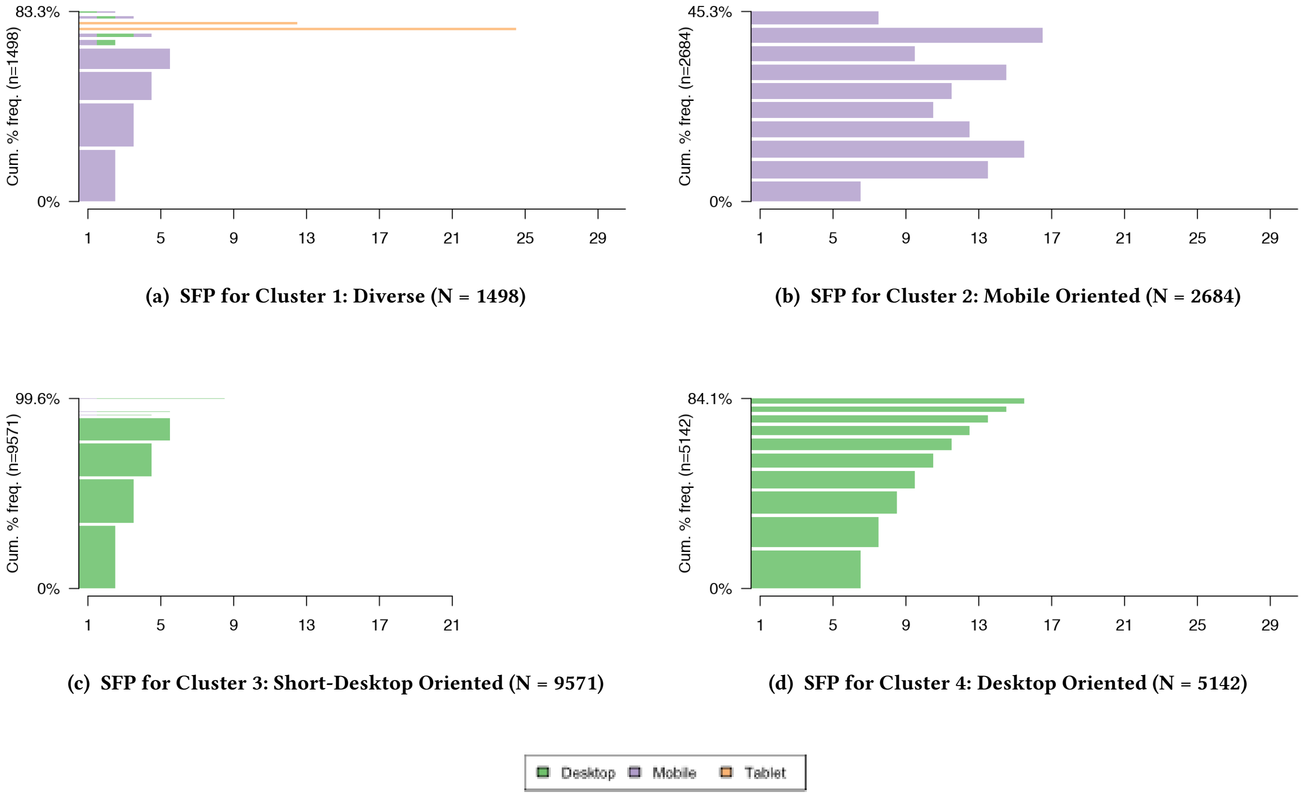
Table 4 describes the resulting clusters. The rows *nTMP1 - nTMP4* and *seq.total* show the distribution of the values for the variables used for clustering, i.e. the number of sequences in the four TMP clusters an d total number of sequences. The last row labeled *grade* shows the the final course grade for students in each cluster. For all the variables the table shows the median, 25th and 75th percentiles.

Table 4: Summary statistics for the 3 student clusters: median, 25th and 75th percentiles.

	Student Cluster 1 N=47 (39.16%) Median(Q1,Q3)	Student Cluster 2 N=52 (43.33%) Median(Q1,Q3)	Student Cluster 3 N=21 (17.5%) Median(Q1,Q3)
nTMP1	10(3.5,19)	7(2,13)	12(9,17)
nTMP2	4(1,7)	3(1,29.5)	80(64,97)
nTMP3	94(80.5,113.5)	59(45.75,67)	83(72,105)
nTMP4	53(43,72.5)	26.5(21.5,33.25)	44(36,59)
seq.total	170(142,202)	104(87.75,122.5)	223(203,262)
grade	68.38(56.56,80.02)	54.91(44.76,62.99)	62.6(54.05,68.56)

From the perspective of the variables outlined in Table 4, the clusters can be described as follows:

- Student Cluster 1 – *Strategic Users* (N = 47, 39.16%): This group of students used predominantly desktop modality which can be demonstrated from a high attachment to profile TMP3 (Short-Desktop) and TMP4 (Desktop). Hence, from the modality use perspective, this group was limited in use of multiple technology modalities. The number of sequences in this cluster was between numbers of sequences of other two clusters. It was the highest performing group in terms of the final course grade.
- Student Cluster 2 – *Minimalist users* (N = 52, 43.33%): This group of students predominantly used technology in a way



(a) SFP for Cluster 1: Diverse (N = 1498)

(b) SFP for Cluster 2: Mobile Oriented (N = 2684)

(c) SFP for Cluster 3: Short-Desktop Oriented (N = 9571)

(d) SFP for Cluster 4: Desktop Oriented (N = 5142)

Figure 2: Sequence frequency plots (SFP) for each TMP profile showing the proportions of the ten most frequent sequences. (Green:Desktop, Purple: Mobile, Orange: Tablet)

consistent with TMP3 (Short-Desktop), then TMP4 (Desktop), and sparingly the other two profiles. The overall number of learning sequences was by far the lowest of the three student clusters. Thus, this low level of efforts, both overall and in terms of dominating short learning sessions from less-portable desktops (TMP2), may explain the group's significantly lower grades in comparison to the other two clusters (1 and 3).

- Student Cluster 3 – *Intensive users* (N = 21, 17.5%): This cluster constitutes the smallest group of students. It represents the most active group of students whose sequences fell into all modality profiles, among which TMP2 (Mobile) and TMP3 (Short-Desktop) were the most prominent and used almost equally. In terms of overall course grade, even though a lower median percentage than the high performing Cluster 1 was recorded, the differences were non-significant.

To test any underlying cluster differences on the overall student grade, we used the non-parametric Kruskal-Wallis test due to serious violations of normality and homoscedasticity. The analyses of the degree of variation in adopted technological modality profiles was found to be significantly associated with the overall academic performance score, with a moderate effect size ($\chi^2(2) = 14.476$, $p = 0.0007$, $\epsilon^2 = .12$). The pairwise comparison of clusters with respect to the final grade (i.e. *percentage*) revealed that Cluster 2 performed significantly lower than Cluster 1 ($p = 0.008$) and Cluster 3 ($p = 0.002$), even after adjustments to the p-values using the Benjamini-Hochberg (BH) procedure. However, the difference between the two high performing groups, i.e. Cluster 1 and 3, was not statistically significant.

3.3 Analysis of cluster differences

After examining the differences between clusters based on final grade, we proceeded to further check for the differences between the discovered clusters with respect to their performance in one type of learning activity: discussions. Since discussion were a graded learning activity in one course only, the further analysis included students from the third year undergraduate course only (N = 37). We maintained the students' assignment to the student cluster as above, since we considered the technology use profile to be a characteristic of the student, rather than the course. This was confirmed by comparison of the four TMP profiles using t-tests (for the two course groups), which resulted in non-significant differences for three of the four profiles and only slightly significant differences for the fourth profile. In total, 342 messages (posts + replies) were collected from this course, which represented the main data source for analyzing cluster differences.

A one-way multivariate analysis of variance (MANOVA) was conducted with the students' cluster assignment as the single independent variable and the measures defined in Table 2 as the dependent variables. Concerning the relative sizes of the clusters, they seem reasonable and consistent with the previous studies [24, 29, 34, 35] that found intensive users are the smallest group. The descriptive statistics for each of the dependent variables are shown in Table 7.

The assumption of homogeneity of covariances was tested using Box's M test and was found to be violated. Thus, Pillai's trace statistic was used, as it is more robust to the assumption violations together with the Bonferroni correction method. A statistically significant MANOVA effect was obtained, Pillai's Trace = 1.36, $F(36, 36) = 2.16$, $p = 0.01$. The multivariate effect size was estimated at multivariate $\eta^2 = .68$, which implies that 68% of the variance in the dependent variables was accounted for by the differences in the student cluster assignment.

As a follow-up, a series of one-way ANOVA with Bonferroni corrections was conducted, for each of the dependent variables that produced non-significant Levene's test (homogeneity of variance) result. The test revealed that assumption was satisfied for all but three variables (*count_PostDiscussion*, *deepCohesion_Post* and *deepCohesion_Reply*), for which Kruskal-Wallis tests were conducted. The Shapiro test of normality showed (weak) violations for four variables (*count_ReplyDiscussion*, *time_PostDiscussion*, *time_ViewDiscussion* and *time_ReplyDiscussion*). However, since ANOVA is considered a robust test against the violations to the normality assumption [16] we use it to test these four variables, instead of opting for a non-parametric method.

The main effect analyses from ANOVA (Table 5) and Kruskal-Wallis test (Table 6) revealed that the models for three count measures (*count_ReplyDiscussion*, *count_PostDiscussion*, and *count_ViewDiscussion*), one time spent measure (*time_ReplyDiscussion*), both word count measures (*post_wc*, *reply_wc*) and four quality measures (*referentialCohesion_Post*, *concreteness_Post*, *syntacticSimplicity_Reply* and *referentialCohesion_Reply*) were statistically significant. To save space, only the significant results are shown in the tables.

Following the significant results, a series of post-hoc analyses was conducted to detect the clusters where statistically significant differences were observed (Table footnotes indicate post-hoc tests, all significant at $p < 0.05$). In terms of counts of messages, the students from Cluster 1 (*strategic users*) posted and read more discussion messages at AODs compared to Cluster 2 students (*minimalist users*). They also replied more often to existing discussion threads than students in Cluster 2 and Cluster 3 (*intensive users*). With respect to the time-spent online, Cluster 1 (*strategic*) students spent more time compared to Cluster 2 (*minimalist users*) in framing their replies to other students' posts in discussions. In terms of the word count, discussion contributions by Cluster 1 were significantly larger than those posted by Cluster 3 and those replied by Cluster 2. In terms of the quality of messages, the discussion contents posted by Cluster 1 (*strategic users*) were more concrete compared to Cluster 2 and Cluster 3, and contained ideas that overlapped across sentences and the entire discussion (referential cohesion) compared to Cluster 3. Moreover, the replies framed by Cluster 1 students were simpler in structure with more familiar words (syntactic simplicity) compared to Cluster 3, and contained a higher number of connections that tied the ideas together for the reader (referential cohesion) compared to Cluster 2.

Table 5: ANOVA - Main and Post-hoc results.

	Levene's		ANOVAs		
Variable	$F(2,34)$	p	$F(2,34)$	p	η^2
count_ReplyDiscussion	2.349	0.111	6.584	0.004[a,b]	0.28
count_ViewDiscussion	1.717	0.195	5.531	0.008[a]	0.25
time_ReplyDiscussion	2.749	0.071	3.446	0.033[a]	0.17
post_wc	1.197	0.314	3.528	0.040[b]	0.17
reply_wc	1.903	0.164	3.933	0.029[a]	0.19
referentialCohesion_Post	0.268	0.766	3.623	0.037[b]	0.14
concreteness_Post	0.161	0.851	8.354	0.001[a,b]	0.25
syntacticSimplicity_Reply	2.183	0.128	3.534	0.040[a]	0.06
referentialCohesion_Reply	1.309	0.283	4.857	0.013[a]	0.07

[a] Cluster 1 vs. Cluster 2.
[b] Cluster 1 vs. Cluster 3.

Table 6: Kruskal Wallis - Main and Post-hoc results.

Variable	$H(2)$	p	ϵ^2
count_PostDiscussion	11.35	0.003[a]	0.30

[a] Cluster 1 vs. Cluster 2.

4 DISCUSSION

The results of clustering of students' learning sequences confirmed the existence of well differentiated patterns (i.e. technological modality profiles) in students' use of modalities. Based on these patterns, students were clustered and these clusters correspond to the students' strategies of using technological modalities for engaging with learning activities and regulating their learning. An underlying assumption that holds true in our study, with respect to the contextual use of LMS, is that the choice of modality for an action in a learning session is a matter of a student's choice rather than determined by the instructional conditions. That is, no specific modality-related instructions were administered to students in this study. Keeping this in mind, our results indicate that the strategies identified were significantly different in terms of modality-use pattern composition with 12% of the variance in the final course grade explained by them. This indicates an important relationship between technological modality strategies and overall academic performance, which up until now has not been researched in detail.

In the second part of our analysis, we studied how technological modality strategies (combinations of technological modality profiles) were associated with participation behaviors in asynchronous online discussions and quality of this participation. We found that approximately 68% of variance in performance at AODs (in terms

Table 7: Descriptive statistics of the dependent variable raw scores: Mean, Standard deviation (SD), Median (Mdn), 25th (Q1) and 75th(Q3) percentiles.

	Stud.Cluster 1 (N = 23)				Stud.Cluster 2 (N = 10)				Stud.Cluster 3 (N = 4)			
Variable	Mean	SD	Md	(Q1,Q3)	Mean	SD	Md	(Q1,Q3)	Mean	SD	Md	(Q1,Q3)
count_ViewDiscussion	77.30	34.93	74.00	(47.5, 94.5)	38.70	21.50	32.50	(23.25, 50.75)	69.50	19.05	66.00	(57.75, 77.75)
count_ReplyDiscussion	5.22	2.59	6.00	(2.50, 7)	2.40	2.22	2.00	(0.5, 3.75)	2.00	0.82	2.00	(1.75, 2.25)
count_PostDiscussion	4.35	1.82	4.00	(3, 5.5)	2.10	1.20	2.00	(1.25, 3)	2.75	0.50	3.00	(2.75, 3)
time_PostDiscussion	12.90	0.62	13.02	(12.58, 13.32)	12.50	1.66	12.98	(12.35, 13.35)	12.53	0.34	12.52	(12.4, 12.65)
time_ReplyDiscussion	9.05	2.33	9.30	(8.03, 11.02)	5.94	4.66	6.40	(1.16, 9.76)	8.61	2.81	8.96	(6.94, 10.62)
time_ViewDiscussion	9.56	2.43	10.32	(9.15, 11.11)	7.77	4.35	9.22	(5.12, 11.33)	7.51	2.41	6.37	(6.26, 7.62)
post_wc	272.22	100.34	262.5	(208.83, 303.7)	218.68	158.57	195.67	(115, 247.62)	140.11	94.11	182.55	(127.95, 194.71)
reply_wc	162.71	45.57	158	(136.81, 190.47)	113.95	85.81	102.25	(72.53, 162.59)	152.1	86.19	116.04	(105.94, 162.21)
narrativity_Post	39.79	13.2	41.61	(29.93, 47.8)	45.81	25.96	45.58	(30.68, 55.29)	29.65	20.04	37.85	(26.29, 41.21)
deepCohesion_Post	76.72	10.77	74.23	(69.53, 81.56)	62.09	30.96	56.68	(46.78, 88.18)	57.14	41.13	67.61	(41.8, 82.94)
referentialCohesion_Post	48.57	19.23	53.72	(31.42, 59.97)	37.2	23.98	44.25	(19.63, 54.06)	24.58	20.33	25.31	(13.69, 36.2)
syntacticSimplicity_Post	35.75	15.51	36.25	(24.61, 48.41)	26.63	17.06	31.2	(14.45, 33.9)	30.98	26.47	34.05	(13.6, 51.44)
concreteness_Post	26.84	10.59	24.9	(21.58, 33.06)	14.55	14.19	12.71	(5.66, 18.05)	10.64	13.4	6.68	(1.24, 16.07)
narrativity_Reply	50.1	13.8	50.5	(42.92, 57.35)	40.83	23.84	50.2	(32.37, 56.88)	47.23	10.48	48.56	(39.78, 56.01)
deepCohesion_Reply	69.78	13.39	67.48	(60.19, 78.17)	54.39	38.41	61.05	(20.89, 85.86)	66.57	18.46	60.74	(53.49, 73.83)
referentialCohesion_Reply	47.67	15.01	46.49	(34.66, 52.82)	36.46	32.38	46.68	(3.43, 52.07)	53.26	21.55	46.66	(42.99, 56.93)
syntacticSimplicity_Reply	30.41	12.55	30.87	(22.21, 37.37)	24.01	21.31	31.14	(0.92, 37.55)	19.86	14.5	20.41	(7.9, 32.38)
concreteness_Reply	30.67	13.92	29.18	(21.15, 36.86)	24.93	23.7	21.21	(8.06, 33.91)	16.92	17.08	12.45	(6.39, 22.98)

of counts of, time-spent online, length of and quality of messages) was explained by the demonstrated strategy for using the LMS tool. These results are important in order to acknowledge that not only does the extent to which consistency of tool-use [29] and 'richness' (in terms of feature affordances) of the tool itself [33] matter, *the diversity in intermix of modality-use for using the tool affects the performance significantly* too.

4.1 Technological-Modality Profiles

It must be emphasized that individual uses of modalities vary from student to student and task by task basis. Therefore, in this study, we first clustered individual study sessions each composed of action sequences based on various modalities. This was followed by clustering of students based on the counts of the occurrences of each session cluster. The purpose of our multi-step analysis is mainly to distinguish between counts of action from various devices and patterns of use of these devices for different actions. By doing so, we are able to emphasize on within-session use of modalities which provides researchers with more granular, low-level interpretations of composition of students' learning sequences as actions performed on different modalities. Hence, perhaps the most interesting insight made through such systematized trace analyses, in line with observations by previous researchers [31, 43], was that *learners employ multi-device support (ranging from PCs, laptops, tablets and mobile phones) across learning sessions, though in different proportions, rather than strictly adhering to just one.*

The various modality-use behaviour patterns observed in our study raises critical questions on the methodology adopted by a majority of the existing studies on mobile learning. It has been pointed out in the literature that a majority of researchers and educators do not take students' use of multiple devices into account in the facilitation and support of learning experiences [11, 12, 31]. Consequently, a rule of thumb in the extant comparative studies on platform (modality) performance [1, 8, 38, 46, 49], involves binning participants into dichotomous groups – mobile users *vs* non-Mobile users – without giving cognizance to their overall technology modality behavior pattern and therefore, the possibility of an overlap between modalities. The strictly binary groupings takes away attention from the nuances involved in their modality profiles, as hinted towards by Stockwell [42] who observed 'extended usage of one platform followed by short bursts on the other' for some learners during a vocabulary activity.

The aim of the study was not to make concrete statements regarding a clear 'winner' amongst combinations of modality profiles (i.e. technological modality strategies) or even modalities themselves. The idea was to generate awareness within the research community of the impact of modalities when interpreting research findings and building learning analytics models, particularly for studies delegating tool-use as a proxy for comparing outcomes and behaviors at tasks. We argue that in addition to capturing the diversity and consistency of tool-use, as stressed by [33], future research should also focus on three main components of modality-use behavior, in relation to students' performance. These include *diversity* (intermix) of modalities used, *consistency* or activeness of modality-use and *transferability* of a modality to new learning tasks. We posit that these will prove useful for gaining a fuller insight into the way how tools support learning and self-regulative activities.

4.2 Strategies and Discussion Performance

The current study found that students in clusters associated with higher overall discussion performance (Stud.Cluster 1 = *Strategic* and Stud.Cluster 3 = *Intensive*) tended to engage in study sessions which were characterized by more active modality-use patterns.

However, we see no association between the use of strategies composed of multiple devices and the participation behaviour (in terms of counts, time spent, word count and quality). That is to say, the students who chose to adopt strategies composed of a variety of different modality profiles to regulate learning (Stud.Cluster 3) did not achieve significantly better results for participation behaviour in discussion activities compared to those who chose only few (Stud.Cluster 1). This indicates that even though students may appreciate control (over learning sessions) offered by such diversity, the 'quality' of that control – i.e. the ability to determine when the use of a modality would be beneficial to learning – is an important metacognitive skill to possess. This is because, while answering quick queries can be done effectively using mobile phones, deeper knowledge construction may require more substantial technology affordances to create strong arguments. Such affordances can be offered by PCs instead, as was observed in this study. This is consistent with recent research findings by Heflin et al. [19] that found students who constructed discussion responses on a mobile device demonstrated significantly less critical thinking than those who used a computer keyboard or wrote responses by hand. Therefore, we posit that students need to develop this knowledge about which type of device and their affordances can be most suitable for a task at hand, as an additional type of metacognitive knowledge similar to the knowledge of relevant learning strategies [48].

Likewise, much like any learning strategy [13, 24, 29], monitoring and optimizing the technological modality-use is necessary for effective learning. Benefits from multi-device support will only go so far in enhancing engagement (as evident by high count measures for viewing discussions) as the same material is available on various devices. However, it is up to the learner to make efficient use of each modality to guarantee maximized academic output. Failure to do so poses serious threats to sustainable seamless learning, which relies substantially on a combined use of multiple device types. Having said that, we reinstates the observation reported in [6, 29, 33] suggesting that leaving the control with the learner or offering only little support is a poor pedagogical practice and instead, must be explicitly addressed.

Lastly, as a by-product from this study, we also provide partial support for the claim by existing research and statistics [32, 44, 45] that alleges a higher engagement rate when courses are delivered using the mobile format. This is true in particular for students from cluster 3 i.e. Intensive users whose substantial level of self-regulation occurred using mobile devices. According to our findings, cluster 3 students had substantially higher mean value (except *count_ReplyDiscussion* and *time_ViewDiscussion*) for counts and the time spent on reading, posting and replying to the discussion posts, compared to Cluster 2. However, the quality measures of their posts were lower than that of cluster 2 students, whose use of profiles involving mobile devices was meager. In fact, looking at Table 7, we see that even though cluster 2 did not post more, their contributions were larger (word count), and they posted more substantial messages, in terms of quality (except for syntactic simplicity score), compared to Cluster 3. However, according to the post-hoc tests, all these differences were non-significant. This might be due to the small group size of clusters because of which we failed to reject the null hypotheses (i.e. no differences exist between Minimalist and Intensive group) even when the true state of nature might be very different from what is stated in the null hypothesis [26]. Thus, more research using bigger participant pool is required to conclusively refute or provide support for this claim.

5 LIMITATIONS AND FUTURE WORK

Since our methodology involved tracking user interaction with the LMS, this may raise a concern about the extent to which our results were dependent upon the learning context and the design of the LMS itself. Hence, future research should aim to replicate or extend our study and investigate the effects of instructional conditions [15] including but not limited to course design, learning activity, mode of assessment, teaching method, domain subject.

Equally so, the interaction with the LMS must be seen as a proxy for the ability to effectively self-regulate using different technological modalities. Some extraneous effects might have been introduced from the type of the LMS used in this study and capabilities offered by it, which might have affected the learning process differently for different study participants. Future work should explore using other other learning management systems such as Moodle, to see the influence on self-regulation, while considering the affordances it provides.

Regarding the validity of our significant results, given the small sample size available in our study, Royall [41] suggests that a highly attained significance level (i.e. small p-value) is greater evidence that null hypothesis is rejected when sample size is small. This is because a small sample size can only result in a small p-value when the observations are generally highly inconsistent with null hypothesis. Having said that, replications of the study with bigger dataset will benefit in solidifying the claims made by the paper.

6 CONCLUSIONS

Taking up the research on tool-use and its ramifications on learning one step further, in this paper we looked at the modalities used by students to access the LMS for studies. We observed different behavioral patterns in the use of various modalities ranging from hand-held devices such as mobile phones and tablets to PCs and desktops. Based on the identified patterns, student clustering was done to group students into clusters which were representative of their use of technological modality strategy. Comparison of these strategies revealed differences in the students' overall academic performance. To further illustrate the research utility of the identified technological-modality strategies, we showed that the construct can explain a significant amount of variance in how students engage with discussions as well as the differences in quality of their posts and replies.

There are several important consequences of the presented study. Having demonstrated the usefulness of the concept of technological modality profile in explaining some differences in students' engagement and outcomes, it may prove to be a useful concept to incorporate into models. Gauging the profiles for the construction of modality-specific learner models will greatly benefit the learning outcome predictions, particularly useful in mobile and seamless learning environments. These models can better explain learning behaviours and outcomes, and detect students strategies which are further used for designing interventions. The methodology adopted in this study also has potential for identification of enhancing and distracting modality-use patterns employed by learner, in addition to classifying learning activities benefiting the most from particular modality combinations. This is vital for learning because selecting modalities that are ill-fitted to the task can undermine knowledge construction and can lead to unintended consequences.

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