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When Do Learners Study? An Analysis of the Time-of-Day and Weekday-Weekend Usage Patterns of Learning Management Systems from Mobile and Computers in Blended Learning

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Abstract

Recent advances in smart devices and online technologies have facilitated the emergence of ubiquitous learning environments for participating in different learning activities. This poses an interesting question about modality access, i.e., what students are using each platform for and at what time of day. In this paper, we present a log-based exploratory study on learning management system (LMS) use comparing three different modalities—computer, mobile, and tablet—based on the aspect of time. Our objective is to better understand how and to what extent learning sessions via mobiles and tablets occur at different times throughout the day compared to computer sessions. The complexity of the question is further intensified because learners rarely use a single modality for their learning activities but rather prefer a combination of two or more. Thus, we check the associations between *patterns* of modality usage and time of day as opposed to the *counts* of modality usage and time of day. The results indicate that computer-dominant learners are similar to limited-computer learners in terms of their session-time distribution, while intensive learners show completely different patterns. For all students, sessions on mobile devices are more frequent in the afternoon, while the proportion of computer sessions was higher at night. On comparison of these time-of-day preferences with respect to modalities on weekdays and weekends, they were found consistent for computer-dominant and limited-computer learners only. We demonstrate the implication of this research for enhancing contextual profiling and subsequently improving the personalization of learning systems such that personalized notification systems can be integrated with LMSs to deliver notifications to students at appropriate times.

Notes for Practice

- Learners' time-of-day (TOD) preferences for engaging in learning have been studied extensively, but how these preferences are impacted when different modalities such as computers and mobiles are available needs better understanding.
- Our results suggest that learning sessions from various modalities are significantly associated with the time of day and day of the week (weekday or weekend), and this holds true for students who made extensive use of different modalities to complete their learning activities (computer-dominant and intensive learners) and those who sparingly used them (limited-computer learners).
- Overall, mobile were found to be more frequent in the afternoon and short-computer sessions at night.
- The modality-TOD associations were similar on weekdays and weekends for computer-dominant and limited-computer learners, two groups that are strikingly different in terms of their academic performance.
- Designers can use the results to target delivery of notifications, i.e., to optimize "the right information at the right time from the right modality."

Keywords

Time flexibility, learner time, mobile learning, technology-enhanced learning, learning analytics, learning management systems

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1. Introduction

The global diffusion of smartphones and tablets, exceeding the market share of traditional desktops and laptops, has created a unique learning environment and opportunities that span time and space. All of these modalities are continuously used throughout the day to create seamless learning environments such that students spend a significant portion of their time connected through devices—e.g., accessing academic resources, completing assignment tasks, and streaming content. A report by ECAR (Pomerantz & Brooks, 2017) states that students are generally connected to two or more devices simultaneously, meaning learners consciously choose when to engage with each of these modalities. That implies that students who have a few modality options at their disposal may reflect about time management differently than older generations. Interestingly, while these temporal aspects are extremely important, the time factor, in general, has not received much attention in educational research (Barbera, Gros, & Kirschner, 2015), and even less attention has been paid to it with respect to various modalities in the learning environment. That is, the question remains as to the behaviour of students when engaging in online learning environments through disparate modalities and points in time. Existing literature has insufficient research in this area, and addressing this gap should enable learning and educational designers to target the delivery of "the right information at the right time from the right modality." Furthermore, knowledge of any associations between time of day and learning sessions taking place could help in implementing well-designed applications that can assist learners to plan a sequence of activities across times and locations. Thus, to better understand how patterns of technological modality use are distributed throughout the day, we conducted this exploratory study.

Existing research suggests that individual differences exist with respect to the technological modality learners prefer to use for their learning. That is, research has found significant impact of students' adopted modality profile, derived from patterns of modality (such as desktops, mobiles) usage for various learning activities, on their academic achievement (Sher, Hatala, & Gašević, 2019; Stockwell, 2010, 2013). There also exists a considerable body of literature that suggests that individual differences exist with respect to the time of day learners prefer to work. That is, learners may have a unique chronotype, such as morningness-eveningness preference (Loureiro & Garcia-Marques, 2015), and these time preferences might even vary depending on the country one resides in (Smith et al., 2002). Moreover, we also found evidence in the literature suggesting significant associations between the learner's chronotype score and their academic achievements (Randler & Frech, 2006; Itzek-Greulich, Randler, & Vollmer, 2016). Romero and Barberà (2011) observed the time spent by adult e-learners on learning activities and reported a close relationship between evening time-slot and better academic performance ($r = 0.6$) in collaborative activities, whereas both morning ($r = 0.9$) and evening ($r = 0.8$) were closely related to academic performance for individual activities. Combining the knowledge derived from these two sets of research—i.e., time of day is related to learning outcomes and modality preference is related to learning outcomes—a discernible research question follows: "Does the choice of modality used by learners for their learning activities relate to their preferences for particular time windows during the day?" This is exactly what our research aims to answer.

We evaluate the research question in the context of blended learning, wherein there is an online component (in addition to a face-to-face component) with a substantial study load that requires a significant amount of time to be dedicated to learning activities outside the classroom. This is important because learning that takes place outside the classroom (i.e., online) exhibits self-initiative on the student's part and contributes to the teacher's understanding of the student's behaviour. Assessing temporal patterns for such activities has the potential to tailor the learning experience of learners to their current situation and needs. For instance, it enables learners to learn with less effort, e.g., in terms of time availability for learning. Additionally, for our analyses, we moved from action-level analyses to session-level analyses of student activity. This was done in accordance with suggestions from Barbera and colleagues (2015), according to which the level of temporal analyses should be more fine grained, e.g., by taking a more "event-centred" approach (wherein the "event" students engage in is taken as the unit of analysis) instead of a variable-centred approach (wherein variables defined at the student level are taken as the unit of analysis). This is because while the former can be useful for answering research questions that assess relationships among variables, it is only the latter that can "answer research questions pertaining to changes and processes" (Barbera et al., 2015, p.12).

The research is timely, as highlighted in the Special Issue of JLA (2017 and 2018), because there has been a growing concern that temporality has been underexplored in both basic and applied learning research, despite the availability of rich datasets (Knight, Wise, & Chen, 2017). The authors emphasize the need for clearer conceptual understanding of temporality and its importance for learning. Such research has the potential to strengthen our understanding of how learning evolves over time (data storytelling) and to build a conceptual framework that tackles temporality in specific contexts (B. Chen, Knight, & Wise, 2018). Thus, our research aims to contribute to the understanding of the temporal construct of time of day against which learning systems can be personalized.

1.1 Temporal Study Patterns

Temporal patterns of student activity, e.g., the sequence and timing of student activity (Barbera et al., 2015), have helped in the multifaceted analysis of student learning behaviour. Previous research has stressed the role of temporal patterns in enhancing the predictive capabilities of student data, by focusing on either the order in which students engage in an activity or the timing of engaging in activities themselves (Greiff, Scherer, & Kirschner, 2017; Saqr, Nouri, & Fors, 2019; Ahmad Uzir, Gašević, Matcha, Jovanović, & Pardo, 2020). Leeuwen, Bos, Ravenswaaij, and Oostenrijk (2019) expanded on the idea by incorporating instructional conditions (flipped classroom model and enhanced hybrid model) along with temporal patterns of weekly activity to determine and interpret the relation between study activities (such as accessing the course book, web lectures) and course performance. Within MOOCs, Boroujeni and Dillenbourg (2018) investigated the study patterns and performed temporal analysis of learners' longitudinal behaviours during the assessment period (of video-watching, submitting, auditing, and being inactive), concluding that fluctuations in learning approaches were easily identifiable with temporal analysis and could indicate students encountering difficulties. In addition to MOOCs, online behaviours in small private online courses have also been studied using temporal analysis, wherein students' online behaviour during a semester was used to identify significant transitions between interactions with content, peers, and instructors (Cheng, Liu, Sun, Liu, & Yang, 2017). While most of these aforementioned studies investigated temporal patterns within an individual learning setup, Malmberg, Järvelä, and Järvenoja (2017) used temporal analysis to examine when the different processes of regulated learning (i.e., co-regulated, self-regulated, and socially shared regulated) and task execution typically occurred during different stages in collaborative learning.

1.2 Time and Modality Flexibility in Learning

There is consensus among researchers and educators regarding the idea that learning takes time (Kolari, Savander-Ranne, & Viskari, 2008; Wolk, 2001). However, the rationale behind *when* this time is devoted to out-of-class learning, mainly using different modalities, needs better understanding. While many researchers have examined the concept of time flexibility from instructional and organization viewpoints (Arneberg et al., 2007; McGorry, 2003), only a limited number of papers have looked at the associations between time flexibility and modality usage from the learner's perspective, and only in very specific application domains. The results of the study by Stockwell (2013) reveal that learners typically use different modalities depending on the time of day to partake in vocabulary activities for an English language learning task. Mobile phone usage took place mostly throughout the morning or very late at night, typically at home, and there was no usage at all in the afternoon or in the evening. In contrast, when using personal computers (desktop or laptop), learners tend to focus their usage in blocks in the afternoon (at university) or after midnight (at home). Similar results were obtained by Casany Guerrero, Alier Forment, Galanis, Mayol Sarroca, and Piguillem Poch (2012), who studied learning management system (LMS) use and witnessed a rise in mobile activity at night (8 p.m. to midnight), while desktop activity dropped during the same hours. Song, Ma, Wang, and Wang (2013) looked specifically at user search behaviour on commercial search engines, and the results of their study revealed significant differences in usage times of three main modalities—desktop, mobile, and tablet—to perform search queries. The queries from desktop were performed mostly during working hours (8 a.m. to 5 p.m.), whereas mobile and tablet usage peaked during the evening (6 p.m. to 10 p.m.).

While much has been revealed from the aforementioned studies, associations between modality use and time of day need to be investigated further in blended learning environments. Moreover, the associations need to be investigated at the level of sessions (sequence of actions) as opposed to individual actions. (Note: The learning action in our study is the smallest unit of student activity in the LMS that is captured by the logging mechanism, for instance, clicking on a link to access an assignment or posting a message to a discussion forum.) Researching these associations will present us with much more nuanced insights into within-session use of modalities and their distribution across different times of day. For instance, looking at actions alone might let us make statements such as "desktops are used more frequently at night," whereas granular low-level interpretations of the composition of students' learning sequences as actions performed on different modalities will allow us to understand the extent to which different usage patterns appear across different parts of day—e.g., "longer sessions on the desktop occur in the morning" and "shorter desktop sessions are more frequent at night."

1.3 Research Questions

In this paper, we look at LMS use from different modalities across a 24-hour day. Since the LMS content (assignments, resources, course content) can be accessed at all times (i.e., the LMS provides instructional flexibility to some extent), learners may choose to interact with it at any time depending on their availability. The choice of time for interaction could in turn be dictated by professional, social, and family commitments. That is, the regulation of learning using the LMS places the responsibility for time management on the learners themselves. The decision to work on mobile or on desktop, from home or at the library, in the afternoon or late at night, depends very much on the available technological modalities, the task the student wants to accomplish, the suitability of the environment the student is in, their own preference, and many other factors. Moreover, the nature of learning outside the classroom (this being in school, at home, or in transit), with various modalities available, makes it difficult to determine how learners engage in learning activities. For instance, are there any differences in completion rates between sending a reminder at 9 a.m. or at 9 p.m., or what impact would a proactive intervention, such as a reminder sent by the system or instructor, have on student learning when received on a modality situated in some physical context, without considering if the student can act on it or not? For this reason, research that enables tracking any associations between devices and time of day can shed light on the potential benefits of each day slot, potentially leading to better design of learning task and recommender systems.

The research questions, thus, are as follows:

1. **RQ1:** Are there any associations between time of day and the patterns of modality usage for different learners in a blended learning environment?
2. **RQ2:** Are these associations different on weekends than on weekdays?

1.4 Significance of the Study

This study contributes to several important viewpoints. *First*, “learners are perpetually in a context” (Sharples, 2015), and there has been growing interest in contextual profiling (i.e., context-aware recommendations) within fields akin to mobile learning (Lima, El-Bishouty, & Graf, 2013; Tortorella & Graf, 2012; Parsons, 2016; Xu, Zhu, Zhang, & Gu, 2008) to allow for a more authentic learning experience aimed at providing adaptivity and personalization. A crucial precursor to creating such systems is understanding how learning in the presence of various modalities is apportioned across a day. Given the amount of information learners have to cope with, knowledge of the temporal context of a learning session (possibly comprising a combination of modalities) can provide valuable insight into the “contextual profiling” mechanism since it will capitalize on the learner’s schedule for engaging in different learning-related activities. *Second*, while all the different modalities are definitely a part of a person’s learning environment and readily at their disposal, it is not necessary that they be continuously used, as some might be led to believe. This is an important consideration because it questions how often and how regularly users engage with a modality during a learning session, and, depending on the time of day, whether it would be beneficial to display different information through a particular modality. We explore this in our paper. *Third*, the time factor has only been cursorily studied, in relation to working hours, time-flexibility, time-on-task, time of day, and day of the week, and it would be informative to see if the results are consistent across different modalities too. *Last*, as pointed out in the systematic review by Chen and colleagues (2020), many researchers struggle with ubiquitous smart-learning environments and their design for supporting personalized learning. To resolve this struggle, designers and teachers need to have a basic understanding of various time characteristics associated with different modalities and how best they can be used. For instance, evening being the commuting time for many may restrict the use of desktop personal computers, while mobile phones, owing to their portability, may be better for use over a short span of time (Rogers, Connelly, Hazlewood, & Tedesco, 2010; Casany Guerrero et al., 2012).

2. Methods

2.1 Study Context

In this study, we analyzed the data produced by 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) from students who were in the same time zone (Pacific Standard Time). Each course lasted 13 weeks and had a combined enrollment of 121 students ($83+38$). The courses used blended delivery, utilizing the university’s LMS to support learning activities and students’ overall schoolwork. The students were experienced in using the LMS because they had 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, and grades; and allowed assignment submission and participation in online discussion activities. In addition to the web-browser versions of the LMS (accessible on desktop/laptop/tablet/mobile), students had access to the mobile app version provided by the LMS vendor. On comparison of the features and functionalities offered by the two versions, no apparent differences were revealed.

Both courses were similar in structure, having a two-hour face-to-face lecture per week, a two-hour in-lab tutorial per week, and weekly two-hour tutorials. Both courses contained assignments, quizzes, and exams, and the third-year course had an additional component of online discussions. Assignments, four in each course, were all individual, comprising programming tasks developed in the programming environment outside the LMS. The assignment specifications were posted in the LMS, students submitted assignments via the LMS, and they received feedback and grades as comments in the LMS. The grades for discussions were posted in the LMS as well. Students could plan their studying using the 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 the 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 (including date), end time, and user-agent.

To group the actions into sessions, we consider a time gap of more than 30 minutes to be a new session. The choice of 30 minutes was data driven, based on each action requiring a reasonable number of minutes, and to allow time for quick breaks within the same session. Once the study sessions were extracted from the events data (see Sher and colleagues (2019) for details on the extraction process), they were filtered to remove any outliers, which resulted in 18,895 study sessions across 120 students (one student was deemed as an outlier; this student registered an excessively high number of study sessions (506 sessions, compared to a median of 206)).

2.3 Data Analysis Techniques

2.3.1 Pre-processing Data

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

First, the modality of access associated with each event in the log data was determined by examining the user-agent field, resulting in four broad categories: computer (desktop and laptop, i.e., larger screens with high resolution, used for sustained long-term work periods and complex tasks) and mobile, tablet, and unknown (for all unclear modalities). Note: The mobile and tablet category included both LMS versions that could be possibly used on cellphones (see Section 2.1), i.e., web browser and dedicated LMS application.

Second, the time of day associated with each learning session was determined using the start time and time spent on the learning session and categorized into four broad time-of-day (TOD) categories, intuitively[1]: morning (5 a.m. to noon), afternoon (noon to 6 p.m.), evening (6 p.m. to 9 p.m.), and night (9 p.m. to 5 a.m.). Time spent on the events in a session[2] was calculated using the difference between the start times of two logged events. This is a common technique used previously in many studies (Kovanović, Gašević, Joksimović, Hatala, & Adesope, 2015; Macfadyen & Dawson, 2010; Lust, Elen, & Clarebout, 2013), 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. A learning session belonged to a TOD category depending on where the majority of time during the learning sessions was spent. For example, if a learning session began at 11 a.m. but went on until 4 p.m., it was categorized as an afternoon session (even though it began in the morning) since out of a total time spent of five hours, four hours were spent on learning actions in the afternoon.

Third, the day of the week category associated with each learning session was determined from the date of the learning action, which was derived from the start time of the activity. The "weekend" category consisted of learning sessions starting on a Saturday or Sunday, and the "weekday" category comprised learning that occurred Monday to Friday.

2.3.2 Technological-Modality Sequence Analysis

In order to investigate the research questions in this study, we first examined the presence of patterns in students' use of several technological modalities. To do so, each session was encoded as a sequence of modalities using a representation format of the TraMineR R package (Gabadinho, Ritschard, Mueller, & Studer, 2011) (see Sher and colleagues (2019) for details on the interpretation of TraMineR sequences). Examples of the derived learning sequences are as follows: Sequence1: *mobile—mobile—computer* and Sequence2: *computer—tablet—computer—computer*.

2.3.3 Clustering

We used agglomerative clustering based on Ward's method (Trevor, Robert, & Friedman, 2009) for two kinds of clustering—sequence clustering and student clustering. For both kinds of clustering, the details on clustering algorithm, distance measures,

[1] By *intuitively*, we mean time slots that better align with how students might organize their day. This was further corroborated using a short survey we did with 10 participants from our department, asking them to discretize time into the four main time intervals.

[2] Time spent on the last event in a session was set at a cut-off limit measuring 15 minutes. This was done because the LMS does not record explicit logout events, as a result of which there was no way of accurately knowing how much time was spent on the last event in a session.

and validation of the number of clusters were the same as reported in Sher and colleagues (2019). We summarize here the main steps of how we obtained the clusters to orient the reader.

First, the modality sequences ($N = 18,895$) (derived in Section 2.3.2) were clustered to detect patterns in students' modality-use behaviours. The sequence-clustering algorithm produced four clusters, i.e., technological-modality profiles (TMPs). Next, for each student, we computed four corresponding variables: $seq.clust_i$, $i = 1:4$, where $seq.clust_i$ was 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 choices*). The student cluster assignments (representative of their technological-modality choices) enabled us to group students and identify whether the underlying associations between time of day (when learners engage in learning sessions) and the TMPs of these sessions varied across student clusters.

2.3.4 Statistical Analyses

Main effect test: To address RQ1 and examine if there was an overall significant relation between the TMP of learning sessions and the time of day these sessions took place, we performed a chi-square test of independence, after summarizing data composed of each session's TMP cluster and the TOD category it belonged to in a two-way contingency matrix. Two-way tables were used in the statistical analysis to summarize the relationship between two categorical variables, in our case TMP cluster and TOD category. The categorical data were summarized as counts (i.e., frequencies) corresponding to each combination of levels within the two variables and were entered in individual cells in the table. Thus, the count in each cell represented the number of sessions that a specific TMP cluster allocation had (i.e., one of diverse, mobile-oriented, short-computer, computer) for each time of day (i.e., morning, afternoon, evening, night). To further highlight how these associations changed depending on the technological-modality choices adopted by the student (i.e., student clusters), three separate chi-square tests of independence were carried out for each of the three student clusters identified, after using Bonferroni corrections to account for possible inflation of Type 1 error from multiple comparisons.

Post hoc test: For significant chi-square tests, indicating significant and meaningful relationships, we followed them up with post hoc analyses to determine the source of statistically significant results using Crosstabs in SPSS. We compared the standardized residuals as suggested by Beasley and Schumacker (1995) given that they are known to maintain Type 1 error (due to multiple comparisons) at a satisfactory level (MacDonald & Gardner, 2000). Those adjusted standardized residuals that were greater than 1.96 indicated the TOD categories that contributed to the significant chi-square finding. Finally, we used the columns proportion test in SPSS to see if the adoption of specific TMPs, say mobile-oriented sessions, at night is different from that in the evening. The test uses z-tests to compare column (i.e., TOD) proportions for each TMP after adjusting for multiple comparisons using Bonferroni corrections.

To address RQ2, a similar main effects test was conducted but with TMP cluster and type of day (weekday/weekend) as the two categorical variables. The columns proportion test approach for the post hoc test was also similar to the one carried out in RQ1, but it was done separately for weekdays and weekends.

3. Results

3.1 Results of Clustering

The results in the following subsections are the same as reported in Sher and colleagues (2019). As they are the basis of our further analysis, they are described here at a level of detail so that the reader can interpret our new results in Section 3.2.

3.1.1 Clustering of Sequences as Manifestations of Students' TMPs

The four sequence clusters, indicating the four different kinds of TMPs that students tended to use when studying and self-regulating their studies through the LMS, can be characterized as follows:

- TMP1 Cluster—*Diverse* ($N = 1,498$, 7.9%): This cluster constituted the smallest number of sequences. The grouping comprised learning sequences composed of actions from a wide range of modalities (computers, 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%): Almost twice as many sequences were in this cluster than in the *Diverse* strategy cluster. Mobile was the most dominant modality for the majority of actions in the sequences belonging to this cluster. Actions from other modalities were present but not frequent. This profile contained the greatest number of learning actions in a session (median = 16 actions in one learning session).

- TMP3 Cluster—*Short-Computer Oriented* ($N = 9,571$, 50.6%): This cluster was predominantly focused on actions from the computer modality. It was the biggest of the four TMP clusters, containing more than half of all learning sequences.

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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 only 22 actions.

- TMP4 Cluster—*Computer Oriented* ($N = 5,142$, 27.2%): This cluster was also predominantly focused on actions performed using the computer modality. However, unlike TMP3, this cluster contained relatively longer learning sessions (median = 9 actions in one learning session).

3.1.2 Clusters of Students Based on the Adopted TMPs

A three-cluster solution was concluded to be the optimal choice after inspection of the dendrogram and using the silhouette method (see Sher and colleagues (2019) for details on student clustering). Table 1 describes the resulting clusters. The rows *nTMP1* to *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 and the total number of sequences. The last row, labelled *grade*, shows the final course grade for students in each cluster. For all the variables, the table shows the median and the 25th and 75th percentiles. We named the three modality choice clusters to reflect how the modalities were used. Intensive users *intensively* used all available modalities at their disposal, limited-computer users made *limited* use of the computer modality for shorter learning sessions only, and computer-dominant users made *predominant* use of the computer modality for mixed-length sessions.

Table 1. Summary Statistics for the Three Student Clusters: Median and 25th and 75th Percentiles

	Student Cluster 1 Computer-Dominant $N = 47$ (39.16%) Median (Q1, Q3)	Student Cluster 2 Limited-Computer $N = 52$ (43.33%) Median (Q1, Q3)	Student Cluster 3 Intensive $N = 21$ (17.5%) Median (Q1, Q3)
nDiverse	10 (3.5, 19)	7 (2, 13)	12 (9, 17)
nMobile	4 (1, 7)	3 (1, 29.5)	80 (64, 97)
nShort-computer	94 (80.5, 113.5)	59 (45.75, 67)	83 (72, 105)
nComputer	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 1, the clusters can be described as follows:

- Student Cluster 1—*Computer-Dominant Users* ($N = 47$, 39.16%): This group of students predominantly used the computer modality, which could be demonstrated by a high attachment to profiles TMP3 (short-computer) and TMP4 (computer). Hence, from the modality use perspective, this group was limited in its use of multiple technological modalities. The number of sequences in this cluster was between the numbers of sequences of the other two clusters. It was the highest-performing group in terms of the final course grade.

- Student Cluster 2—*Limited-Computer Users* ($N = 52$, 43.33%): This group of students predominantly used technology in a way consistent with TMP3 (short-computer), then TMP4 (computer), and sparingly the other two profiles (TMP1 and 2). The overall number of learning sequences was by far the lowest of the three student clusters. Thus, this low level of effort, both overall and in terms of dominating short learning sessions from less-portable computers (TMP3), may explain the group's significantly lower grades than in 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 those who generated the most sequences, whose sequences fell into all modality profiles, among which TMP2 (mobile) and TMP3 (short-computer) were the most prominent and used almost equally. In terms of overall course grade, even though a lower median percentage than the high-performing computer-dominant group was recorded, the differences were non-significant.

These clusters were able to differentiate between students' final grade at $\varepsilon^2 = 0.12$ power and discussion participation at $\eta^2 = 0.68$ (Sher et al., 2019). The pairwise comparison of clusters with respect to the final grade (i.e., percentage score) revealed that limited-computer learners performed significantly lower than computer-dominant ($p = 0.008$) and intensive ($p = 0.002$) learners, even after adjustments to the p-values using the Benjamini–Hochberg procedure. However, the difference between the two high-performing groups, i.e., computer-dominant and intensive, was not statistically significant (Sher et al., 2019).

3.2 Associations between TMPs and Time of Day

After examining the different strategies adopted by the students with respect to modality use, we proceeded to check if there were any underlying associations between TMPs, within each of these strategies, and different times of day when the learning sessions were carried out.

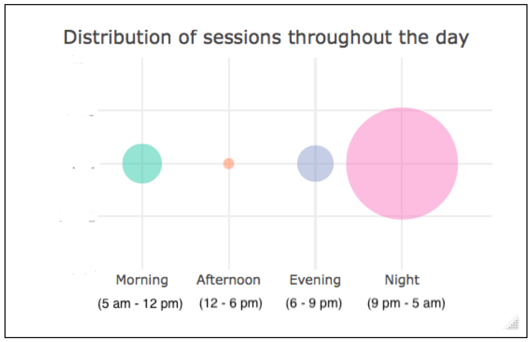
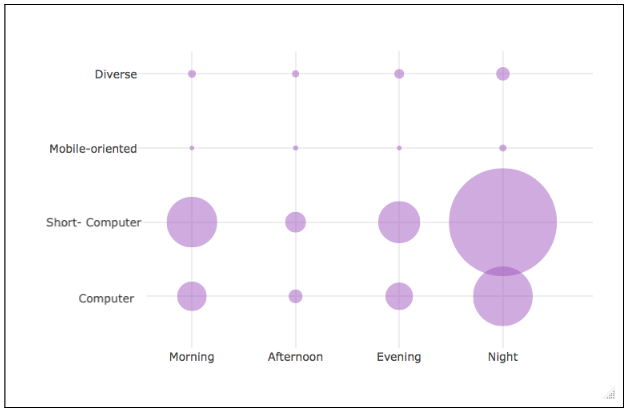


Figure 1. Bubble plot depicting the spread of sessions across the four major TOD categories. The sizes correspond to the number of sessions, with the largest comprising 9,119 actions and the smallest 1,984 actions.

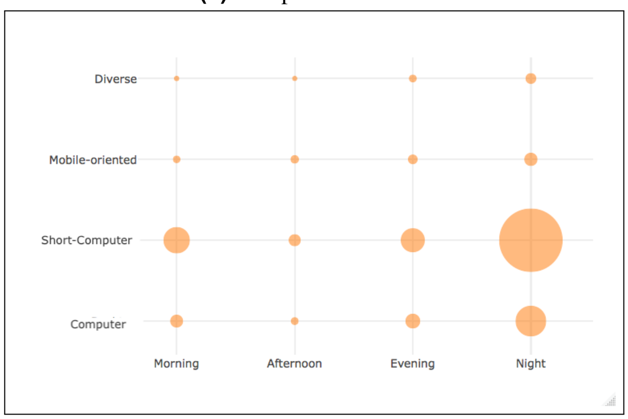
Figure 1 depicts the bubble plot for the distribution of all the learners' sessions across the four major TOD categories, with the additional dimension of size representing the counts of sessions. The figure reveals a preference for night for carrying out learning-related activities, while the proportions of sessions during the morning and evening hours were almost comparable. The fewest learning sessions were observed in the afternoon. Furthermore, to establish if these observed trends were consistent among students adopting different strategies for modality use (technological modality choices identified in Section 3.1.2), we generated similar plots for each of the three student clusters identified in the previous section. Figure 2 depicts the distribution of the learners' sessions across TOD after stratification into each modality choice cluster (normalized based on the cluster size). The figure shows that not only were the preferences consistent across all three modality choices, but the ratio of *morning:afternoon:evening:night* sessions was also maintained.

Figure 2. Bubble plot depicting spread of sessions across time of day for the three modality choices identified in Section 3.1.2.

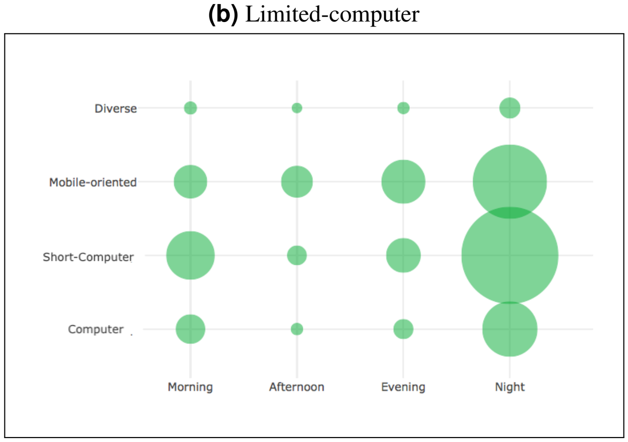
Even though the distribution of sessions across time of day was found to be consistent throughout the three modality choices, we were interested in determining if the associations between the modality profiles (in each of these strategies) and time of day were also replicated across the four TMPs. The bubble plots in Figure 3 visually depict the number of sessions (normalized based on the strategy cluster size) for all the different profiles across the TOD categories, within each of the three modality choices. The bubble plots are useful for seeing at a glance how many sessions were recorded for each time slot from each modality profile, i.e., the bubble sizes are scaled across both dimensions—time of day and TMP (and a third dimension of technological modality choice cluster to allow cross-cluster comparisons). The figure indicates that for the majority of the TMPs in each of the three modality choices, night was the dominant time of day for learning activities to take place, while afternoon registered the lowest traffic. One possible explanation for the large number of night sessions might be that the night TOD category encompasses a larger part of the day (nine hours from 9 p.m. to 5 a.m.), hence the higher count of sessions, whereas the low session traffic in the afternoon can be attributed to the fact that learners are full-time students and therefore must be attending lectures during the day.



(a) Computer-dominant



(b) Limited-computer



(c) Intensive

Figure 3. Bubble plot depicting distribution of TMPs across times of day for the three modality choices. The bubble sizes in (a), (b), and (c) have been scaled in the range $[10, 100]$ to allow cross-strategy comparisons; i.e., bubbles of the same sizes in (a), (b), and (c) represent the same number of sessions.

Looking closely at the computer-dominant learners in Figure 3a, we see differences with respect to short-computer sessions in that there were far fewer (8.7%) short-computer sessions in the afternoon than in the morning (22.8%), in the evening (18.7%), and at night (49.8%). Similarly, for the limited-computer students (Figure 3b), the number of diverse learning sessions in the morning (14.6%) was almost half the number of sessions in the evening (27.7%) and one third the number of sessions at night (45%), while it was almost comparable to the number of sessions in the afternoon (13.5%). Thus, to augment these visual inspections and test whether there were any underlying associations between the type of session (modality profile) and the time of day when sessions take place, we conducted a chi-square test of independence (for $n = 18,895$ sessions from all 120 students) with two categorical variables: session cluster allocation (diverse, mobile-oriented, short-computer, and computer) and the TOD category (morning, afternoon, evening, and night) the session belonged to. The chi-square test revealed a significant association between the cluster allocation for a session and the time of day the session was carried out ($\chi^2(9) = 374.90$, $p < 0.001$).

To confirm whether the aforementioned associations were consistent for all three learner modality choices (i.e., the three student clusters introduced in Section 3.1.2—computer-dominant, limited-computer, and intensive), chi-square tests were carried out again but this time controlling for the additional layering variable, i.e., technological modality choice. This is important since only some strategies could demonstrate differing patterns of modality usage depending on the time of day, while other strategies could have had the same pattern of modality usage throughout the day. The results of the chi-square test of independence were similar to before, when learning sessions from all students were tested collectively, and revealed significant associations between time of day and learning sessions for all three modality choices: $\chi^2(9) = 124.76$, $p < 0.001$; $\chi^2(9) = 153.51$, $p < 0.001$; and $\chi^2(9) = 150.13$, $p < 0.001$ for computer-dominant, limited-computer, and intensive students, respectively.

The significant p-values indicate that TMP and time of day were associated. Furthermore, we were interested in finding which TMP $\times$ TOD combinations were driving this significance; i.e., we wanted to ascertain if the proportion of diverse sessions, say in the evening, was more than expected. The observed and expected frequencies are shown for all three strategies in Table 2 (see the "Count" and "Expected Count" rows). To assess the source of the significance and determine which differences between observed and expected frequency were significant in statistical terms, the adjusted standardized residuals were analyzed (see the "Adjusted Residual" rows in Table 2). An adjusted residual higher (or lower) than 1.96 (2.0 is used by convention) indicates that the number of cases in that cell was significantly larger (or smaller) than would be expected if the null hypothesis (i.e., the two variables—TOD and TMP—were unrelated) was true, with a significance level of 0.05. However, in our case, given the multiple comparisons within each strategy (four levels of TMP profiles $\times$ four levels of TOD categories = 16 comparisons), we used an alpha value of 0.05/16 = 0.003 to assess significance, resulting in a threshold value for adjusted residual of 2.96 (Sharpe, 2015).

When examining all possible combinations of TMP and TOD, those with significant adjusted residuals are highlighted in grey in Table 2. As can be seen from the highlighted cells in Table 2, a higher than expected number of diverse sessions from the computer-dominant students were carried out in the afternoon and evening, while a significantly lower than expected number of diverse sessions took place at night. These patterns were entirely reversed for short-computer sessions in that a lower than expected number of short-computer sessions from the computer-dominant students were carried out in the afternoon and evening, while a significantly higher than expected number of short-computer sessions took place at night. For the limited-computer students, a significantly larger than expected proportion of diverse, mobile-oriented, and short-computer sessions took place in the evening, in the afternoon, and at night, respectively, whereas mobile sessions at night and short-computer sessions in the afternoon and evening had lower than expected observed numbers. For intensive learners, the proportion of mobile-oriented sessions in the afternoon and evening was significantly greater than expected by chance and significantly lower than expected in the morning and at night. These patterns were reversed for short-computer sessions in that the proportion of short-computer sessions in the afternoon and evening was significant lower than expected by chance, while it was significantly greater than expected in the morning and at night.

Having determined the categories with significant deviations from expected values, we assessed whether the differences in the percentages of sessions conducted across different times of day were significant for each TMP in the three modality choice groups. Table 2 (see row "% within TOD") shows the percentages of each modality profile in each TOD cluster. For instance, for computer-dominant learners, the diverse modality profile made up 12.7% of all afternoon sessions but only 6.7% of all morning sessions. On the other hand, the limited-computer learners' computer-oriented sessions made up roughly the same proportion of evening and night sessions (26.6% and 26.1%, respectively). Nonetheless, to determine if the differences in these percentages were significant, we examined the results of the column proportions tests in SPSS, which are depicted by assigning a subscript letter to the categories of the column variable, in our case TOD categories. For each pair of columns, the column proportions (for each row) were compared using a z-test, and Bonferroni adjustments were made for multiple comparisons. If a pair of values was significantly different, the values had different subscript letters assigned to them. Supposing we know, for all computer-dominant users, mobiles make up 7.5% of all afternoon sessions but only 2.7% of all night sessions. Then if the post hoc chi-square test reports that these two percentages are significantly different (different subscripts), we can say greater than expected mobile phone sessions are tended to in the afternoon than at night by computer-dominant users.

For computer-dominant students, a significantly smaller proportion of diverse learning sessions occurred at night (6.2%; subscript b) than in the afternoon (12.7%) and evening (10%) (both subscript a), while a significantly greater proportion of short-computer learning sessions occurred at night (59.1%) than in the afternoon (49.3%) and evening (53.2%). However, for mobile-oriented sessions, the proportion of afternoon sessions was significantly larger (7.5%) than in the evening (3.1%), in the

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Table 2. SPSS Crosstabulation Results. Alpha value adjusted for multiple comparisons ($p < 0.003$). Adjusted residual values highlighted in grey represent significant differences between the expected and adjusted counts.

Student Cluster				TOD			
				Morning	Afternoon	Evening	Night
Computer-Dominant	TMP	Diverse	Count	125_b	107_a	168_a	250_b
			Expected Count	144.4	64.9	129.7	311
			% within TOD	6.7%	12.7%	10%	6.2%
			Adjusted Residual	−1.9	**5.7**	**3.9**	**−5**
		Mobile	Count	49_b	63_a	53_b	108_b
			Expected Count	60.7	27.3	54.5	130.6
			% within TOD	2.6%	7.5%	3.1%	2.7%
			Adjusted Residual	−1.7	**7.3**	−0.2	−2.8
		Short-computer	Count	1089_b	415_a	895_a	2384_b
			Expected Count	1062.6	477.4	954.3	2288.6
			% within TOD	58.1%	49.3%	53.2%	59.1%
			Adjusted Residual	1.4	**−4.6**	**−3.3**	**4.2**
		Computer	Count	611_a	257_a	567_a	1294_a
			Expected Count	606.3	272.4	544.5	1305.8
			% within TOD	32.6%	30.5%	33.7%	32.1%
			Adjusted Residual	0.3	−1.2	1.3	−0.5
Limited-Computer	TMP	Diverse	Count	68_b	63_a	129_a	205_b
			Expected Count	88.8	48.7	97.5	230
			% within TOD	6.5%	10.9%	11.2%	7.5%
			Adjusted Residual	−2.6	2.3	**3.7**	−2.4
		Mobile	Count	$123_{b,c}$	146_a	177_b	267_c
			Expected Count	136.1	74.7	149.6	352.7
			% within TOD	11.7%	25.3%	15.3%	9.8%
			Adjusted Residual	−1.3	**9.4**	2.7	**−6.9**
		Short-computer	Count	600_b	238_a	541_a	1540_b
			Expected Count	557.2	305.6	612.3	1443.8
			% within TOD	57.1%	41.3%	46.9%	56.6%
			Adjusted Residual	2.9	**−6**	**−4.7**	**5.2**
		Computer	Count	259_a	129_a	307_a	709_a
			Expected Count	268	147	294.5	694.5
			% within TOD	24.7%	22.4%	26.6%	26.1%
			Adjusted Residual	−0.7	−1.8	0.9	0.9
Intensive	TMP	Diverse	Count	84_a	57_a	76_a	166_a
			Expected Count	83.9	43.7	73	182.4
			% within TOD	7.7%	10.1%	8%	7%
			Adjusted Residual	0	2.2	0.4	−1.7
		Mobile	Count	296_b	279_a	405_a	718_b
			Expected Count	371.9	193.8	323.6	808.8
			% within TOD	27.3%	49.3%	42.9%	30.4%
			Adjusted Residual	**−5.5**	**8**	**6.2**	**−5.4**
		Short-computer	Count	452_b	153_a	308_a	956_b
			Expected Count	409.3	213.3	356.2	890.2
			% within TOD	41.6%	27%	32.6%	40.5%
			Adjusted Residual	**3**	**−5.6**	**−3.6**	**3.9**
		Computer	Count	254_b	77_a	156_a	522_b
			Expected Count	221	115.2	192.3	480.6
			% within TOD	23.4%	13.6%	16.5%	22.1%
			Adjusted Residual	2.8	**−4.2**	**−3.3**	2.9

morning (2.6%), and at night (2.7%). Further, no consistent preference for time of day was visible across the computer-oriented sessions (all subscript *a*).

For the limited-computer students, a significantly smaller proportion of the diverse and mobile-oriented learning sessions occurred at night than in the evening and afternoon, but a larger proportion of the short-computer learning sessions occurred at night. Similar to computer-dominant students, limited-computer students displayed no consistent preference for TOD for computer-oriented sessions.

For intensive learners, for short-computer and computer sessions, the proportion of night sessions was significantly greater than the proportion of evening and afternoon sessions. On the contrary, for the mobile-oriented sessions, the proportion of night sessions was significantly smaller than that of evening and afternoon. However, much like the computer sessions from the computer-dominant and limited-computer users, the intensive learners' diverse sessions did not display any consistent preference for any particular time of day.

These results indicate that depending on the type of learning session (TMP), different times of day might be more preferable based on a learner's modality choice. Even though the results indicate no clear "winner" (in terms of preference or adoption) among the TOD categories, the results indicate that some preferences overlap based on the learners' modality choices. For instance, both the computer-dominant and intensive users were shown to have the highest proportion of mobile-oriented sessions in the afternoon and the lowest in the morning. Similarly, both computer-dominant and limited-computer users had the highest proportion of short-computer sessions at night and the lowest in the afternoon. Such an overlap provides opportunities for synchronizing the time of recommendation and/or feedback delivery for different learners. This is especially useful in cases when it might not be feasible to personalize the time of delivery for each individual student in the cohort due to system restrictions or inability to access enough information regarding the learner's schedule.

3.3 Associations between TMPs and Weekdays/Weekends

Since the literature supports claims that learning behaviour may depend not only on time of day but also on day of the week, and more specifically type of day (weekday or weekend), we studied the hypothesis separately for weekdays and weekends. This was done to account for the behavioural differences that might originate depending on when learning occurred throughout the week (Duck, Rutt, Hoy, & Strejc, 1991). Figure 4 depicts the distribution of learning sessions on weekdays and weekends for students adopting varying TMPs. Visual inspection reveals that the distribution of sessions across different times during the day on weekends was nearly the same as on weekdays for all the strategies, with the maximum activity taking place at night and the minimum in the afternoon.

Figure 4. Bubble plot depicting spread of sessions across weekdays and weekends for the three modality choices: 1 = computer-dominant, 2 = limited-computer, 3 = intensive.

The associations between the type of day during the week (weekday vs. weekend) and the time of day when the learning sessions occur, for each modality choice, were further confirmed by chi-square tests, which revealed significant associations for computer-dominant ($\chi^2(3) = 87.48$, $p < 0.001$), limited-computer ($\chi^2(3) = 36.84$, $p < 0.001$), and intensive ($\chi^2(3) = 63.57$, $p < 0.001$) learners, even after adjustments were made for multiple comparisons. The post hoc analyses using column proportion tests (see Table 3) revealed that for each strategy, the proportion of sessions at all times of day (morning, evening, afternoon, and night) differed significantly between weekdays and weekends, as indicated by *a* and *b* subscripts in Table 3, except for evening sessions for the limited-computer students, wherein similar proportions on weekdays and weekends were observed. On closer inspection, it was revealed that weekdays witnessed significantly greater afternoon and evening learning sessions, whereas weekends saw a significant surge in morning and night learning sessions, regardless of the learners' modality choice. These results indicate that students were in tandem regarding what time of day they would preferably engage with learning activities, based on whether the learning was scheduled to take place on weekdays or on weekends. These preferences are not surprising since the participants were full-time students engaging in classroom learning during the day throughout the five-day work week, leaving little room for morning learning sessions when getting ready for classes or at night when they are tired. Our next steps involved confirming whether these results remain constant for all four TMPs associated with each modality choice.

Figure 5 depicts the distribution of sessions across the TMPs for each of the three modality choices on weekdays (left column) and weekends (right column). The figure indicates that on both weekdays and weekends, short-computer learning sessions were the predominant TMP, regardless of the modality choices adopted by the learner, followed by computer for computer-dominant and limited-computer users, or mobile-oriented sessions for intensive learners. In fact, on closer inspection of the mobile-oriented sessions of the intensive learners, we observed that on weekdays, while the numbers of morning and

(a) Computer-dominant weekday

(b) Computer-dominant weekend

(c) Limited-computer weekday

(d) Limited-computer weekend

(e) Intensive weekday

(f) Intensive weekend

Figure 5. Bubble plot depicting spread of sessions on weekdays and weekends for the different TMPs across the three modality choices. The bubble sizes in (a), (b), (c), (d), (e), and (f) have been scaled in the range [10, 100] to allow cross-strategy comparisons.

Table 3. Crosstabulation for Time of Day (TOD) with Day of Week (DOW) for Each of the Three TMPs—Computer-Dominant, Limited-Computer, and Intensive. The percentages depict the proportion of TMPs of sessions on weekdays and weekends after stratification into each choice group. Column subscripts (*a* and *b*) signify the result of the comparisons of weekend and weekday proportions using the z-test (after Bonferroni adjustments). Proportions with different subscripts differ significantly.

			Day of Week	
stud_cluster			Weekday	Weekend
Computer-dominant	TOD	Morning	$20.9\%_a$	$27.3\%_b$
		Afternoon	$11.2\%_a$	$5.2\%_b$
		Evening	$20.7\%_a$	$17.2\%_b$
		Night	$47.2\%_a$	$50.4\%_b$
Limited-computer	TOD	Morning	$18.3\%_a$	$22.8\%_b$
		Afternoon	$11.4\%_a$	$5.9\%_b$
		Evening	$21.5\%_a$	$18.7\%_a$
		Night	$48.8\%_a$	$52.6\%_b$
Intensive	TOD	Morning	$20.5\%_a$	$28\%_b$
		Afternoon	$12.7\%_a$	$6\%_b$
		Evening	$20.1\%_a$	$14.6\%_b$
		Night	$46.8\%_a$	$51.4\%_b$

afternoon sessions were almost comparable (number of sessions = 220 and 253, respectively), on weekends, the number of morning sessions (number of sessions = 76) was larger than the number of afternoon sessions (number of sessions = 26). Similarly, for limited-computer students on weekends, the numbers of mobile-oriented sessions in the morning and at night were 29 and 51, respectively, whereas a noticeably larger difference between the two times of day was observed on weekdays (numbers of sessions = 94 and 216, respectively).

To test whether these observations were statistically significant, separate chi-square tests were conducted for each of the six plots in Figure 5 (after Bonferroni adjustments for multiple comparisons) to examine if the modality profiles were independent of the time of day when the learning sessions were carried out, on both weekdays and weekends. The tests revealed high statistical significance for four of these tests—computer-dominant weekday ($\chi^2(9) = 117.99$, $p < 0.001$), limited-computer weekday ($\chi^2(9) = 120.30$, $p < 0.001$), limited-computer weekend ($\chi^2(9) = 42.08$, $p < 0.001$), and intensive weekday ($\chi^2(9) = 135.26$, $p < 0.001$)—but only marginally significant results for the remaining two—computer-dominant weekend ($\chi^2(9) = 26.80$, $p = 0.002$) and intensive weekend ($\chi^2(9) = 23.15$, $p = 0.006$). That is, for learners with computer-dominant and intensive modality choices, there were only marginally significant associations between the TMPs of the learning sessions and the time of day these sessions were carried out on a weekend.

Post hoc analyses (see Table 4) contradicted the visual observations we made (from the bubble plot in Figure 5)—i.e., the numbers of morning and afternoon sessions are comparable—for the intensive students' mobile-oriented sessions on weekdays. Instead, the column proportion tests indicated that the proportion of mobile-oriented sessions in the afternoon was significantly greater than the proportion of mobile-oriented sessions in the morning. On the contrary, on weekends, the two proportions could not be differentiated. Similarly, the proportion of limited-computer students' mobile-oriented learning sessions in the morning and at night could not be differentiated from each other on both weekdays and weekends.

Post hoc analyses for computer-dominant users: The proportions of computer-dominant learners' computer sessions across morning, afternoon, evening, and night were indistinguishable on weekends (all subscripts are *a*). In other words, on weekends, the proportion of computer sessions remained constant throughout the day. Similar trends were observed for short-computer sessions on weekends. However, these trends were replicated across weekdays only for computer sessions, whereas for short-computer sessions, the proportion of morning and night sessions was significantly greater than that of afternoon and evening sessions. For mobile-oriented sessions on both weekdays and weekends, the proportion in the afternoon was higher than that in the morning, in the evening, and at night, all three of which were indistinguishable from each other. For diverse sessions on weekdays, the proportion of afternoon and evening sessions was greater than that of morning and night sessions, but these results did not hold on the weekend.

Post hoc analyses for limited-computer users: The proportions of limited-computer learners' computer sessions across morning, afternoon, evening, and night were indistinguishable on weekdays and weekends (all subscripts are *a*). In other words, the proportion of computer sessions on both weekdays and weekends remained constant throughout the day. Further, the proportions of diverse sessions in the morning and evening on weekends were similar (subscript *b* common in both), whereas on weekdays, the latter was significantly greater than the former. The proportion of mobile-oriented sessions that were conducted in the afternoons was significantly greater than those in the morning, in the evening, or at night on both weekdays and weekends. The proportions of short-computer sessions at night on weekdays and weekends were comparable to that of the morning sessions but greater than the proportions of sessions in the afternoon and evening.

Table 4. SPSS Crosstabulation Results for TMPs of the Sessions with Time of Day on Weekdays and Weekends, across the Three Modality Choices. In each of the six sub-tables, column subscripts (*a*, *b*, and *c*) signify the result from the comparisons of TOD proportions using the z-test (after Bonferroni adjustments). Proportions with different subscripts differ significantly.

Panel A: Computer-Dominant

	Time of Day			
TMP	Morning	Afternoon	Evening	Night
Diverse	$5.8\%_b$	$13.6\%_a$	$10.6\%_a$	$6.6\%_b$
Mobile	$2.5\%_b$	$7.2\%_a$	$3.2\%_b$	$2.5\%_b$
Short-computer	$59.3\%_b$	$48.3\%_a$	$52.9\%_a$	$58.6\%_b$
Computer	$32.4\%_a$	$30.9\%_a$	$33.3\%_a$	$32.2\%_a$

(a) Type of Day = Weekday, Modality Choice = Computer-dominant

	Time of Day			
TMP	Morning	Afternoon	Evening	Night
Diverse	$9.2\%_b$	$5.5\%_{a,b}$	$7\%_{a,b}$	$4.7\%_a$
Mobile	$2.9\%_b$	$9.9\%_a$	$3\%_b$	$3.2\%_b$
Short-computer	$54.7\%_a$	$57.1\%_a$	$54.3\%_a$	$60.6\%_a$
Computer	$33.1\%_a$	$27.5\%_a$	$35.7\%_a$	$31.6\%_a$

(b) Type of Day = Weekend, Modality Choice = Computer-dominant

Panel B: Limited-Computer

	Time of Day			
TMP	Morning	Afternoon	Evening	Night
Diverse	$6.1\%_b$	$10.8\%_a$	$10.6\%_a$	$7.8\%_{a,b}$
Mobile	$11.3\%_{b,c}$	$24.7\%_a$	$15.4\%_b$	$9.8\%_c$
Short-computer	$57.2\%_b$	$41.6\%_a$	$47.6\%_a$	$56\%_b$
Computer	$25.3\%_a$	$22.9\%_a$	$26.4\%_a$	$26.4\%_a$

(c) Type of Day = Weekday, Modality Choice = Limited-Computer

	Time of Day			
TMP	Morning	Afternoon	Evening	Night
Diverse	$7.7\%_{a,b}$	$12.3\%_{a,b}$	$14.4\%_b$	$6.3\%_a$
Mobile	$13.2\%_b$	$31.6\%_a$	$14.9\%_b$	$10\%_b$
Short-computer	$56.8\%_{a,c}$	$38.6\%_{a,b}$	$43.1\%_b$	$59.3\%_c$
Computer	$22.3\%_a$	$17.5\%_a$	$27.6\%_a$	$24.4\%_a$

(d) Type of Day = Weekend, Modality Choice = Limited-Computer

Panel C: Intensive

	Time of Day			
TMP	Morning	Afternoon	Evening	Night
Diverse	$7.4\%_a$	$9.4\%_a$	$8\%_a$	$6.9\%_a$
Mobile	$26.6\%_b$	$49.5\%_a$	$42.8\%_a$	$29.8\%_b$
Short-computer	$42.8\%_b$	$27\%_a$	$32.1\%_a$	$40.5\%_b$
Computer	$23.3\%_b$	$14.1\%_a$	$17\%_a$	$22.7\%_b$

(e) Type of Day = Weekday, Modality Choice = Intensive

	Time of Day			
TMP	Morning	Afternoon	Evening	Night
Diverse	$8.9\%_a$	$16.4\%_a$	$8.1\%_a$	$7.4\%_a$
Mobile	$29.5\%_a$	$47.3\%_{a,b}$	$43\%_b$	$32.7\%_{a,b}$
Short-computer	$38\%_a$	$27.3\%_a$	$35.6\%_a$	$40.3\%_a$
Computer	$23.6\%_a$	$9.1\%_a$	$13.3\%_a$	$19.6\%_a$

(f) Type of Day = Weekend, Modality Choice = Intensive

Post hoc analyses for intensive users: The proportions of intensive learners' computer and short-computer sessions in the morning, in the afternoon, in the evening, and at night were indistinguishable on weekends (all subscripts are *a*). In other words, the proportion of computer-oriented sessions on weekends remained constant throughout the day. However, these trends were not replicated on weekdays; i.e., the proportions of morning and night sessions for the short-computer and computer TMPs were significantly greater than those of the afternoon and evening sessions on weekdays. An interesting observation for the mobile-oriented learning sessions was that the proportion of these types of sessions taking place in the afternoon was significantly greater than those occurring in the morning and at night only on weekdays but not on weekends. On the contrary, the proportion of diverse learning sessions remained constant throughout the day on both weekdays and weekends.

3.4 Summary of Results

These observations led us to conclude, in a nutshell, that intensive learners who make use of multiple modalities to augment their learning exhibit differing temporal patterns on weekdays than on weekends. On the other hand, computer-dominant and limited-computer learners were quite consistent in their temporal patterns such that (1) on both weekdays and weekends, significantly greater mobile sessions took place in the afternoon, and (2) on both weekdays and weekends, the proportion of computer sessions remained constant throughout the day, except for short-computer sessions, whose proportion was constant throughout the day on weekends, but on weekdays, morning and night witnessed significantly more mobile sessions. In other words, different dynamics are at play depending on whether the learning sessions took place on the weekend or on a weekday,

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and, thus, there is a potential for personalization of feedback pertaining to the specific TMPs, based not only on time of day but also on day of the week.

4. Discussion

The setting for this work is part of a comprehensive program of research focusing on how the influx of modern devices, such as computers, tablets, and smartphones, from technological advancements in learning are affecting the learning strategies, aptitudes, routines, and ultimately academic achievements of learners. This study advances the previous work by Sher and colleagues (2019), which focused on the technological modality's impact on learning outcomes. In this paper, we determine when and how learners access different modalities throughout the day (RQ1) and shed light on how weekend access differs from weekday access (RQ2). In this exploratory study, we looked at differences in students' time flexibility (across time of day and day of the week) and modality flexibility (choice of computers, mobiles, and tablets) in individual activities related to the use of the LMS in two blended courses. We used trace data to determine contextual TOD preferences from usage logs, as opposed to the current paradigm of surveys and questionnaires (Romero & Barberà, 2011; Stockwell, 2010; Luo, Pan, Choi, & Strobel, 2018; Davidson & Ritchie, 2016).

While most previous studies had examined the study-time patterns at the granular level of a single modality or a single action, we established a relationship with the sequential patterns of using differing modalities throughout the day. Doing so helped us narrow down the time of day (collapsed into four TOD categories—morning, evening, afternoon, and night) when users are engaged intensively with the learning sessions (longer sessions such as computer sessions) versus when they are spontaneously engaged (e.g., shorter mobile-oriented sessions). Our results revealed that learning sessions from various modalities were significantly associated with the time of day these sessions were carried out. More interestingly, the associations held true for students with varying technological modality choices, i.e., who made extensive use of different modalities to complete their learning activities (computer-dominant and intensive learners), and those who sparingly used them (limited-computer learners). We also revealed that the associations were similar on weekdays and weekends for computer-dominant and limited-computer learners, two groups that are strikingly different in terms of their academic performance, as reported by Sher and colleagues (2019).

The temporal patterns discovered in the paper played a major role in shaping our understanding of a learner's choice of a particular modality over another. For instance, learning on a computer usually tends to be far more meticulously planned (Stockwell, 2013) than for its mobile and tablet counterparts, or for an activity (such as assignments) that might require lesser distraction, which some might say can be introduced by the opportunistic use of mobile phones and tablets in various contexts. Given that the study was situated in the context of programming-oriented courses that consist of coding assignments, we saw that learners with varied modality choices gravitated toward certain times of day, mostly nights, in order to be able to engage in learning sessions on their computers. However, such concrete temporal patterns were visible only for *short* computer sessions. Engagement in long computer sessions was somewhat more consistently dispersed throughout the day for all learners except intensive learners, who demonstrated a preference for night-time. A possible rationale for this finding could be that unlike computer-dominant and limited-computer learners, intensive learners do not rely entirely on computers for all their learning needs and therefore were successful in reserving the use of a specific modality for a specific time-frame during the day. Nevertheless, this finding warrants further qualitative research that should provide a deeper insight into their time-management skills and course-planning strategies and potentially reveal more reliable explanations.

Learning sessions on the mobile phone, on the other hand, which one would assume to be more spontaneous and for small actions only (Casany Guerrero et al., 2012), were found to take place mostly in the afternoon (and relatively less at night) across all learners, regardless of their modality choice. This was a surprising finding because it was expected that learners would take advantage of the mobile modality to engage in learning especially in the evening (on their way home, when computer use would be cumbersome, if not entirely impractical), much like the results reported by Song and colleagues (2013) and Casany Guerrero and colleagues (2012), who found that mobile phone usage was restricted to late-night hours between 8 p.m. and midnight when learners would most probably be in a stationary position (say, at home). Instead, we found that they frequently opted to use the mobile modality in the afternoons during class times. This might suggest that students use mobile phones more on campus when they experience some sort of modality restrictions, perhaps preventing them from accessing their laptops or computers mid-lecture (Lee, Ahn, Nguyen, Choi, & Kim, 2017). However, we found that a significantly higher use of mobile phones in the afternoon was prevalent on weekends too when the learners may not be experiencing any modality restrictions. This further solidifies our finding that the afternoon time slot is indeed the preferred time for mobile learning sessions. This finding is also partially supported by Tabuenca, Kalz, Drachsler, and Specht (2015), who found that students were most active on their mobile phones from 9 a.m. to 3 p.m. They also found the 6 p.m. to 10 p.m. time range (which overlaps with the evening slot defined in our study) to be highly active for students' use of personal mobile devices, but in our study, this was valid only for intensive learners, who constitute the majority of mobile users. In fact, for both computer-dominant and limited-computer learners, evening registered lower-intensity mobile learning sessions than morning, afternoon, and night.

4.1 Time of Day and Academic Performance

The construct of time is a principal component of a student's learning process and, appropriately, time of day has been used as an indicator of quality of learning times (Romero & Barberà, 2011; Blake, 1967), and by extension academic performance (Gromada & Shewbridge, 2016; Romero & Barberà, 2015). Although learners vary in their capacity to organize quality learning time, their time allocations become particularly crucial at the post-secondary level. This is because college settings often comprise fewer hours of structured classroom time, so students' academic success relies on their ability to use time effectively.

While assessing the relation between time of day and academic performance was not the main aim of this study and hence was not studied in depth, we can still draw some conclusions. As Figure 2 suggests, the learning sessions from two of the main high-performing groups—computer-dominant and intensive—were performed mostly at night. This is in contrast to the observation by Romero and Barberà (2011), where adult e-learners' academic performance was more strongly related to morning and evening. A possible explanation might be the contextual differences introduced by the course settings. Their study looked at fully online learners engaging in a social sciences course, graded based on written assignments. By contrast, the participants in our study were full-time students in programming-oriented courses that required them to spend a fair amount of time working on their programming assignments using specific software on computers. By virtue of our participants being in class for most of their day, evening (and late night) undoubtedly emerged as the preferred time of day for computer-oriented sessions.

Judging one's performance, especially as it relates to the effort exerted, is difficult for many university students. The challenge mainly originates from not knowing how much time other students devote to working on the course. Hence, one possible direction to improve the outcomes for students in the lowest-performing group, i.e., limited-computer users, is to raise their awareness of how much more other students are studying, likely leading to better outcomes. Considering that afternoon and post-afternoon (evening and night) are the highly preferred times for mobile and desktop activities, respectively, and the most closely related to strong academic performers (such as computer-dominant and intensive learners), raising awareness of low-performing students about the connection between more time spent overall and at particular times may lead to self-correction of their patterns. As some students undertake other work or engage elsewhere during the day, pointing out the significant differences in time devoted to studying at night can be a good starting point to adjusting their time allocation. Furthermore, since routines and time commitments on weekdays may be fixed, instructional interventions that promote learners' use of a greater part of their available time on weekends to study in the time-frames observed above may improve learning outcomes. Alternatively, if leveraging temporal patterns associated with high performance fails to offer some feedback or improvement for low-performing students, their routines may need to be assessed since they might be confronting particular challenges because of temporal orientations, defined by their professional and social activities and the digital world. In such scenarios, it might be worth pointing out that *how* they study may be equally or more important to success, compared to *when* they do so.

4.2 Implications for Research and Practice

Even though some results on TOD preferences were found to vary for certain groups of students, there were also some commonalities across all TMP strategies that can be adapted for practical purposes (such as afternoon for mobile sessions and evening for computer sessions). Further, the underlying idea that the study seeks to promote remains constant; i.e., personalized delivery of learning-related recommendations for each individual learner is possible and also promising. As of now, a typical recommender system cannot aptly judge both the amount and the quality of the time a learner has to engage in a task, thereby wasting both learner time and modality as a true knowledge asset. Our findings can be viewed from the perspective of quality of learning time. That is, given the knowledge of high-quality learning times, students would be able to organize and regulate their activities asynchronously, leading to greater productivity.

While universities do not and cannot systematically consider flexibility of students' time schedule to hold classes, knowledge of their preferred time of day can be leveraged for sending them notifications, reminders on their preferred modality type, or even feedback regarding their academic submissions. Typically, notifications are sent at a random time of day or whatever time has been hard-coded in the LMS app—which might not be based on theoretical/empirical reasoning, both of which might result in undesirable learning impacts (Tabuenca et al., 2015; Stockwell, 2010). For instance, we observed in the Stockwell (2010) study that the push mechanism was used to roll out reminders at 5 p.m. sharp (schedule-based notifications (Tabuenca, Kalz, Börner, Ternier, & Specht, 2014)) onto students' mobile phones, justifying that evening is when many students commute home. However, the expected outcome was not achieved. The author found no instances of learners acting on the activities within a six-hour period after receiving the email notification from the server. While it may be partly to do with the appropriateness of the content of the messages, as suggested by Stockwell (2010), it would not be entirely unpragmatic to think that the timing or

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the target modality for pushing these reminders might not have been optimized to suit learner needs. This is especially true since our results report afternoon as the more favourable time for mobile-oriented learning sessions. Therefore, there is a need to embed the practice of research into design of educational technologies, such as LMSs and recommender systems, so that learners are not forced to conform to the global settings the technology offers; it is rather that the technology takes into account their aptitudes, strategies, and context.

The problem experienced in the Stockwell (2010) study is a common occurrence in distance and e-learning, mainly because the online (learning management) system is regarded as one that can be used anywhere and anytime, and where the instructional content is delivered without considering whether learners have sufficient time to act on it. This means there is a fair possibility that they might receive it at an *inappropriate* time, say late evening when they are tired (Grundspenkis, Lavendels, Novitsky, & Sitikovs, 2006) or while commuting (Srinivasan, Koehler, & Jin, 2018), which in turn results in ineffective learning. Considering that we found some recurrent temporal patterns for learners with varying TMPs, we urge LMS designers to consider them while designing notifications in LMSs and recommender systems. The more flexible, personalized nature of notification time has the potential to shape achievement outcomes in ways that have yet to be clearly understood. A practical implementation of the utility of the modality-time associations that is worth mentioning here was exemplified by Xu and colleagues (2008), who used time of day and day of the week (among other variables, such as location and user type) as contextual variables (tracked from user log files) to create an information system. The information system delivered context-aware, application-specific information depending on which device—phone, personal digital assistant, laptop, desktop, wall display—the request was made from. Although the authors do not discuss results from the use of the system, the learning analytics field would benefit from empirical analysis of such systems.

A prominent ongoing debate, in relation to the process of tailoring notification delivery in the aforementioned personalized learning systems, concerns the effects of timing of push notifications—random versus fixed (Fischer et al., 2010; Tabuenca et al., 2015; Morrison et al., 2017). Tabuenca and colleagues (2015) studied learner perceptions regarding whether mobile notifications should be sent at random or fixed times and found that students preferred the latter over the former, given that it allows them to plan their day. While we agree to and can envision the benefits of not bombarding learners with notifications at random times, we are skeptical of the prospect of fixed-time notifications. Unless modality is taken into consideration, "fixed" time entails sending notifications, at any level of required effort or urgency, to learners at pre-fixed times on all modalities without capitalizing on the unique capabilities that each modality provides. As we observed in our study, significantly different learning patterns emerged based on time of day and modality, so we envision the potential of learning algorithms (for a system's design) that enable the content of notifications to fit with the timing and modality, to ultimately provide timely and actionable feedback. Some recommendations for doing so are discussed next.

Tabuenca and colleagues (2015) noted that notifications that foster participation in studying will be acted on the moment learners receive them. Thus, notifications that usually correspond to ongoing activities in the LMS should be delivered in a temporal context and via a modality that maximizes a learner's chances of acting on them. For instance, grade release, informal feedback, and generic tips on planning for self-regulated learning (SRL) require less strain on mental capacities and can be delivered at times when students are not likely engaged in other in-depth learning activity. This could be in the form of a pop-up notification on mobile at the time of otherwise low engagement, say afternoon on a weekday. On the other hand, prompts concerning the performance phase in SRL or any feedback at the "process level" (Hattie & Timperley, 2007), for instance, where competency assessments must be completed (assignments, exams, quizzes) or prepared for (review resources relevant to the upcoming course assignments), require longer uninterrupted learning sessions. These should, therefore, be sent on the computer when the learner is likely to engage in longer study time, which happens in the evening on weekdays and weekends. An exception to this rule would be learners who incorporate many different modalities in their learning environments, i.e., intensive learners. This group would benefit from such notifications if they were sent in the morning on weekdays or weekends. Finally, prompts from the monitoring activities in the LMS where information is mainly *consumed* rather than *created*, such as tracking self-progress in discussion forums or reading other's discussions, can be delivered on a computer in the morning on weekdays or at night on weekends. Given that a shorter time span is sufficient for such activities, these temporal patterns work even if the learner is not likely to be engaged for a long duration in a study session. In the context of the LMS, the notifications are predominantly initiated by an educator through their actions, such as posting a mark for the assignment, posting a submission comment, changing the deadline, posting updated content, and making an explicit announcement. As educators are working according to their own schedules, they should not be reasonably expected to time their actions to the times that would be the most appropriate to deliver to students, especially not being aware of immediate individual students' online presence. One possibility is to tag the notifications based on their type either automatically (such as release of the grades) or explicitly by an instructor for announcement or assignment comments and deliver those notifications based on policies originating from findings such as ours.

The ability to share and distribute information to learners via learning systems is important for extending learning outside the formal classroom (Cheon, Lee, Crooks, & Song, 2012). Based on the results of our study, learners' TOD preferences are linked to the sequence of their learning actions on these systems from different devices. This subsequent knowledge is paramount for helping to personalize and make learning available at times that are more suitable to learners—both academically and personally. When talking about the major challenges for enabling personalized learning within a global education system, Goodyear (2011) emphasized the need to understand how learning activities are distributed across different contexts, especially since learners continuously need to adapt to diverse environments to accommodate changing (learning) needs. In order to achieve that, we have offered some prescriptions above to help (a) researchers understand the opportunities afforded by the incorporation of varying modalities into learners' active learning environments as they go about their day (in classrooms, at home, and outdoors) and (b) designers understand and conceptualize all temporal aspects of the (mobile/computer/tablet) learning systems to be as effective as possible in delivering the objectives. While we acknowledge that the prescriptions offered are rather limited, we emphasize the need to pursue this line of inquiry to better facilitate students' academic success. Overall, a vast amount of research still needs to be done with respect to the temporal aspects of learning in the presence of novelty devices, and us exploring and finding associations in this paper is just getting one step closer to Goodyear's (2011) vision.

4.3 Limitations and Future Work

While many instructors and LMS designers may have expectations of seamless (even blended) learning as a means of having learners engage in learning activities from different devices at any time and at any place, the observation from the current study is that learners undertake these activities at a range of times. However, there can be some ambiguities depending on how these time periods/day slots were defined, i.e., morning (5 a.m. to noon), afternoon (noon to 6 p.m.), evening (6 p.m. to 9 p.m.), and night (9 p.m. to 5 a.m.), which usually depends on personal lifestyle and culture. Therefore, it would be interesting to see this study replicated across different cultures and with diverse cohorts, such as distance learners, lifelong learners, mature learners, and e-learners, for whom the distribution of the 24 hours of the day into slots might be different.

Second, while the main achievement of this study is that it provides temporal insights into the use of a university LMS from multiple technological modalities, our immediate next steps will involve looking at each learning activity in isolation to study the trajectory of modalities used throughout the day. Doing so would allow us to infer if the TOD preferences are stable across different learning activities. Detecting such insights could therefore help instructors plan lessons and provide personalized support to their students, ultimately increasing productivity. This line of inquiry could also be extended to examine the generalizability of our findings.

Third, since our methodology involves tracking user interaction with the LMS within a programming course, this may raise a concern about the extent to which our results depended on the learning context. Hence, stability of temporal patterns needs to be assessed, taking into consideration other courses with varying course structure in terms of milestone definitions, submission deadlines, and assessment type. Likewise, the influence of the learner's background, demographics, educational context, and study approaches could lead to new insights.

Fourth, for the analyses of this study, the learning sessions comprised actions accumulated across the entire semester, i.e., four months or approximately 120 days. However, the rather low median number of total sessions, for all three student groups, indicates that students may have been working seriously on the course only couple of days a week, not every day. Thus, it would be interesting to see if the distribution of the sessions across the day was uniform throughout the semester or if in fact we could identify clusters of *intensive* days and *keep-in-touch* days, based on the intensity of sessions on that particular day. Moreover, we will also be studying what roles different modalities play for each of these days and the impact on the academic outcome, if any.

Finally, the many methodological choices made as part of this study must be explicitly pointed out for consideration by future researchers. Single sessions (sessions comprising only one action) were eliminated since we were more interested in the sequence of actions rather than individual actions. This was because we wanted to gain insight into general patterns of study sessions, which usually comprise a few different activities undertaken in one sitting. Single actions originate from one modality and thus don't tell us much about whether continued use of a modality was observed for other activities too, after a student completed one activity on a particular modality.

We set the clustering methodology upfront before we knew what the results would look like, and we expected greater variance in the sessions themselves. However, after observing the results, we see that the methodology may have been overly complex. A simple approach may suffice for future research, namely grouping sessions based on two criteria: modality used (computer, mobile, tablet) and session length (short, long), to create six TMPs (e.g., short-computer, long-computer, and short-mobile).

5. Conclusion

With contemporary technology enhanced learning (TEL) environments proliferating at unprecedented rates, there is a gap in our current understanding of the temporal frameworks that are at play when interpreting students' learning activities. In this paper, we move one step beyond chronotype to study associations between TOD preferences (such as morning, afternoon, evening, night) and the different modalities (e.g., smartphones, tablets, laptops) present in such environments. That is, the study sought to determine precisely when learners undertook activities on mobile phones and computers to identify differences between the LMS usage patterns with respect to the time of day. Understanding how specific times of day may orient, inform, and/or constrain the unfolding activity is highly relevant and beneficial given the continuously evolving relationship between modern technologies and students' learning environments in this day and age. Moreover, enabling personalized learning systems within TEL environments has a few obstacles, part of which is to understand how learning activities are distributed across differing times during the day (morning, evening, etc.) from various devices.

The results from the study revealed patterns of use indicating that there are quite significant differences in how learners undertake learning using multiple modalities. These differences go beyond simple preferences for one type of modality over the other. Learners typically selected different times of day to engage with the LMS depending on whether the activity required them to use computers or mobiles or whether the session was long or short. For instance, short computer sessions were observed to be more prominent at night (9 p.m. to 5 a.m.) than at other times during the day, and mobile sessions were significantly higher in number in the afternoon (noon to 6 p.m.) than during the rest of the day. Furthermore, preferences on weekdays were found to be different from those on weekends for all students and instead depended on the session's modality profiles and learners' modality choice, among other contextual factors.

Being in a constantly changing environment throughout the day implies that numerous influencing factors surrounding a learner can impact their learning behaviour, their concentration, and ultimately their ability to use a specific modality at a particular time. While there is no control over these TOD aspects, it is important to keep these in mind when considering the implications of pedagogical design, dictating the use of mobile modalities such as smartphones or tablets versus desktop computers. Consequently, we have proposed a personalized notification system that can be seamlessly integrated with the LMS to deliver notifications, based on their type, to a student at the time of day when the student is most likely to be able to act on it.

Statement on Ethics

Informed consent was obtained from all study participants. All collected data was treated confidentially. This research has been approved by the university ethics board (2014s0127).

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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