Technology-enhanced learning: Using learning analytics to unveil students' use of multiple devices in blended learning

by

Varshita Sher

M.Sc., University of Oxford, 2015
B.Sc., University of Delhi, 2014

Thesis Submitted in Partial Fulfillment of the
Requirements for the Degree of
Doctor of Philosophy

in the
School of Interactive Arts and Technology
Faculty of Communication, Art and Technology

© Varshita Sher 2019
SIMON FRASER UNIVERSITY
Fall 2019

Copyright in this work rests with the author. Please ensure that any reproduction or re-use is done in accordance with the relevant national copyright legislation.

Approval

Name:	**Varshita Sher**
Degree:	**Doctor of Philosophy**
Title:	**Technology-enhanced learning: Using learning analytics to unveil students' use of multiple devices in blended learning**
Examining Committee:	**Chair:** Robert Woodbury University Professor
	Marek Hatala Senior Supervisor Professor
	Dragan Gašević Supervisor Professor Faculty of Information Technology Monash University
	Phillip Winne Internal Examiner Professor Faculty of Education
	Alyssa Wise External Examiner Associate Professor Learning Sciences and Educational Technology Steinhardt School of Culture, Education, and Human Development, NYU
Date Defended:	**November 26, 2019**

Abstract

In recent times, there has been a substantial interest in capitalizing on the abundance and the ubiquity of mobile and personal technologies for their educational use. Even though use of emerging technologies in education is associated with emerging educational practices, their role in educational setting is still largely under-researched. This doctoral research aims to bridge this gap in knowledge by understanding the learning habits and behaviours of students using different devices (such as desktops, tablets, mobile) for learning.

Our first goal is to explore how mobile devices are used when regulating learning via learning management systems (LMS) in the context of blended learning. To do so, we examine the extent to which various technological modalities (including mobile devices, tablets, desktops) are either used sequentially and/or simultaneously to influence the overall academic performance and study habits at various learning activities. Next, with the intent of understanding associations between temporal patterns and modality preferences, our second goal is to assess how learning takes place during different times of the day and on weekdays/weekends. Further, given the substantial differences between utility of each modality for a learning activity, the fourth goal is to demonstrate how considering the modality for learning actions can lead to improvement in predictive power of learning models generated from student engagement data. Our fifth and final goal is to investigate whether preferences for a modality evolve over time and, if so, analyze the role it plays in consistency of work habits and student persistence in learning.

Each of these goals has been previously published or submitted for review to a peer-reviewed journal/conference. The full texts of these studies are included in this cumulative format dissertation. In each of these studies, the log data for analyzing the aforementioned research questions was collected from undergraduate students at our university from courses that followed a blended delivery format, utilizing the university's learning management system (LMS), Canvas, to support learning activities and students' overall schoolwork. The overall aim of this thesis is to extend current theoretical understanding of the way students move between technological modalities, physical and temporal contexts and learning activities.

Keywords: Multi-device use; Mobile Learning; Learning Analytics; Learner Models; Blended Learning; Seamless Learning; Trace Analysis, Temporal Analysis

This is for you, Nani, and your everlasting desire to see me achieve the highest of accolades. Miss you.

Acknowledgements

This PhD journey was a fruitful, unforgettable, and profoundly life-changing experience for me. It certainly would not have been possible without the guidance and support of several individuals.

I would like to extend my deepest gratitude and appreciation to my supervisor, Professor Marek Hatala, for his encouragement, patience, and incredible support throughout my thesis. Thank you for accommodating all the drop-in-anytime sessions, weekend emails, Victorian vocabulary and last, but not the least, helping me achieve my graduation timeline as I planned. I cannot begin to express how truly grateful I feel to have you as my supervisor, who not only helped me grow academically but also personally.

I would also like to thank Professor Dragan Gašević for sharing his expertise and providing insightful comments throughout my thesis work. I really appreciate the frequent Skype calls and cannot thank you enough for all our fluent communications despite the time differences.

Sincere thanks to my fellow lab mates Sina Nazeri, Ladan Fatehi, Halimat Alabi, Fatemeh Salehian Kia and other amazing colleagues at Simon Fraser University. Thank you for all the support and so many good memories over the years. I would also like to thank Meenakshi for being more than a friend and keeping me sane, both emotionally and mentally, during the doctoral journey.

A very special thanks to my parents, Mr. Vinod Sher and Mrs. Sangeeta Sher, for their endless encouragement and unwavering belief in me and my abilities. You have no idea how much your words motivated me when times were tough. To my amazing sister, Ishitaa, thank you for your unconditional love and moral support since childhood. To my brother-in-law, Vidit, thank you for your warm encouragement and the playful banter we share. To my dearest Nani, who passed away before the completion of this thesis, thank you for the values you instilled in me and making me the woman I am today. Thanks to all my near and dear ones, who in their own special ways, kept me going on my path to success. Big shout out to my four-legged fur ball, Zu, whose antics cheered me up and de-stressed me as I wrote my thesis.

Finally, I would like to express my deepest appreciation to my boyfriend, Subhash, for his love and understanding over the past four years. Thank you for brightening my day, making me smile, planning all our mini-vacations and ensuring there isn't a single dull moment. I now look forward to embark upon the new journey with you.

Table of Contents

Approval ii

Abstract iii

Dedication v

Acknowledgements vi

List of Tables xiii

List of Figures xv

1 Thesis Summary 1

2 Introduction 5

2.1 Format of the Dissertation 5

2.2 Research Questions 5

2.2.1 Research Question I 6

2.2.2 Research Question II 6

2.2.3 Research Question III 7

2.2.4 Research Question IV 7

2.3 Publications and Contributions 7

2.3.1 Publications 8

2.3.2 Author's Role 11

2.4 Target audience for the research 11

3 Background 12

3.1 Learning Analytics 12

3.2 Technology-enhanced learning 13

3.3 Use of Various Modalities for Learning 15

3.3.1 Use of Mobile Phones for Study 15

3.3.2 Use of Laptops for Study 18
3.3.3 Use of Desktops for Study 19
3.3.4 Use of Tablets for Study 19
3.3.5 Comparison of modalities for learning 20
3.4 Trace Analysis 22
3.5 Theoretical framework 23
3.5.1 Framework for the Rational Analysis of Mobile Education model . . 23
3.5.2 Framework for Student Use of Multi-Devices for Learning 24
3.6 Positioning of Thesis Work 26
3.6.1 Categorization of modalities 26
3.6.2 Modality-use under investigation 27
3.6.3 Research Goals 27

4 Sequential Analysis of Multi-device Use 29
4.1 Overview 29
4.2 Publication 30
4.3 Introduction 30
4.4 Methods 33
4.4.1 Study Context 33
4.4.2 Learning traces and study sessions 33
4.4.3 Data Analysis Techniques 35
4.5 Results 39
4.5.1 Clustering of sequences as manifestations of students' technological-modality profiles (TMP) 39
4.5.2 Clusters of students based on the adopted technological-modality profiles 41
4.5.3 Analysis of cluster differences 42
4.6 Discussion 45
4.6.1 Technological-Modality Profiles 45
4.6.2 Strategies and Discussion Performance 46
4.7 Limitations and Future Work 48
4.8 Conclusions 49

5 Temporal Analysis of Modality-usage patterns 50
5.1 Overview 50
5.2 Publication 51

5.3 Introduction . . . 51
5.3.1 Time and modality flexibility in learning . . . 53
5.3.2 Research questions . . . 54
5.3.3 Significance of the study . . . 54
5.4 Methods . . . 55
5.4.1 Study Context . . . 55
5.4.2 Learning traces and study sessions . . . 56
5.4.3 Data Analysis Techniques . . . 56
5.5 Results . . . 59
5.5.1 Results of clustering . . . 59
5.5.2 Associations between technological modality profiles and time of day 61
5.5.3 Associations between technological modality profiles and weekdays/weekends . . . 68
5.6 Discussion . . . 74
5.6.1 Temporal patterns of modality usage . . . 74
5.6.2 Time of day and academic performance . . . 76
5.6.3 Implications for Research . . . 77
5.6.4 Limitations and Future Work . . . 80
5.7 Conclusion . . . 80

6 Modality-inclusive Learner Models 82
6.1 Overview . . . 82
6.2 Publication . . . 83
6.3 Introduction . . . 83
6.3.1 Contribution and Research Questions . . . 85
6.3.2 Theoretical Framework . . . 85
6.4 Methods . . . 87
6.4.1 Study Context . . . 87
6.4.2 Data Collection and Procedure . . . 87
6.4.3 Study Design . . . 89
6.4.4 Outcome variables . . . 91
6.4.5 Statistical analyses . . . 92
6.5 Results . . . 94
6.5.1 Prediction of student course grades: LMS vs. Modality features . . . 94
6.6 Discussion . . . 98
6.7 Limitations and Future Work . . . 102

6.8 Conclusion 103

7 Consistency in learning in presence of multiple modalities 105

7.1 Overview 105
7.2 Publication 106
7.3 Introduction 106
7.3.1 Time series analyses of work patterns 108
7.3.2 Consistency in Learning Behaviours 109
7.4 Method 111
7.4.1 Study Context 111
7.4.2 Learning traces and time series 112
7.4.3 Data Analysis Techniques 113
7.5 Results 114
7.5.1 Clustering of students based on consistency in assignment activities 115
7.5.2 Analysis of cluster differences based on assignment grade 119
7.5.3 Clustering of students based on consistency in discussion activities . 120
7.5.4 Analysis of cluster differences based on discussion grade 123
7.6 Discussion 124
7.7 Conclusions 127

8 Discussions of Cumulative Results 128

8.1 Context of Interpretation of Thesis 128
8.2 Physical affordances of learning tools 129
8.3 Implications of the Research 130
8.4 Critical Reflection 133

9 Conclusions and Future Directions 136

9.1 Summary of the present work 136
9.2 Impact of the present Work 138
9.2.1 Research Goal I: Access to and use of multiple devices 138
9.2.2 Research Goal II: Learning activities and Modality affordances . . . 139
9.2.3 Research Goal III: Temporal associations with modalities 139
9.2.4 Research Goal IV: Modalities and Academic Success 139
9.3 Directions for future work 140

Bibliography 142

Appendix A Details of the Learning Tasks **163**

List of Tables

Table 3.1 Summary of Mobile Learning Systems 17

Table 4.1 Breakdown of activities and access (in terms of number of actions) from different modalities 35

Table 4.2 Extracted features: Dependent variables examined in the study 36

Table 4.3 Characteristics of sequences (in terms of lengths i.e. action count) in the technological-modality profiles 40

Table 4.4 Summary statistics for the 3 student clusters: median, 25th and 75th percentiles. 41

Table 4.5 Descriptive statistics of the dependent variable raw scores: Mean, Standard deviation (SD), Median (Mdn), 25th (Q1) and 75th(Q3) percentiles. 43

Table 4.6 ANOVA - Main and Post-hoc results. 44

Table 4.7 Kruskal Wallis - Main and Post-hoc results. 44

Table 5.1 Summary statistics for the three student clusters: median, 25th and 75th percentiles. 60

Table 5.2 SPSS Crosstabulation results; alpha value adjusted for multiple comparisons ($p < 0.003$). Adjusted residual values highlighted in gray shade represent significant differences between the expected and adjusted counts. 66

Table 5.3 Crosstabulation for Time of Day (TOD) with Day of week (DOW) for each of the three technological modality strategy – Strategic, Minimalist and Intensive. The percentages depict the proportion of technological modality profiles of sessions on weekdays and weekends after stratification into each modality strategy. Column subscripts (a and b) signify the result from the comparisons of weekend and weekday proportions using z-test (after Bonferroni adjustments). Proportions with different subscripts differ significantly. 71

Table 5.4 SPSS Crosstabulation results for technological modality profiles of the sessions with the time of the day on weekdays and weekends, across the three modality strategies. In each of the six sub-tables, column subscripts (*a*, *b* and *c*) signify the result from the comparisons of time of day proportions using z-test (after Bonferroni adjustments). Proportions with different subscripts differ significantly. 72

Table 6.1 Breakdown of activities and access (in terms of the number of actions) from different modalities. 89

Table 6.2 Extracted features: Predictor variables examined in the study 90

Table 6.3 Descriptive statistics of the predictor variables across different modalities – Desktop, Mobile and Tablet. Continuous but skewed variables are presented as Median along with the first and third quartiles: Md(Q1, Q3) and categorical data is presented as percentages (N = 165). . . . 92

Table 6.4 The association between the variables of students' use of the LMS and Modality features and ln (log natural) student course grades: results of multiple linear regression models. 95

Table 7.1 Prototype activity patterns for the five student clusters (Cluster1 : Cluster5) at the eight assignment tasks (A1 : A8). The x-axis represents number of days before the assignment, starting from 10th day before the deadline up to the day of submission and the y-axis represents the number of assignment views. To allow cross graph comparison, all graphs have been plotted with x-axis scale [-10,0] and y-axis [0,15]. . 118

Table 7.2 Prototype activity patterns for the six student clusters (Cluster1 : Cluster6) at the three discussions tasks (Disc1 : Disc3). The x-axis represents the number of days before the discussion, starting from 10th day before the deadline up to the day of submission and the y-axis represents the number of discussion views. To allow cross graph comparison, all graphs have been plotted with x-axis scale [-10,0] and y-axis [0,15]. 123

List of Figures

Figure 3.1 Learning Analytics Reference Model [40] 13
Figure 3.2 Device Use and Importance for Academic Success (Source: [84]) . . 15
Figure 3.3 Student smartphone, tablet, desktop, and laptop ownership (Source: [30]) 16
Figure 3.4 FRAME model by Koole [140] 24
Figure 3.5 Framework for Student Use of Multi-Devices for Learning by Krull [145] 25

Figure 4.1 Examples of technological modality sequences encoded in the TraMineR format 37
Figure 4.2 Sequence frequency plots (SFP) for each TMP profile showing the proportions of the ten most frequent sequences. (Green:Desktop, Purple: Mobile, Orange: Tablet) 39

Figure 5.1 Bubble plot depicting the spread of sessions across the four major time-of-day categories. The sizes correspond to the number of sessions, the largest comprising 9,119 actions and smallest 1,984 actions. 62
Figure 5.2 Bubble plot depicting spread of sessions across time of day for the three modality strategies identified in Section 5.5.1 63
Figure 5.3 Bubble plot depicting distribution of modality profiles across times of day for the three modality strategies. The bubble sizes in (a), (b) and (c) have been scaled between [10,100] to allow cross-strategy comparisons. 64
Figure 5.4 Bubble plot depicting spread of sessions across weekday and weekends for the three modality strategies: 1 = Strategic, 2 = Minimalist, 3 = Intensive. 69

Figure 5.5 Bubble plot depicting spread of sessions on weekday and weekends for the different technological modality profiles across the three modality strategies. The bubble sizes in (a), (b), (c), (d), (e), and (f) have been scaled between [10,100] to allow cross-strategy comparisons. 70

Figure 6.1 Comparison of the two regression models for the assignment activity. Model 1 comprises of assignment views aggregated across all modalities as predictors, whereas features for Model 2 are conceived by slicing the view traces into their respective modalities. Similar models can be generated for the remaining nine LMS features analyzed in this study. 93

Figure 7.1 Box plots representing five number summary for the five student clusters. The box plots are color-coded by the student cluster they belong to. The y-axis represents all possible assignment-assignment pairs and the x-axis denotes the corresponding DTW measures for each pair. 116

Figure 7.2 Box plots representing five number summary for the six student clusters. The box plots are color-coded by the student cluster they belong to. The y-axis represents all possible discussion-discussion pairs and the x-axis denotes the corresponding DTW measures for each pair. 121

Figure A.1 Marking criteria for the discussion tasks. 164

Figure A.2 Guidelines for participation in the discussion tasks. 165

Chapter 1

Thesis Summary

Research is what I'm doing when I don't know what I'm doing.
- Wernher von Braun

The introduction of rapid technological advancements has changed the face of current educational landscape and has created more educational opportunities for both instructors and learners. Unlike traditional teaching methods in physical classrooms, tablets, smart phones and other technological modalities[1] are paving way for virtual or online learning such that the interactions among learners and between learner and information have profoundly changed [53]. These modalities offer a range of benefits such as supporting interactive lessons, remote access to learning experiences, and promoting personalized individual learning. Research also has evidence suggesting lectures made interactive by requiring students to use their laptops or mobiles to vote on, ask, and discuss questions, led to increment in most students' engagement, attendance and preparation [101, 282].

An October 2011 article in *The Economist* posited that, with the number of PCs already surpassing 1 billion in 2008, the number of mobile devices too would reach 10 billion in 2020 [68]. Notably, state-of-the-art progress has been made in the mobile learning field, owing to the portability, interactivity and low costs compared with other electronic devices. Mobile phones have carved a niche for themselves in the learning environment and paved way for out-of-classroom learning, as a result of which we have witnessed a surge in the number of extant mobile learning systems (MLS) such as LearnTracker [242], iTree [178], and MeLOD [81]. From a theoretical perspective, review of trends in mobile learning studies

[1] In the remainder of this thesis, we refer to devices such as mobiles, desktops, tablets as technological modalities to specify that their use is strictly for educational purposes (such as accessing educational softwares, learning tutorial videos or an educational mobile app, and online tutoring) and distinguish it from instances when they are used for other functions (such as social networking, text messaging or random browsing).

were found to be focused on discussions surrounding their acceptance by students based on demographics, intention and ease of use measures [255, 153], assessing common student activities performed by the learner using a mobile device [106, 272, 242, 237, 260], and developing frameworks for designing and deploying mobile learning experiences in different learning contexts [278, 157, 82, 140]. Though admittedly important studies, this digital era stipulates the need for conducting similar research with respect to *multi-device* use in learning environments to support and regulate learning.

Most educators do not take into account students' use of multiple devices in the design, facilitation or support of learning experiences [145]. This can be partly attributed to the scarcity of research concerning the use of multiple devices for learning and the dominant focus mainly on use of mobile technologies. Given that patterns and context of use differ substantially when comparing stationary desktop technologies with personal handheld technologies [248, 146], it is imperative to gain basic understanding of characteristics of each specific modality and conceptualize all aspects of the multi-device learning (in authentic learning environments) to be as effective as possible in delivering the objectives.

This research is timely because although smartphones and internet access are near-ubiquitous in universities, homes and commute, there is relatively little research which reports in detail on the ways in which students actually use combination of these modalities in their everyday learning and lives, and impact, if any, on their academic achievements. Moreover, a generic trend across studies on multi-device use [145, 54] points to the use of self-reported questionnaires as the most common data collection strategy, which although cheap and convenient to administer, lacks reliability due to flawed introspective abilities of participants. One way to address this issue is to make use of the vast amounts of data available within online learning environments which are used for delivering learning material and participating in learning activities, and that is the central idea of this thesis.

In this PhD thesis, we use trace data to investigate how learners adapt their use of multiple modalities, such as desktops, laptops, mobiles and tablets, to the learning context. We assess learner's log data derived from multiple modalities, while they engage in authentic learning tasks such as online discussions and assignments, so as to provide insights into the personal dimension of student learning. Through this thesis, we aim to provide a comprehensive view of learning habits and behaviours of student engagement using different devices for learning and explore the pedagogical and technological implications that ensue, to provide more effective support mechanisms for such students.

In this thesis, we first present the sequential analysis of learners usage of several modalities for regulating learning via learning management systems (LMS). We detected four major modality-use patterns: diverse, mobile-oriented, short-desktop and desktop. Based on the combination of usage of each of these patterns, students were categorized into three meaningful clusters: strategic, minimalist and intensive, representing the adopted technological modality strategy. By definition, strategic users employed only desktop-related modality-use patterns to engage in learning whereas diverse users tended to leverage both mobile and short-desktop profiles, and minimalist predominantly (but sparsely) made use of short-desktop sessions only. Looking specifically at the impact of these modality strategies on the performance in online discussion task and overall academic achievement, we found students' adopted technological modality strategies explained a large amount of variance ($\eta^2 = 0.68$) in their engagement and quality of contributions in discussions.

Next, we investigate the temporal aspects of the usage of different modalities. To put it another way, we assess if certain patterns of modality-usage are prominent at specific times during the day and specific days during the week. We analyze the associations between *patterns* of modality-usage and time of the day as opposed to the *counts* of modality-usage and time of the day. This led us to analyzing the problem at the granularity level of sessions (instead of an individual action) which resonates better with how learners engage in a task - learning at stretch for a continuous time period (without breaks or interruptions) and for a prolonged period of time. The results suggested that learning patterns from various modalities were significantly associated with the time of the day. Not only that, depending on whether the learning session took place on a weekend or weekday, specific modality patterns were more prominent than others. These results held true for students with varying modality strategies (as identified in Chapter 4) i.e. those who made extensive use of different modalities to complete their learning activities (strategic and intensive learners) and those who sparingly used them (minimalist learners). Overall, we found that mobile and short-desktop sessions were more prominent during afternoon and night time, respectively and weekdays witnessed significantly greater afternoon and evening learning sessions, whereas weekends saw a significant surge in morning and night learning sessions.

Following this, we highlight the potential for improvement of predictive power of the learning outcomes from student engagement data after considering the modality for each learning action. While traditional learner models are generated from logs that do not take into account the modality utilized by the learner, we present arguments in favour of a modality-inclusive learner model which has potential to improve prediction accuracy of academic success compared to its traditional modality-agnostic counterpart. We train our model using (count or time spent) measures from trace data which has been coded with the modality-source of each action and compare it against the null model wherein predictors are generated from cumulative measure. As was hypothesized, models that considered modality for learning actions were better at predicting learning outcomes than the null model for various LMS activities such as engaging with assignments, feedback on manuscript submissions, and viewing syllabus. We were also able to determine modalities conducive or unfavorable for particular LMS activities although the magnitude of variance explained by the modality differed based on the activity.

Finally, we investigate the consistency with which a modality is used for different phases of a particular activity during the semester. We also assess if the aspect of consistency in multi-device usage has the potential for a significant impact on academic achievements. We investigated consistency in two different learning contexts – assignment-reviewing and discussion-reading behaviour. To do so, we first generate the time-series patterns of modality usage for each (assignment or discussion) activity phase and compare similarity of modality-usage patterns between any two subsequent phases using data time warping (DTW) distance. We resort to the use of DTW measure instead of the euclidean distance since the former allows non-linear alignments between the two time series so as to accommodate sequences that are similar but out of phase. Our findings revealed that the use of desktop modality varied during subsequent assignment/discussion activities whereas mobile phone usage was constant throughout the course. Evidence of significant associations between these patterns and learner's academic performance were also found.

Chapter 2

Introduction

> *The important thing in science is not so much to obtain new facts as to discover new ways of thinking about them.*
>
> *- William Lawrence Bragg*

2.1 Format of the Dissertation

The overall dissertation is structured into chapters with each one focusing on one or more research questions, except Chapter 3 which provides an introduction to necessary background knowledge to orient the readers for comprehending this thesis. Chapter 4 reflects on the sequential use of multiple devices for learning activities using trace analyses and establish associations between patterns of usage and academic performance. Chapter 5 extends upon the research problem identified and addressed in Chapter 4 to include the associations of the identified patterns with time of the day and day of the week preferences for learners. While both Chapter 4 and Chapter 5 focus on the conceptualization stage of learning analytics development, Chapter 6 focuses on the implementation stage and introduces a framework for a technological-modality inclusive learner model with improved accuracy for predicting academic outcomes. Chapter 7 sheds light on how consistent are engagement patterns with a modality during different phases of a learning activity and examine impact of the consistency profile on learner's academic performance. We culminate the thesis with a cumulative discussions of results in Chapter 8 and overall conclusions and directions for future work in Chapter 9.

2.2 Research Questions

This doctoral research aims at addressing the lack of awareness regarding the learning processes of students, with respect to the various technological modalities (such as desktops, mobiles, tablets) used for engagement with learning. Our research aims to bridge the extant gaps in technology-enhanced learning and explore the use of various technological modalities in an educational context from a learner's perspective. In doing so, we intend to improve the design of learning experiences and the level of support provided to students so that they can take advantage of seamless learning experiences in and out of classroom.

The research aims to provide an empirical, comprehensive, and systematic understanding of learning in presence of multiple devices and its impact on learning - right from the identification of learning strategies employed by modality-specific learners, to the learning activities benefiting the most from a particular modality, to assessing the temporal and contextual settings dictating use of specific modalities, and finally to the construction of technological modality-specific learner models for learning outcome prediction. We focus on using advanced data mining techniques and learning analytics methods to analyze digital trace data for understanding the learning habits and behaviours. To accomplish the proposed goals, the primary research questions in the presented doctoral research are:

2.2.1 Research Question I

The first goal of this research is to explore how multiple devices are used when regulating learning via learning management systems (LMS) in the context of blended courses. To do so, we examine the extent to which various technological modalities (including desktops, tablets, mobile devices) are either used sequentially and/or simultaneously to influence the overall academic performance and study habits at various learning activities. In order to achieve that, we study the following two research questions:

RQ1.1*: Can we detect patterns in students' use of multiple modalities that are indicative of their adopted technological modality strategy when using an LMS tool? If so, what kind of strategies emerge?*

RQ1.2*: Is there an association of the identified strategies with students' performance in online discussions and overall academic performance?*

2.2.2 Research Question II

The introduction of mobile technology as a pedagogical tool has witnessed many enthusiastic supporters who successfully incorporate mobility in their everyday learning routine. However, it is still unclear what contextual factors dictates the students' decision to adopt or resist a technological modality in the first place. The following research questions ascertain whether learners' patterns of modality usage are driven by their inherent preferences for particular time of the day or day of the week they must engage in learning.

RQ2.1*: Are there any associations between time of day and the patterns of modality usage for different learners in a blended learning environment?*

RQ2.2*: Are these associations different on a weekend compared to weekdays?*

2.2.3 Research Question III

We formulate the following question to empirically demonstrate the importance for understanding the modality-source of the traced event in log data as an essential step when developing and interpreting predictive models of academic success and attrition. We aim to bring to light the deficiencies of platform-independent prediction models within the broader learning analytics communities and to investigate the potential for improvement of prediction power of learner models after considering the modality of access for each learning event.

RQ3*: To what extent is the predictive strength of LMS features influenced by distinguishing the modality of learner access when predicting course grade?*

2.2.4 Research Question IV

Existing literature is brim with solid evidence of the power of regulating study habits and student persistence in learning. Despite the proven relevance for undertaking such research, it has not been applied to study the consistency of learners' preferences for particular technological modalities in learning. That is, it is yet to be ascertained how engagement with various modalities fluctuate as the learner participated in different phases of a learning activity and any underlying impact it may have on their academic achievements.

RQ4.1*: How consistent are students' work patterns across subsequent activities of the same type, when engaging with them from multiple modalities? That is, can we identify conceptually and practically meaningful clusters of students with distinct consistency patterns?*

RQ4.2*: Is there an association of the identified patterns with students' academic performance?*

2.3 Publications and Contributions

In this section, we present the publications that were created during this research endeavor and point out the main contributions from each.

2.3.1 Publications

Publications: Chapter 4

Paper Overview

The focus of this paper is on exploring the multi-device usage of several technological modalities at authentic learning tasks in the learning management systems, and detect if there is some impact of the choice of modalities on the learning outcomes.

Research Contribution:

- We explore the multi-device use of modalities for engaging in learning in blended learning environments.
- Sequence of actions performed by learners across different modalities were analyzed to determine recurring patterns of usage .
- We found four prominent technological modality profiles: *diverse*, *mobile-oriented*, *short-desktop* and *desktop*. Based on the proportion of usage of each of these four profiles, students were clustered to detect unique technological modality strategies employed.
- Our results were able to confirm a significant impact of these modality strategies on the learner's academic achievement and performance at online discussions.

Research Output:

1. Sher, V., Hatala, M., and Gašević, D. (2019). On multi-device use: Using technological modality profiles to explain differences in students'learning. In *Proceedings of the 9th International Conference on Learning Analytics & Knowledge* (LAK19), March 4–8, 2019, Tempe, AZ, USA. ACM, New York, NY, USA, Article 4, 10 pages. https://doi.org/10.1145/3303772.3303790 (best paper nomination)

Publications: Chapter 5

Paper Overview

The focus of this paper is to emphasize upon the temporal aspects related to multi-device usage. That is, we illustrate how learner preferences for modality-usage are associated with specific time-slots during the day and also on whether learner engagement takes place on a weekday or weekend.

Research Contribution:

- We provide an overview of learners' time-of-the-day (TOD) preferences for engaging in learning activities from different modalities such as desktops and mobiles in a blended learning environment.
- Our results suggest that learning sessions from various modalities are significantly associated with the time of the day (TOD) and day of the week (weekday or weekend), and it holds true for students who make extensive use of different modalities to complete their learning activities and those who sparingly use them.
- Overall, we found that mobile and short-desktop sessions were more prominent during afternoon and night time, respectively.
- The modality-TOD associations were similar on weekdays and weekends for strategic and minimalist learners, two groups which are strikingly different in terms of their academic performances.

Research Output:

1. Sher, V., Hatala, M., and Gašević, D. (2019). When do learners study?: An analysis of the Time-of-Day and Weekday-Weekend usage patterns of LMS from mobile and desktops in blended learning. Invited manuscript submitted to the Journal of Learning Analytics, currently under review.

Publications: Chapter 6

Paper Overview

The focus of this paper is to demonstrate the usefulness of considering modality for learning actions on improvements in predictive power of the learner models.

Research Contribution:

- We examined the effects of including the modality-source (mobiles vs. desktops vs. tablets) of a learning activity on the predictive capabilities of learner models.
- We found that tracing the modality source of log data is helpful in improving the accuracy of learner models, compared to the traditional models that are composed of one intermixed stream of data.

- Our results revealed that the magnitude and direction of the variance in the learning outcome, explained by the modality, differs based on the learning activity such as assignment viewing or engaging with feedback.

Research Output:

1. Sher, V., Hatala, M., and Gašević, D. (2019). Investigating effects of considering mobile and desktop learning data on predictive power of learning management system (LMS) features on student success. In *Proceedings of the 12th International Conference on Educational Data Mining*, 2019, pp. 651 - 654

2. Sher, V., Hatala, M., and Gašević, D. (2019). Investigating effects of considering mobile and desktop learning data on predictive power of models of student success. Manuscript submitted to the Journal of Learning Analytics, currently under second round of review. The article, an extension to the Sher, Hatala and Gašević (2019) study, provides more comprehensive interpretations of findings from modality-inclusive learner models in blended learning environments.

Publications: Chapter 7

Paper Overview

The focus of this paper is to reflect upon the changes in modality usage over the course of their studies. That is, we assess how engagement with various modalities fluctuate as the learner participated in different phases of a learning activity.

Research Contribution:

- We provide an overview of how consistent the patterns of modality-usage are during various phases of a learning activity.

- Using the time-series data of student LMS engagement prior to the task deadline, we identified three distinct profiles for consistency in learning strategies: *highly consistent*, *incrementally consistent*, and *inconsistent users*.

- We also found evidence of significant associations between these patterns and learner's academic performance at two learning contexts - assignments and online discussions.

Research Output:

1. Sher, V., Hatala, M., and Gašević, D. (2019). Analyzing the consistency in within-activity learning patterns in blended learning. Manuscript submitted to the Tenth

International Learning Analytics and Knowledge (LAK) Conference, currently under review.

2.3.2 Author's Role

For all the publications mentioned in the previous section, I was the main author. That is, I developed the coding for mapping the user-agents (from each learning action) to respective modalities, designed methodological approaches for analyzing respective research questions, performed the statistical analyses of results, generated interpretations from the findings, and wrote the text in the research publications. Furthermore, the co-authors contributed in shaping the ideas and revising the written text.

2.4 Target audience for the research

This research will be of interest to LMS designers in field of educational technology who aim to design dashboards or personalized learning system for various platforms such as desktops, tablets and mobile phones. When developing tools for mobile learning, designers need to know their intended audience, the tools they are currently using and the physical and contextual settings in which they will be using the tools. This work will also help instructors in blended and seamless learning environments who deliver their lectures, learning activities, and/or course materials on various platforms such as mobile apps or web-content and want to gain better understanding of students' learning patterns when augmented with digital technology. With the focus on the development of targeted interventions, educational practitioners and researchers also represent an important target group which would benefit from this research since the learning processes of students can now be analyzed with an added dimension of technological modality. Finally, given the focus of the doctoral research on the use of mobile learning analytics for improving accuracy of learner models in the field of educational technology, the education policymakers will be also interested in the outcomes of the proposed research, primarily in its implications for research and practice aspects.

Chapter 3

Background

There is nothing more practical than a good theory.
- Ludwig E. Boltzmann

3.1 Learning Analytics

Learning Analytics (LA) is considered an emerging research field that aims to make sense of the large volume of students' interaction data with educational resources in order to understand and improve learning [221]. According to the definition formulated eight years ago at the very first Learning Analytics and Knowledge Conference back in 2011, learning analytics is the "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [1]. Even though a relatively young research field, it has now transpired into a multidisciplinary research area that draws on data mining and machine learning methods and techniques [75] from diverse range of research fields including educational psychology, learning sciences, technology and information visualization [57]. A systematic overview of learning analytics and its related concepts are depicted in the (self-explanatory) reference model in Figure 3.1.

The impact of learning analytics on educational practice has been widely recognized within the learning analytics community. In practice, learning analytics has proven quite successful in informing educators about students' engagement and academic performance and helping students achieve objectives more closely aligned with the learning process, such as reflection, adaptation, personalization, and recommendation. The potential of learning analytics has been extensively used for developing prediction models to predict (and improve) students' final course outcomes and to identify "at-risk" students (and attrition rate) [58, 12, 118]. Learning analytics in the form of visualizations and dashboards have helped address the well-recognized problems of delay in students receiving relevant, timely and

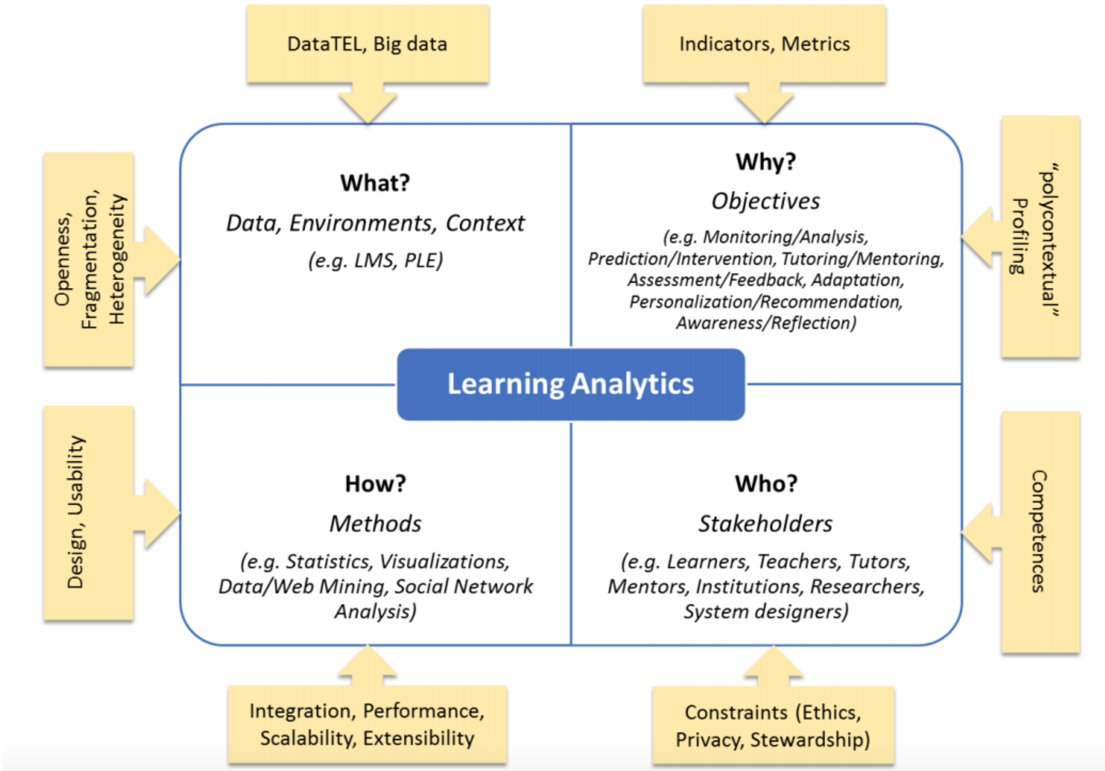


Figure 3.1: Learning Analytics Reference Model [40]

personalized feedback on their learning [20, 34, 212, 92]. A number of studies have also applied learning analytics techniques to assess and evaluate students' progress and infer their learning strategies during online discussions [269], MOOCs participation [132], use of online resources [163] and video technologies [187], and face-to-face learning [120].

In this thesis, we consider learning analytics as a technology-enhanced learning (TEL) research area wherein the main focus is on developing methods that analyze and detect patterns within the vast abundance of data collected from educational contexts and utilize those methods to support and enhance learning experience. We discuss features and aspects associated with TEL in more details in next section.

3.2 Technology-enhanced learning

The teaching and learning landscape is constantly evolving across all tiers of global education system. Of lately, the education sector has witnessed modernization of aspects of student learning experience with improvements in technology and communications. The influx of prevalent, popular and affordable technologies with internet connectivity have yielded promising affordances to support formal learning in educational context [31, 32, 129, 108].

Their increasing popularity as an instructional tool for learning has brought a new perspective into how teaching is delivered and supported. Technology-enhanced learning (TEL), thus, is used to describe the process of inculcating use of technologies (such as educational softwares, personal digital assistants, mobile phones, tablets, Web 2.0 tools and ICTs) in a way that the learning environment is enhanced for both instructors and students, such that it enables them to engage in ways that would not have been feasible in face-to-face or distance approaches [215].

Technology-enhanced learning is significant for many reasons, other than being the need-of-the-hour in this digital era. TEL allows ways of enhancing existing modes of course delivery and new modes, ranging from content-based to open and community-orientated models of learning [276]. The proliferation of TEL interventions in the higher education sector has enabled flexibility with regard to when and/or where students undertook their learning activities [52] and promoted redesign of activities or parts of modules to provide active learning opportunities for students [51]. Overall, these have been successful in effectively promoting qualitatively richer learning among students [245, 232]. Furthermore, considering the different forms of teaching, learning and assessments these technologies can support, the field of *blended learning*[1] has also leveraged them for gamification of learning [236, 236], adopting e-submissions [69], computer-aided assessments [115, 230, 222], and utilizing collaborations via Web 2.0 technologies such as blogs, wikis and social media [220, 158].

The goal of this thesis is to investigate one specific sub-category of TEL technologies, namely technological modalities (such as desktops, tablets, and mobile phones) in blended learning given that they are considered important for successfully accomplishing academic tasks. For instance, Figure 3.2 shows the importance of each of these modalities towards academic success from 2012 to 2018, as reported by the ECAR 2018 survey[2] [84]. Unsurprisingly, laptops continue to be a superior modality over the past years with 98% of students reporting using them in at least one course last year and 94% rating them very or extremely important [84]. Furthermore, smartphone usage is witnessing an upward trend for the third year in a row, and both desktops and tablets have surprisingly regained popularity after two consecutive years of decline in importance and use. In the next section, we explore in more detail how these modalities have been used for study purposes in the literature.

[1]Blended learning, or hybrid learning, focuses on transforming the nature of traditional lecture course through inclusion of Information and Communication Technologies (ICT) such that students are able to more actively engage with course content both inside and outside of the classroom [85]

[2]The findings were developed using a representative sample of 64,536 students from 130 institutions in 9 countries and 36 US states.

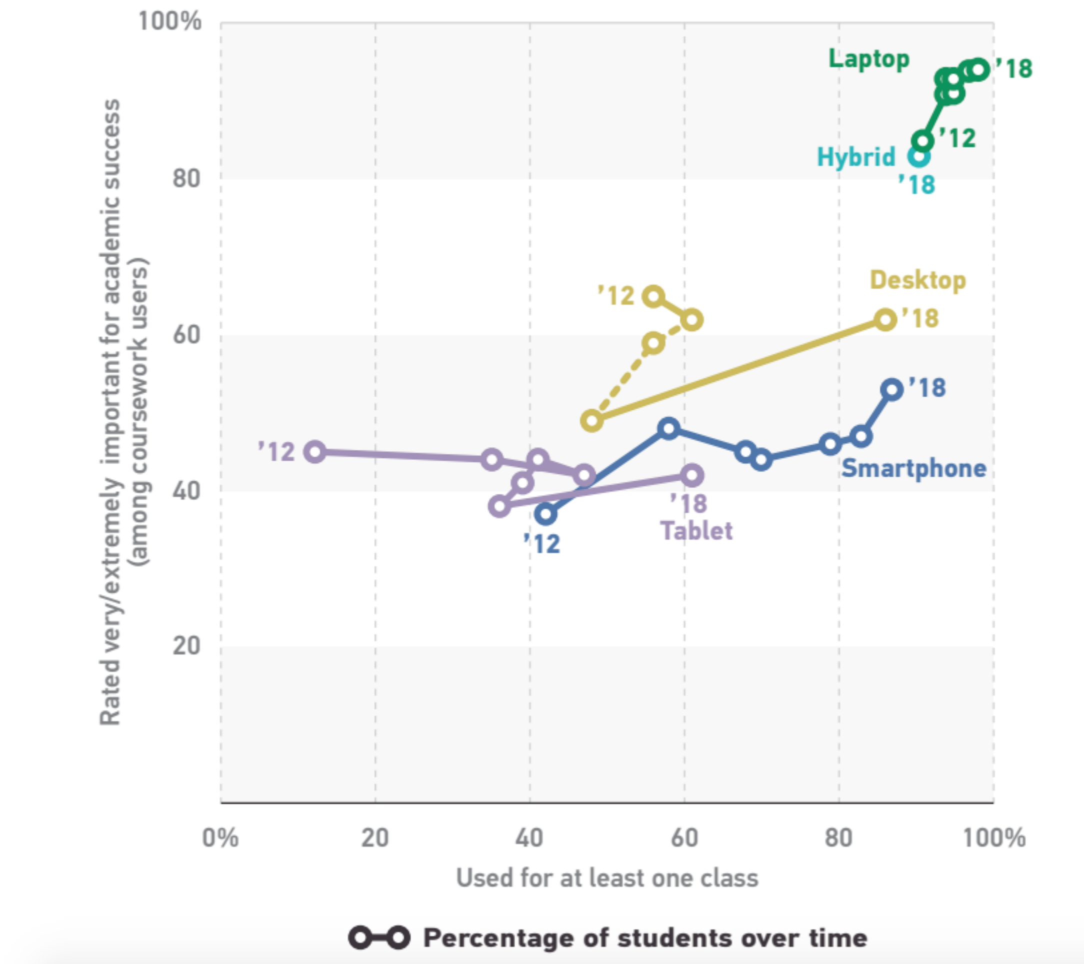


Figure 3.2: Device Use and Importance for Academic Success (Source: [84])

3.3 Use of Various Modalities for Learning

With the device ownership steadily increasing with each passing year, learners have a combination of them available at their disposal at any given time (see Figure 3.3 for statistics on device ownership). The aim of this section is to reflect upon the uses of different modalities in the educational context. We begin with individual discussions targeting usage of specific modalities for learning activities and finally we present a discussion regarding comparisons of different modalities for learning.

3.3.1 Use of Mobile Phones for Study

While most theories of learning have been predicated on the assumption that learning occurs in a school classroom, under the supervision of an instructor, mobile learning's underlying assumption is that learners are always 'on-the-move', meaning that learning transcends

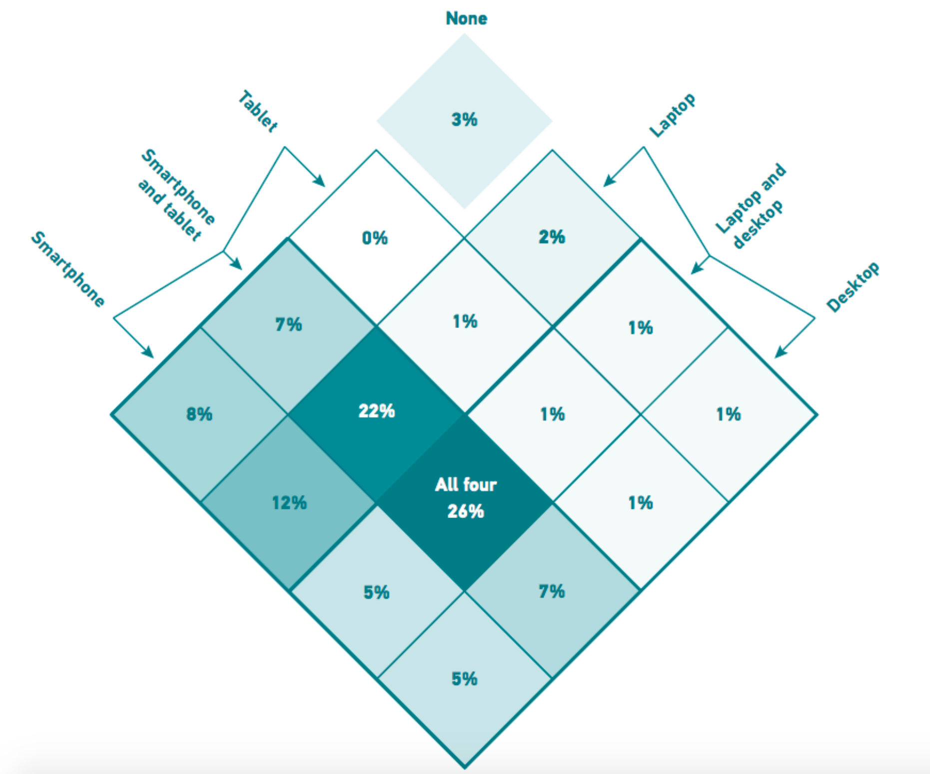


Figure 3.3: Student smartphone, tablet, desktop, and laptop ownership (Source: [30])

classroom and lecture hall barriers. Mobile technology has brought about equal learning opportunities for all, even those located in remote locations without access to a formal classroom, thus making the 'industrial-era model of education' [3] – one teacher lecturing to an entire class at a specific location and time – obsolete. It has eradicated some of the challenges associated with access to education - high cost of hardware and access to computer and internet - such that evidently, learners are utilizing them for a variety of purposes that go beyond personal use like making calls, entertainment and socialization. Accordingly, the popular, prevalent and affordable mobile-phone technology has been used for creating, distributing, and tracking content as learners engage and participate in learning activities.

In order to support mobile learning, specialized systems called *mobile learning systems* have been developed which not only manage the educational content but also provide its adaptation and adequate visualization on the small screen of mobile devices. Table 3.1 focuses upon some state-of-the-art progress made in the field of mobile learning systems technology since the advent of the pervasive wireless devices. The review of literature on

[3] The Invented History of 'The Factory Model of Education'. [264]

mobile learning systems in this section was done with the intent of showcasing how majority of research on mobile in the LA field is directed towards their use as a designated app, fulfilling specific functionality[4].

Mobile Learning System	**Learning Setting**	**Data Usage**	**Learning Impact**
LearnTracker [242]	Online Learning	Logged time	Promote Self Regulation
Schoology [272]	Flipped Learning	Assignment views, Discussions posts	Evaluate learner progress
MeLOD [81]	Informal Setting (educational school visit)	Buildings visited, comments, voting, requests for educational content	Detection of non-participants
HeadsUp [106]	Collaborative Learning	Group allotments, Distribution of discussion prompts	Evidence of active engagement and critical thinking
mLearning [260]	Blended Learning	Access to video and lecture notes, SMS interactions, instant polls	Evidence of voluntary engagement, identification of active learners
iTree [178]	Collaborative Learning	number of posts, number of times posts read, number of replies to the post and ratio of total forum posts to the replies	Encourage regular and effective participation in discussion
Unnamed [218]	Blended Learning	broadcasting real-time classroom teaching, SMS interactions, instant polls	Increased classroom interactivity, quick instructor feedback

Table 3.1: Summary of Mobile Learning Systems

As part of these systems, mobile devices have been used for self-monitoring and reflection by logging time devoted to an activity [242]. These devices have also been used for engaging in interactive discussions and other collaborative tasks [272, 106, 178], in addition to everyday tasks like viewing assignments, accessing study material, and viewing lecture videos [272, 273]. In some cases, live-broadcast of real-time classroom teaching (i.e. sharing audio, video , lecture notes) have been possible especially for students who own mobile phones [260, 218].

The portable, interactive and low cost features of a mobile phone have also been leveraged for short text messaging to enhance student-instructor interaction and for conducting instant polls to create a more active and responsive audience of learners [218, 260, 262, 81]. Mobile phones have also been used to support informal learning experiences outside of the classroom, for instance on a visit of a city and its historical buildings, mainly to augment information retrieval in absence of instructor support and enhance intrinsically motivated learning [211, 81, 96].

[4] In such circumstances, use of mobile does not represent a choice per se (as there is no alternative but to access the app-related content via mobile) and thus, is unable to tell us much about their general purpose use in a naturalistic setting, say for accessing material or engaging in learning activities on LMS, where either one of the other modalities could have very well been used for the same purpose.

Some conflicting feelings and attitudes towards the use of mobile phones have been identified in literature mainly due to their perceptions as distractors in classroom and the privacy concerns in mobile phones [272, 247], while others perceive a positive impact of mobile learning on their learning motivation, learning engagement, learning style and attitude towards learning [243, 181].

Contextual Profiling in Mobile Learning Systems

To allow for a more authentic learning experience in mobile setting, aimed at providing adaptivity and personalization, 'contextual profiling' is usually conducted. It is useful for providing valuable insights into what type of learning activities can facilitate mobile learning and thus, fully capitalize on the capabilities of the mobile device used by learners and learner's characteristics. When learners are presented with a learning activity, contextual information in terms of what device functionalities/features are available and frequently used by learners can be useful for providing a personalized learning experience to mobile learners in mobile ubiquitous environments. For instance: Lima et al. [157] introduced a client-server framework where device sensors could detect low usage of messaging feature on the server end, and thus avoid suggesting activities such as assignment writing on the client end. Taking contextual profiling a step further, Tortorella and Graf [246] considered learner's context in combination with learner's characteristics, in particular, their learning styles, to provide learning material in a suitable format in the mobile setting.

3.3.2 Use of Laptops for Study

Laptops are no longer a nascent technology affordable only by a few individuals, but rather a quintessential tool augmenting classroom learning for academic use such as note-taking, web based research, communication, organising, and using software and web-based interactive tools [126]. Owing to their portability, larger screens, and presence of physical keyboard for typing, they are critical for school work as evidenced by their increasing ownership (matching that of smartphones) [84].

Past research assessing benefits of laptops have suggested that students who were allowed to use them spent more time involved in collaborative work, participated in more project-based instruction, produced writing of higher quality and greater length, gained increased access to information, improved research analysis skills, and spend more time doing homework on computers (for a detailed review see Gulek and Demirtas [100]). Even though the benefits have been witnessed across several disciplines [100], several factors are indicative of the effectiveness and use of laptops in classroom including, course format (structured vs. unstructured laptop use) [127], personal characteristics (such as student motivation, self-regulation deficit, behavioral intentions) [88, 125], classroom management and faculty perceptions [4, 33] and learning activities (necessitating specific programming software, web-based learning tool or video podcasts) [128, 8, 16].

Despite the clear benefits associated with laptop-use, some teachers are still wary of students bringing laptops to lectures as non-academic Internet use has been commonly observed among students who brought laptops to class and was inversely related to class performance [195, 126, 67]. Since most of our research was situated in a contextual setting wherein the courses were programming-oriented (STEM course requiring use of dedicated softwares and higher processing capabilities), the use of laptops was inevitable.

3.3.3 Use of Desktops for Study

Desktops comprise one of the early technology suites to be integrated into the academic arena to support learning activities [177]. With their big screens, high resolution, and capability to use multiple monitors simultaneously, they are still exceedingly useful for activities such as video conferencing (in distance learning), supporting augmented reality (AR) applications, accessing the university learning management system, exchanging emails and accessing course material [177, 261, 150, 46]. These are generally used in combination with some other mobile technology [2] to create a seamless learning environment [35, 145], although it is hypothesized that when learners have sufficient time, they resort to desktop PC as they are 'more convenient to use' for an educational interaction [35].

Having said that, in recent times we are witnessing a shift in people's preferences regarding desktop PCs. Due to lack of portability which hinders the notion of ubiquitous 'anytime anywhere' learning, and reliance on constant power supply, a growing trend of people are trading in their desktops for the more 'trendier' mobile tablets.

3.3.4 Use of Tablets for Study

Even though tablets were projected to overtake desktops by 2015 (as cited in Rossing et al. [206]), they are one of the primary modalities that failed to live up to the expectation. Nonetheless, tablets are still widely popular owing to their large-size touch screen for convenient operation, multimedia functions for sound and video playbacks, Wi-Fi/3G enabled network for easy connectivity, as well as small size for easy portability [180].

A review of the literature revealed that common learning activities undertaken using tablets include collaborative learning [206, 205], reading required text [63], accessing learning resources via LMS [95], language learning [43], and accessing multimedia learning materials [184]. The studies evaluating perceptions of tablets for learning revealed that students generally found tablets easy to use [65, 63], especially since they act as replacements for school books [229]. However, there were some challenges known to be associated with tablets such as difficulty in writing on tablets [226], short battery life [74], and physical discomfort associated with tablet use resulting in headaches and eyestrain [74, 229].

3.3.5 Comparison of modalities for learning

The pervasiveness of smartphones and other modalities is moving learners towards learning from multiple devices rather than just relying on one [6]. For instance, laptops for writing assignments and shared collaborations [263], tablets for reading e-books [196] and smartphones for recording lectures using phone camera [10]. Today, depending upon the learner's physical context (location), intentional context (purpose) and features of the modality itself [145], different modalities are used to support student objectives.

With the choice of so many modalities available, it is essential to ask the question - *Are some modalities better suited than others for learning activities?*. Although an important question, only a handful of researchers have attempted to target it so far. Reid and Pechenkina [197] found students preferred tablets or smartphones for surfing the Internet for information or answering a quick online quiz, although students reported these modalities were not conducive for typing and submitting their assignments. In a surprising case study, Barden and Bygroves [18] revealed high-quality, sophisticated academic texts could very well be created using mobile devices as well and in fact disclosed the possibility of some learner's aversion to 'slow and cumbersome' laptop modality.

Nakahara et al. [178] favored the desktop for browsing and posting activities, considering the mobile phone's limited bandwidth, small screen and 'awkward' text input functions. On the contrary, a case study survey conducted by ECAR (Educause Center for Analysis and Research) [2] found that students prefer accessing academic progress information and course material via their mobile devices. Cross et al. [53] reported that reading module material, accessing module material and preparing for an assignment were found to be the three most common study activities performed via mobile technology, based on a systematic literature review. Wong [272] found mobile phones were preferred over desktop computers for viewing course videos, based on the former's higher activity counts. Tabuenca et al. [242] found push notifications work better on phones than on a desktop web-version of the app. These results were again based upon an aggregation of the count data.

We only found two full-fledged studies by Stockwell [233, 234] where the main aim was the comparison of modalities - mobile phones and desktop computers - with respect to the time required to complete interactive vocabulary activities and the academic score achieved. The data collected via server logs kept a record of the modality the learners used to complete an activity, the type and difficulty level of activity, activity start and end time, and the score attained for the activity. Even though both the studies lacked solid inferential analyses, they were successful in making higher level observations based on preliminary descriptive analysis of the data.

The results from Stockwell [233] revealed that a significant number of learners did not use the mobile phone at all and a majority used a combination of both the modalities for all the vocabulary activities. With respect to the scores achieved, the two modalities did not differ much, irrespective of the degree of difficulty of the activity. However, the amount of time required to complete each activity was longer for mobile phone users by at least 1.4 minutes. Additionally, a great deal of variation was observed in how learners used the combination of the two modalities for completing the activities. For instance, the usage of the two modalities was interleaved throughout the semester, swapped mostly at the end of an activity. This was looked at in detail in his follow-up study.

In his follow-up study, Stockwell [234] focused on investigating *how* the activities were completed on both the modalities. The data collected via server logs included the amount of time spent using each modality, when and where learners engaged in the activities, and the effect of a "push mechanism" email which they could opt to have study notifications sent on a daily basis. The results from the study revealed quite large differences in the ways learners undertake learning using the two modalities. In terms of when and where learners participated in the learning activity, learners typically selected different times depending on whether they use a PC or a mobile phone, with mobile phone usage taking place mostly across the morning or very late at night, most typically at home, and essentially no usage at all in the afternoon or in the evening. In contrast, when using PCs, learners tend to focus their usage in blocks in the afternoon or after midnight, working primarily at home at night and at the university during the afternoon. Overall, while the usage of mobile phones was regular over the week, the PC usage was concentrated around the time a quiz was due in class.

The study also brings to light the stark differences between student perceptions of their learning and their actual learning. The perceptions of preference for mobile phone use on transit and push notifications did not match measurements from trace data. Overall, the study established a gap between what teachers have in mind regarding the way that mobile technologies *should* be used and the ways in which learners *actually* use, which could have potential pedagogical implications.

With this in mind, we refrain from relying solely on user perceptions while analyzing the learner's patterns of modality usage in our research. We proceed with a more promising approach, namely, application of learning analytics derived using *trace data*, to determine a true evaluation of the learning experience from various modalities. We discuss trace analysis in detail in the next section.

3.4 Trace Analysis

It is quite evident in the literature that there exist calibration issues between student perceptions of learning and their actual usage of learning systems, mainly due to the flawed introspective abilities of participants [280]. These can have serious implications on their learning assessments. Thus, emanates the need for analyzing the time-stamped trace data that is capable of fully representing the actual use patterns and provide nuanced insights into the learner's real-time cognitive and metacognitive learning processes [214].

Trace analysis involves the collection of data through physical traces of the learners, i.e. time-stamped record of every keystroke and mouse click, in the learning environment whilst they engage in a learning task [86]. This data is later parsed for the purpose of analyzing user's log traces of activities such as viewing an academic resource, posting at forums. The process of synthesizing patterns and performing sequential analysis and process mining on the trace data helps in revealing sustained and replicable insights and drawing useful conclusions. Thus, collecting the data as-and-when any interaction happens allows far more superior explanation of how learning occurs behind the scenes, than would have been possible through the use of self-reports. This is because the self-reports represent learners' *perceptions* of their own beliefs and abilities, *statically* and *outside* of the actual learning environment.

The digital traces (or log data) have been extensively 'mined' and analysed to identify patterns of learning behaviour that can provide insights into education practice. That is, the analysis of interaction trace data from LMS (learning management system) (along with personal data and academic information collected from SIS (student information systems)) using data mining techniques have assisted educators in uncovering the black-box of student's learning process such as deep thinking, behavioral intention and motivation in learning [171, 202]. For instance, Fincham et al. [77] identified patterns indicative of learning strategies (such as highly-active and disengaged) within trace log data in a flipped classroom, based on the compositions of their study tactics (such as video actions, summative and formative assessment actions and course-content access actions). Siadaty et al. [223] studied the effects of technological scaffolding intervention on self regulated learning (SRL) in workplace environment by mapping trace data onto events (such as requesting collaborations, choosing a learning path) that represent enactment of specific SRL activity (such as goal setting, planning, evaluation and reflection). Similarly, literature has evidence where learner's log trace files were utilized for creating theoretically grounded constructs (i.e. proxy observable behaviour) for measuring the complex roles of goal orientations [280, 130], cognitive engagement [223, 103], and instructional conditions [87] in learning and problem solving. In addition, analyzing log file's trace data has also been used to build performance prediction models [87, 141], which has tremendous potential for pedagogical support.

Despite a prevalent understanding of the importance of experiential/trace data (obtained via digital footprints) in learning analytics [186, 265], only limited number of studies have utilized interaction trace data to draw inferences and insights on students engagement in multi-device learning. Through this research, we aim to bridge that gap and provide more conclusive results for multi-device research.

3.5 Theoretical framework

3.5.1 Framework for the Rational Analysis of Mobile Education model

The pioneer work to explore how students make use of several handheld devices for learning was undertaken by Koole [140]. Their Framework for the Rational Analysis of Mobile Education (FRAME) model, designed within a distance education context, described mobile learning as a "process resulting from the convergence of mobile technologies, human learning capacities, and social interaction". The model was designed to guide mobile learning practitioners to be able to design more effective mobile learning experiences by "assessing the degree to which all the areas of the FRAME model are utilized within a mobile learning situation" [140].

According to the FRAME model, learners consume and create information, both individually and as a group, and any interaction with information is mediated through the technology rendering it more meaningful and useful. Thus, the FRAME model takes into consideration the technical characteristics of mobile devices as well as social and personal aspects of learning [139] and is well represented by the Venn diagram in Figure 3.4, in which three main aspects intersect - Device, Learner and Social Aspect.

The Device aspect (D) refers to the physical, technical, and functional characteristics of a mobile device. The Learner aspect (L) refers to individual's cognitive abilities, memory, prior knowledge, emotions, and possible motivations. The Social aspect (S) refers to the process of social interaction to exchange information, and acquire knowledge. The intersection of the Device and Learner aspect occurs at Device Usability (DL) which focuses on the

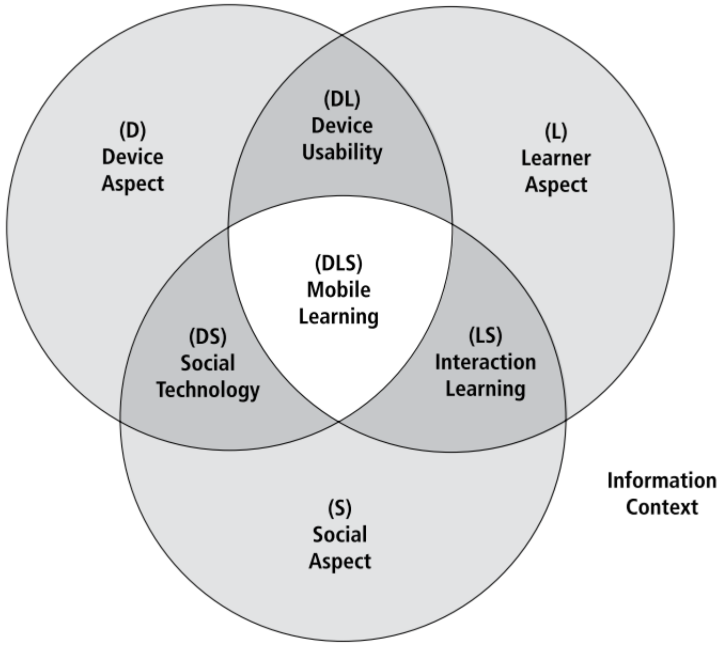


Figure 3.4: FRAME model by Koole [140]

hardware and software characteristics of mobile devices such that cognitive load is reduced and task completion rates increase. The intersection of the Device and Social aspect at Social Technology (DS) describes how mobile devices enable communication and collaboration amongst multiple individuals and systems. The intersection of the Learner and Social aspect at Interaction Learning (LS) describes how individuals who are situated within unique cultures and environments, interact with other people in formal or informal learning settings. Finally, the model claims that effective mobile learning occurs at the intersection of these three aspects (DLS).

3.5.2 Framework for Student Use of Multi-Devices for Learning

Recently, the applications of the FRAME model were extended by Krull [145] to account for how multiple devices are used for different learning activities. That is, they broaden the device aspect to include fixed technologies (such as desktop PCs), in addition to handheld devices and also focus on how devices are used separately or together. The proposed Framework for Student Use of Multi-Devices for Learning is depicted in Figure 3.5. The framework, designed within a open and distance learning (ODL) context, was designed to assist educators to design more effective learning experiences or offer better learning support for ODL students using multiple devices.

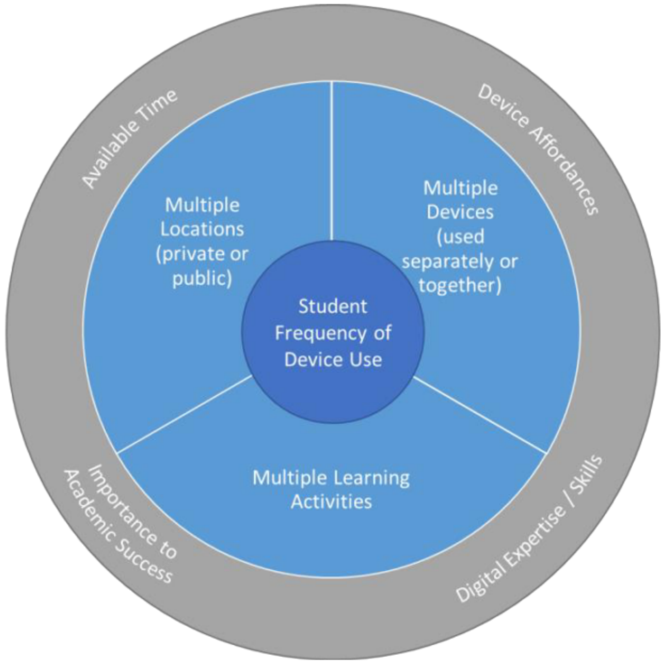


Figure 3.5: Framework for Student Use of Multi-Devices for Learning by Krull [145]

The framework, in particular, identifies the main influencing factors (inner blue circle in Figure 3.5) regarding how frequently a particular device will be used for learning. These include, location or environment of the student, learning activity or goal to achieve, and the devices students access and use for learning. According to the framework, portable devices are more likely to be used in multiple locations than fixed devices. In addition, larger devices are used for a wider range of activities, while handheld devices are used for more specific activities, although students can either make use of their devices separately or together.

In addition to these factors, several other factors were highlighted (outer gray circle in Figure 3.5) which influence the learner's modality preference but to a much lesser extent. These include, time availability with respect to task complexity, perceived importance of the device to academic success, digital expertise of the student and device affordances. According to the framework, depending on time availability, students may want to quickly take advantage of a few minutes of spare time or set time aside for more complex learning activities. The perceived usefulness of the modality for academic success, the more frequently the modality will be used. Additionally, the higher the level of digital expertise, the more frequently the student will use the device (which in turn improve levels of digital expertise as students become more comfortable with a modality). Finally, physical features of a modality such as screen size, cost and quality and type of internet access also plays in role in deciding whether it would be utilized for learning or not.

Both the frameworks discussed in this section will be used as a basis to explore the concepts in the literature and in the empirical work in the upcoming chapters.

3.6 Positioning of Thesis Work

3.6.1 Categorization of modalities

As evidenced in Section 3.1, we live in a world where technological modalities of all sizes and intents present a ubiquitous environment of potential learning tools. The physical differences in size, weight and features between mobile phones, tablets and personal digital assistants on the one hand, and desktop and laptop computers on the other, allow range of devices being utilized for specific learning contexts. The affordances of these devices could also be explained with respect to factors such as size, portability, ease of use, immediacy, and popularity. For instance, using a device that is small enough allows bite-sized information to be downloaded and consumed on the go [161].

From these various perspectives, the distinction between modalities could be based on either one of these factors and thus, has “more to do with the way a device is used than features of the device itself” [189]. In this thesis, we analyze the students who engage with LMS in a blended environment and thus, *resource access* (accessing online/downloading resources), *resource submission* (uploading learning related resources such as assignments) and *resource sharing* (facilitate collaborative work by sharing files) transpire as important affordances [228]. Notably, all these affordances depend considerably upon the screen size of the modality in question, among other factors like mobility. Thus, one of the design decisions implemented while investigating the research questions in this thesis was categorization of modalities on the criterion of size mainly.

For this reason, we group all small-size handheld smartphones as “Mobiles”, followed by mid-size range “Tablets” and finally group large-screen laptops and PCs together into one category called “Desktop”. The decision to lump the large-sized laptops and desktop PCs together into one frame was based on the design of the learning activities we investigated. The assignments were mostly sit-down programming tasks, to be completed and uploaded using a software only available on desktop PCs or laptops. Similarly, the discussion activity being *generative* in nature (asked to come up with own solution), as opposed to *negotiative* (two contrasting alternative solutions to debate) [268], meant students were not required to constantly monitor the discussion forum to see who agrees/disagrees with their ideas, for which a mobile modality would have been ideal. The generative task required them to produce a high quality artifact that requires a significant amount of research and web browsing, greatly facilitated using the large screen PCs or laptops. In addition, upon assessing the impressions of the LMS on laptops and PCs, both had virtually the same interface, further solidifying our decision to group them together.

3.6.2 Modality-use under investigation

A majority of the literature, as illustrated in Section 3.3.1, points towards use of mobile phones mainly for hosting apps, which are designed to cater to some specific functionality in the learning context. These mobile apps have proven beneficial for directing learning in terms of facilitating systematic learning, individually focused learning, and improvement of instructor-student interaction, among other things. However, in this thesis we want to take a different stance in regards to the utility of mobile phones in TEL environment i.e. we are interested in looking at how mobile is used in context of LMS, not as a designated app, but purely as a vehicle to access material alongside other modalities like desktop and tablet. In other words, when all modalities have similar affordances in terms of the learning material and activities contained in them, would varied patterns of usage for a particular modality be observed?

Interestingly, we found that only a limited number of studies have attempted to do so in past, and even fewer who did so using digital log traces of learners. For instance, Stockwell (2010) compared the learner's usage of desktop and mobiles for engaging in vocabulary activities. He found that while the scores obtained via both the modalities were similar, the average completion time for students who chose to complete activities on the mobile phones was longer compared to those who chose to complete them via desktops. Thus, by targeting this kind of (mobile-)use, we aim to understand if and how a (mobile) modality may be adopted, especially if there is no requirement to do so specifically. At a more holistic level, the overarching aim of this thesis was to gain a better understanding to what extent and for which activities students choose to access LMS using certain modalities, especially if there is no requirement to choose any one in particular. Additionally, we study to what extent consideration of the modality of access may benefit learning analytics models in explaining learning outcomes. We define the research goals in next section.

3.6.3 Research Goals

The research problem to be addressed by this study is the lack of understanding regarding how students make use of multiple modalities in the learning environment in order to augment their face-to-face learning. Hence, the work presented in this thesis was conducted with four primary research goals (RG) in mind, analyzed using learning analytics methods and data mining techniques.

RG I: Which handheld and stationary modalities do student use in blended learning environments? Can we detect an overlap in terms of usage of different modalities through analysis of trace data of user's interactions with learning platform?

RG II: What type of activities do students engage in using these modalities? Is there a distinction in terms of what devices facilitate particular activities based on their device affordances?

RG III: How do learners spend their time on these modalities as part of the blended learning environment?

RG IV: What role does choice of modality play on a learner's academic performance? How can we leverage analytics surrounding modality used by learners in a way that can better inform their learning achievements?

To address the four aforementioned research problems in a methodologically rigorous and sound manner, we focused our efforts on several related problem domains, organized as four individual thesis chapters (Chapter 4-7). Each chapter focuses on one or more research problems. Results from Chapter 4 shed light on the patterns of usage that emerge when students make use of multiple modalities in blended learning environment (RG I). Synthesis of the results from Chapter 4 and 7 collectively help in explaining how device affordances can influence the way modalities are used for a learning activity (RG II). Chapter 5 is dedicated to assessing how learners manage their time in presence of multiple modalities and also if their time-distribution is different depending on the day of the week (RG III). Finally, Chapter 4 and Chapter 6 confirm associations between modalities and academic outcomes and how quantitatively extracted measures from student accesses to course material from multiple modalities can have potential to improve prediction power of the learner models, developed for each course (RG IV).

Chapter 4

Sequential Analysis of Multi-device Use

We become what we behold. We shape our tools and then our tools shape us.
- John Culkin, 1967

4.1 Overview

This chapter addresses the following research questions:

1. **RQ1**: Can we detect patterns in students' use of multiple modalities that are indicative of their adopted technological modality strategy when using an LMS tool? If so, what kind of strategies emerge?

2. **RQ2**: Is there an association of the identified strategies with students' performance in AODs and overall academic performance?

With increasing abundance and ubiquity of mobile phones, desktop PCs, and tablets in the last decade, we are seeing students intermixing these modalities to learn and regulate their learning. However, the role of these modalities in educational settings is still largely under-researched. Similarly, little attention has been paid to the research on the extension of learning analytics to analyze the learning processes of students adopting various modalities during a learning activity. Traditionally, research on how modalities affect the way in which activities are completed has mainly relied upon self-reported data or mere counts of access from each modality. We explore the use of technological modalities in regulating learning via learning management systems (LMS) in the context of blended courses. We used data mining techniques to analyze patterns in sequences of actions performed by learners (n = 120) across different modalities in order to identify technological modality profiles of sequences. These profiles were used to detect the technological modality strategies adopted by students.

The modality-use profiles reported in this paper showed several interesting implications for both educational practice and research on the digital-device use in academia. In our results, we found a moderate effect size ($\epsilon^2 = 0.12$) of students' adopted strategies on the final course grade. Furthermore, when looking specifically at online discussion engagement and performance, students' adopted technological modality strategies explained a large amount of variance ($\eta^2 = 0.68$) in their engagement and quality of contributions. These results stress on the need to acknowledge not only the extent to which consistency of tool-use [142] and 'richness' (in terms of feature affordances) of the tool itself [164], but also *the diversity in intermix of modality-use for using the tool*, which is highly capable of effecting the performance significantly too as evidenced.

4.2 Publication

The following sections include the verbatim copy of the following publication:

> Sher, V., Hatala, M., and Gašević, D. (2019). On multi-device use: Using technological modality profiles to explain differences in students'learning. In *Proceedings of the 9th International Conference on Learning Analytics & Knowledge* (LAK19), March 4–8, 2019, Tempe, AZ, USA. ACM, New York, NY, USA, Article 4, 10 pages. https://doi.org/10.1145/3303772.3303790

4.3 Introduction

The education sector has witnessed modernization of aspects of learning with advancements in technological modalities brought about by the digital era. With the influx of prevalent, popular and affordable modalities (such as mobile phones and tablets), the multi-device use to access course materials is becoming more prominent and has yielded promising affordances to support formal learning. According to the 2017 ECAR study[1] [192], student device ownership has steadily increased compared to previous years (97% of students owned smartphones, 95% owned laptops and 53% owned tablets) with over three-quarter (78%) of the students connected to two or more devices simultaneously. However, the mere access to and use of these modalities are insufficient for guaranteeing effective learning. That is to say,

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

although students use various modalities extensively, the use is 'widespread but not deep' [54]; that is, the use of many of these modalities have not yet achieved their full potential for academic purposes. The challenge for educators and designers, thus, is one of understanding and exploring the impact, if any, of students' patterns of usage of these modalities on their learning and overall academic performance.

Existing research in learning analytics has identified differences in patterns of tool-use by students [142, 164, 116] and has shown significant relationships of those patterns with academic performance [166, 163, 137]. However, the modality of tool access has rarely been studied within the learning analytics research. Typically, scores of counts and time spent online extracted from the log files are accumulated across all device modalities, and the consequences of the adopted modalities on the result interpretation, if any, are not analyzed. This is particularly problematic given that there is a critical paucity of student-facing learning analytics dashboards or recommender systems that are specifically created for the use on mobile or tablet devices [250], in comparison to their wide-spread desktop counterparts. That is, challenges may emerge if students predominately use mobile and tablet modalities for their studying. Additionally, learning activities are often completed by students using multiple modalities, used either sequentially or simultaneously [145, 234], and so, identifying patterns of the use can help examine the changes in the study habits of students.

Despite the many benefits of studying the impact of the adopted technological modalities in learning, determining the patterns of use itself is a complex and challenging task. Most of the existing studies that compare different modalities have relied on count data [242, 272], self-reports and questionnaires [2, 145], or in some cases, mere assumptions [178], to make statements about modality-use patterns. Thus, the aim of this paper is to bridge several of the previously discussed gaps and explore the *sequential* patterns in use of technological modalities in an educational context. We focus on using data mining techniques and learning analytics methods to analyze students' learning sequences and provide insights into how students learn and regulate their learning using different technological modalities. We further demonstrate how understanding differences in adopted modality-use patterns can be used to explain variance in the performance in asynchronous online discussions (AODs). Thus, the two main research questions for this study are:

1. **RQ1**: Can we detect patterns in students' use of multiple modalities that are indicative of their adopted technological modality strategy when using an LMS tool? If so, what kind of strategies emerge?

2. **RQ2**: Is there an association of the identified strategies with students' performance in AODs and overall academic performance?

The study is based on the Multi-Device Learning Framework proposed by Krull [145] which considers how different devices can be used together. The framework suggests that patterns of use differ considerably between modalities based on three major aspects – multiple devices, learning activity, and contextual environment (location). Combined and complimentary use of modalities, say fixed desktop technologies and mobile technologies, serve different functions in supporting the learning process; for instance, mobile phones 'to check', tablets 'to immerse' and desktop 'to manage' ([109], as cited in [7]). A survey conducted by ECAR [2] found that students prefer accessing academic progress information and course material via their mobile devices. For viewing course videos, Wong [272] found mobile phones were preferred over desktop computers. Nakahara et al. [178] posited that desktops are favored for browsing and posting activities, considering the mobile phone's limited bandwidth, small screen and awkward text input functions. Tabuenca et al. [242] found push notifications work better on a mobile phone app than on a desktop web-version of the app. The results of the Stockwell [234] study revealed that learners typically use different modalities depending on the time of a day; mobile phone usage takes place mostly across the morning or very late at night, most typically at home, and no usage at all in the afternoon or in the evening. In contrast, when using PCs, learners tend to focus their usage in blocks in the afternoon or after midnight, working primarily at home at night and at the university during the afternoon. Looking specifically at rate of mobile use for learning activities, Stockwell [233] revealed that a significant number of learners did not use the mobile phone at all and a majority used a combination of both mobile and desktop computers for completing vocabulary activities. Even though their scores did not differ much, the amount of time spent by mobile phone users for completing each activity was longer by at least 1.4 minutes.

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

4.4 Methods

4.4.1 Study Context

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

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

4.4.2 Learning traces and study sessions

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

The study sessions were extracted from the events data in two subsequent steps. In the first step, the study sessions representing continuous sequences of events where any two events were within 30 minutes of one another were identified. Since there does not exist a unified time-on-task estimation method within the learning analytics community [143], the 30-minute threshold was chosen as in previous studies [77, 142, 121]. Given that the LMS serves mainly as a content-providing host, i.e. tracking, reporting, and delivering the educational material, a closer analysis showed that 80th percentile of the continuous time spent on activities was 11.6 minutes, which seemed insufficiently short, while 85th percentile was 48.9 minutes, which seemed overly long.

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

The two-step process resulted in 26,935 study sessions across 121 unique students for the 13 active weeks of the two courses. To gain an insight into the general pattern of study sessions we removed outliers following a similar process as reported in [121, 77]. Specifically, study sessions comprising of a single event were removed along with students with excessive study session counts (one student registered 506 sessions, compared to a median of 206). Removing these outliers resulted in 18,895 study sessions across 120 students.

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

4.4.3 Data Analysis Techniques

Pre-processing data

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

First, the modality of access associated with each event in the log data was determined from the examination of the user-agent field, and resulted in four broad categories: Desktop, Mobile, Tablet, and Unknown (for all unclear modalities). The Desktop category included access from a web browser running on desktop computers or laptops. The Mobile category included both LMS versions that could be possibly used on cellphones (see Section 4.4.1), i.e. web browser or dedicated LMS application. The Tablet category included access from tablets. The Unknown category included all other modalities, which we could not categorize with certainty. In terms of access to technological modality, the majority of students (86%) used a combination of Mobiles and Desktops, the most common device ownership combination [29], for at least one learning sequence. 8% used all three major modalities (Desktop, Tablets, Mobiles), and 6% used Desktop only.

Secondly, the count measures were extracted based on the number of times each learning action was performed by each student. Table 4.1 contains the types and total counts of learning actions, categorized into activities, captured by LMS.

Table 4.1: Breakdown of activities and access (in terms of number of actions) from different modalities

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

Thirdly, the time-on-task variable (time spent on activity) was calculated using the difference between the start times of two logged events. This is a common technique used previously in many studies [142, 168, 165], 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.

Fourthly, the word count for the messages was obtained by counting the total number of words in the message and the quality of the messages (scaled to a value between 0 and 100) in the discussions was calculated using the Coh-Metrix framework. It is a well-established computational linguistics facility for analyzing discussion texts over several measures of cohesion, language and readability [93]. Out of the several possible measures, we look at five main measures - Narrativity, Deep Cohesion, Referential Cohesion, Syntactic Simplicity and Concreteness. These measures were chosen since these account for almost 50% of the variance in a text [94] and are shown as strong indicators of social knowledge construction [119, 144].

Table 4.2 shows the extracted variables, divided into four groups: counts, time spent, word counts and quality. We have three variables related to the counts and three variables related to time spent on the three main actions in a discussion activity (posting, reading and replying), along with two variables for word counts and ten variables (5 measures x 2 message types) related to quality of the messages.

Table 4.2: Extracted features: Dependent variables examined in the study

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

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

Technological-modality sequence analysis

In order to examine the presence of patterns in students use of several technological modalities, we relied on the analyses of their learning sessions by following an approach similar to the approach proposed for detection of learning strategies from trace data [121]. Each session was encoded as a sequence of modalities using a representation format of the TraMineR R package [83]. Figure 4.1 presents few examples of learning sequences. As the example indicates, the sequences could be composed of either *absolute* (sequence 1, 3 and 4) or *mixed* sessions (sequence 2), thereby explaining the diversity in their composition. Additionally, the varying lengths of sequences (sequence 1 vs. sequence 3) are reflective of the differences in density of activities in a session. These sequences were used later for clustering to obtain students' technological-modality profiles.

```
  Sequence
1 Mobile-Mobile-Mobile
2 Mobile-Mobile-Desktop-Desktop-Desktop-Desktop
3 Mobile-Mobile-Mobile-Mobile-Mobile-Mobile-Mobile-Mobile-Mobile
4 Tablet-Tablet-Tablet-Tablet
```

Figure 4.1: Examples of technological modality sequences encoded in the TraMineR format

Clustering

Following the proposals by previous researchers [142, 77, 121], we used agglomerative clustering based on Ward's method for two kinds of clustering. First, the modality sequences (N = 18,895) were clustered to detect patterns in students' modality-use behaviours (i.e. *technological-modality profiles*). The computation of the distance (similarity) between sequences, required for the clustering algorithm, was based on the optimal matching distance metric [83]. According to this metric, the distance between two sequences of states is the minimal cost, in terms of insertions, deletions, and/or state substitutions required to transform one sequence into another. Since any substitution cost can be replaced with a combination of insertion and deletions, the cost of insertion/deletion in our analyses was set at a half the maximum substitution cost, a widely used cost setting [110], to avoid pseudo-substitutions. These computed distances were then normalized, to account for differences in sequence lengths, by dividing the distance by the length of the longer sequence.

The optimal number of sequence clusters were obtained from (a) inspection of the resulting dendrogram, and (b) calculating the "dunn index" proposed by Dunn [64], and computed using the clValid R package [26]. The Dunn Index is the ratio between the smallest distance between observations not in the same cluster to the largest intra-cluster distance. It has a value between 0 and infinity and should be maximized.

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

The optimal number of student clusters was obtained from (a) inspection of the resulting dendrogram, and (b) using the "silhouette statistic" proposed by Rousseeuw [124, 208] and computed using the clValid R package [26]. The Silhouette value measures the degree of confidence in a particular clustering assignment and lies in the interval [-1,1], with well-clustered observations having values near 1 and poorly clustered observations having values near -1.

Statistical Analyses

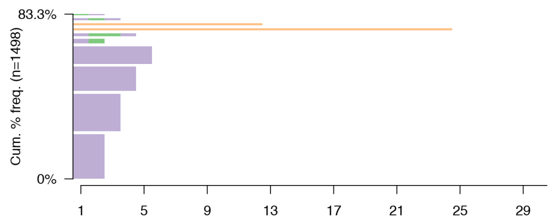
To examine if there was a significant difference between the identified student groups, we performed a multivariate analysis of variance (MANOVA). The student cluster assignment was treated as the single, independent variable along with the dependent variables described in Table 4.2: three measures of counts, three measures of time-spent, two measures of word counts and ten measures of quality.

Assumptions: Before running the MANOVA, we checked the homogeneity of covariance assumption using Box's M test and the homogeneity of variance using Levene's test. The Shapiro-Wilk test was performed to check for multivariate normality. To protect from the violations of the test assumptions, we log-transformed the data and used the Pillai's trace statistic which is considered to be a robust against assumption violations. [23].

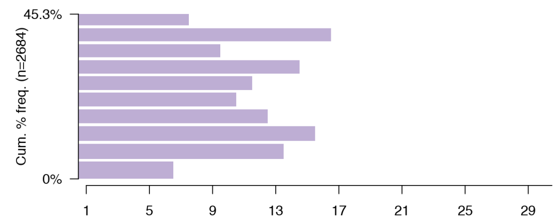
Main effect test: In case of a significant MANOVA result, a follow-up univariate one-way analyses of variance (ANOVA) were conducted on each dependent variable that produced non-significant Levene's test result. To prevent the inflation of type I error rates due to the multiple ANOVA comparisons, the Bonferroni correction was adopted. In case of significant Levene's test (i.e., the homogeneity of variance assumption was violated), the non-parametric Kruskal-Wallis test was used. Finally, the measures of eta-squared (η^2) and epsilon-squared (ϵ^2) were used to report the effect sizes for ANOVAs and Kruskal-Wallis tests, respectively and interpretations were done using Cohen's [48] primer, the most commonly used primer for effect size interpretation.

Post-hoc test: The significant Kruskal-Wallis tests were followed up by Dunn test for multiple comparisons (also using Bonferroni corrections). This is an appropriate test for comparing groups with unequal numbers of observations [277]. After significant ANOVAs, Tukey's honest significant difference (HSD) test was used to check for the differences among the individual pairs of clusters.

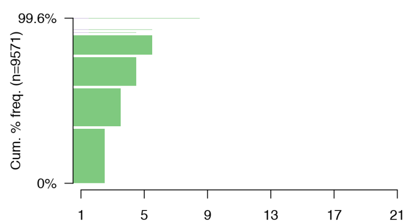
4.5 Results



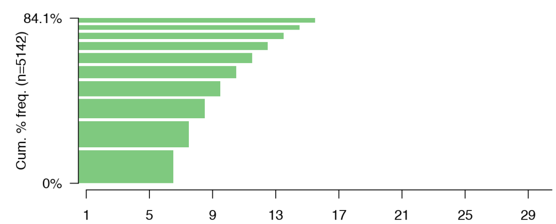
(a) SFP for Cluster 1: Diverse (N = 1498)



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



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



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

Figure 4.2: Sequence frequency plots (SFP) for each TMP profile showing the proportions of the ten most frequent sequences. (Green:Desktop, Purple: Mobile, Orange: Tablet)

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

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

Table 4.3 provides descriptive statistics for the sequence lengths in each profile cluster. Additionally, Fig 4.2 presents sequence frequency plots for each of the four profiles. These represent the ten most frequent sequences in each profile. The bar widths are proportional to the frequencies of occurrence. Thus, the y-axis indicates the cumulative percentage of the top 10 sequences. The bar lengths along the x-axis is the number of actions in the sequence. For instance, the most frequent sequence in the TMP3 cluster is a sequence of two actions on Desktop. It accounts for almost 38.72% of 9,571 sequences in TMP3. The second most frequent sequence consists of three actions on Desktop (26.76% of 9,571 sequences), is indeed very similar to the previous one. It is interesting to note that for this cluster (similar to clusters 1 and 4), the 10 most frequent sequences account for about 99.6% of all the sequences, which reflects a small diversity, i.e., a small number of different patterns than those plotted. However, the 10 most frequent sequences in TMP2 cluster account for only about 45.3% of all the sequences, which reflects a high diversity. Upon inspection, it was revealed that a majority of the remaining sequences were also similar in composition (actions completed on Mobile) to the ones plotted, but were even longer.

Table 4.3: Characteristics of sequences (in terms of lengths i.e. action count) in the technological-modality profiles

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

Drawing from Table 4.3 and Fig 4.2, the four clusters can be characterized as follows:

- TMP1 Cluster - *Diverse* (N = 1,498, 7.0%): This cluster constituted the smallest number of sequences. The grouping comprised learning sequences composed of actions from a wide range of modalities (desktops, mobiles, tablets, and unknown). This strategy cluster contained relatively short learning sequences (median = 3 actions in one learning session).

- TMP2 Cluster - *Mobile Oriented* (N = 2,684, 14.2%): This cluster was twice as large as the *Diverse* strategy cluster. Mobile constituted the most dominant modality for majority of actions in the sequences belonging to this cluster. Actions from other modalities were present but not frequent. This profile contained the longest number of learning actions in a session (median = 16 actions in one learning session).

- TMP3 Cluster - *Short-Desktop Oriented* (N = 9,571, 50.6%): This cluster was predominantly focused on actions from the Desktop modality. It was the biggest of all the four TMP clusters containing almost half of all learning sequences. The learning sessions (and, thus sequences) in this cluster tended to be short (median = 3 actions in one learning session) with the longest session composed of 22 actions only.

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

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

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

Table 4.4 describes the resulting clusters. The rows *nTMP1 - nTMP4* and *seq.total* show the distribution of the values for the variables used for clustering, i.e. the number of sequences in the four TMP clusters an d total number of sequences. The last row labeled *grade* shows the the final course grade for students in each cluster. For all the variables the table shows the median, 25th and 75th percentiles.

Table 4.4: Summary statistics for the 3 student clusters: median, 25th and 75th percentiles.

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

From the perspective of the variables outlined in Table 4.4, the clusters can be described as follows:

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

- Student Cluster 2 – *Minimalist users* (N = 52, 43.33%): This group of students predominantly used technology in a way consistent with TMP3 (Short-Desktop), then TMP4 (Desktop), and sparingly the other two profiles. The overall number of learning sequences was by far the lowest of the three student clusters. Thus, this low level of efforts, both overall and in terms of dominating short learning sessions from less-portable desktops (TMP3), may explain the group's significantly lower grades in comparison to the other two clusters (1 and 3).

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

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

4.5.3 Analysis of cluster differences

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

Table 4.5: Descriptive statistics of the dependent variable raw scores: Mean, Standard deviation (SD), Median (Mdn), 25th (Q1) and 75th(Q3) percentiles.

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

A one-way multivariate analysis of variance (MANOVA) was conducted with the students' cluster assignment as the single independent variable and the measures defined in Table 4.2 as the dependent variables. Concerning the relative sizes of the clusters, they seem reasonable and consistent with the previous studies [142, 165, 166, 121] that found intensive users are the smallest group. The descriptive statistics for each of the dependent variables are shown in Table 4.5.

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

As a follow-up, a series of one-way ANOVA with Bonferroni corrections was conducted, for each of the dependent variables that produced non-significant Levene's test (homogeneity of variance) result. The test revealed that assumption was satisfied for all but three variables (*count_PostDiscussion*, *deepCohesion_Post* and *deepCohesion_Reply*), for which Kruskal-Wallis tests were conducted. The Shapiro test of normality showed (weak) violations for four variables (*count_ReplyDiscussion*, *time_PostDiscussion*, *time_ViewDiscussion* and *time_ReplyDiscussion*). However, since ANOVA is considered a robust test against the violations to the normality assumption [90] we use it to test these four variables, instead of opting for a non-parametric method.

Table 4.6: ANOVA - Main and Post-hoc results.

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

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

Table 4.7: Kruskal Wallis - Main and Post-hoc results.

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

[a] Cluster 1 vs. Cluster 2.

The main effect analyses from ANOVA (Table 4.6) and Kruskal-Wallis test (Table 4.7) revealed that the models for three count measures (*count_ReplyDiscussion*, *count_PostDiscussion*, and *count_View- Discussion*), one time spent measure (*time_ReplyDiscussion*), both word count measures (*post_wc*, *reply_wc*) and four quality measures (*referentialCohesion_Post*, *concreteness_Post*, *syntacticSimplicity_Reply* and *referentialCohesion_Reply*) were statistically significant. To save space, only the significant results are shown in the tables.

Following the significant results, a series of post-hoc analyses was conducted to detect the clusters where statistically significant differences were observed (Table 4.6 and 4.7 footnotes indicate post-hoc tests, all significant at $p < 0.05$). In terms of counts of messages, the students from Cluster 1 (*strategic users*) posted and read more discussion messages at AODs compared to Cluster 2 students (*minimalist users*). They also replied more often to existing discussion threads than students in Cluster 2 and Cluster 3 (*intensive users*). With respect to the time-spent online, Cluster 1 (*strategic*) students spent more time compared to Cluster 2 (*minimalist users*) in framing their replies to other students' posts in discussions. In terms of the word count, discussion contributions by Cluster 1 were significantly larger than those posted by Cluster 3 and those replied by Cluster 2. In terms of the quality of messages, the discussion contents posted by Cluster 1 (*strategic users*) were more concrete compared to Cluster 2 and Cluster 3, and contained ideas that overlapped across sentences and the entire discussion (referential cohesion) compared to Cluster 3. Moreover, the replies framed by Cluster 1 students were simpler in structure with more familiar words (syntactic simplicity) compared to Cluster 3, and contained a higher number of connections that tied the ideas together for the reader (referential cohesion) compared to Cluster 2.

4.6 Discussion

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

In the second part of our analysis, we studied how technological modality strategies (combinations of technological modality profiles) were associated with participation behaviors in asynchronous online discussions and quality of this participation. We found that approximately 68% of variance in performance at AODs (in terms of counts of, time-spent online, length of and quality of messages) was explained by the demonstrated strategy for using the LMS tool. These results are important in order to acknowledge that not only does the extent to which consistency of tool-use [142] and 'richness' (in terms of feature affordances) of the tool itself [164] matter, *the diversity in intermix of modality-use for using the tool affects the performance significantly* too.

4.6.1 Technological-Modality Profiles

It must be emphasized that individual uses of modalities vary from student to student and task by task basis. Therefore, in this study, we first clustered individual study sessions each composed of action sequences based on various modalities. This was followed by clustering of students based on the counts of the occurrences of each session cluster. The purpose of our multi-step analysis is mainly to distinguish between counts of action from various devices and patterns of use of these devices for different actions. By doing so, we are able to emphasize on within-session use of modalities which provides researchers with more granular, low-level interpretations of composition of students' learning sequences as actions performed on different modalities. Hence, perhaps the most interesting insight made through such systematized trace analyses, in line with observations by previous researchers [234, 145], was that *learners employ multi-device support (ranging from PCs, laptops, tablets and mobile phones) across learning sessions, though in different proportions, rather than strictly adhering to just one.*

The various modality-use behaviour patterns observed in our study raises critical questions on the methodology adopted by a majority of the existing studies on mobile learning. It has been pointed out in the literature that a majority of researchers and educators do not take students' use of multiple devices into account in the facilitation and support of learning experiences [71, 73, 145]. Consequently, a rule of thumb in the extant comparative studies on platform (modality) performance [178, 2, 53, 272, 242], involves binning participants into dichotomous groups – mobile users *vs.* non-Mobile users – without giving cognizance to their overall technology modality behavior pattern and therefore, the possibility of an overlap between modalities. The strictly binary groupings takes away attention from the nuances involved in their modality profiles, as hinted towards by Stockwell [233] who observed 'extended usage of one platform [modality] followed by short bursts on the other' for some learners during a vocabulary activity.

The aim of the study was not to make concrete statements regarding a clear 'winner' amongst combinations of modality profiles (i.e. technological modality strategies) or even modalities themselves. The idea was to generate awareness within the research community of the impact of modalities when interpreting research findings and building learning analytics models, particularly for studies delegating tool-use as a proxy for comparing outcomes and behaviors at tasks. We argue that in addition to capturing the diversity and consistency of tool-use, as stressed by Lust et al. [164], future research should also focus on three main components of modality-use behavior, in relation to students' performance. These include *diversity* (intermix) of modalities used, *consistency* or activeness of modality-use and *transferability* of a modality to new learning tasks. We posit that these will prove useful for gaining a fuller insight into the way how tools support learning and self-regulative activities.

4.6.2 Strategies and Discussion Performance

The current study found that students in clusters associated with higher overall discussion performance (Stud.Cluster 1 = *Strategic* and Stud.Cluster 3 = *Intensive*) tended to engage in study sessions which were characterized by more active modality-use patterns. However, we see no association between the use of strategies composed of multiple devices and the participation behaviour (in terms of counts, time spent, word count and quality). That is to say, the students who chose to adopt strategies composed of a variety of different modality profiles to regulate learning (Stud.Cluster 3) did not achieve significantly better results for participation behaviour in discussion activities compared to those who chose only few (Stud.Cluster 1). This indicates that even though students may appreciate control (over learning sessions) offered by such diversity, the 'quality' of that control – i.e. the ability to determine when the use of a modality would be beneficial to learning – is an important metacognitive skill to possess. This is because, while answering quick queries can be done effectively using mobile phones, deeper knowledge construction may require more substantial technology affordances to create strong arguments. Such affordances can be offered by PCs instead, as was observed in this study. This is consistent with recent research findings by Heflin et al. [106] that found students who constructed discussion responses on a mobile device demonstrated significantly less critical thinking than those who used a computer keyboard or wrote responses by hand. Therefore, we posit that students need to develop this knowledge about which type of device and their affordances can be most suitable for a task at hand, as an additional type of metacognitive knowledge similar to the knowledge of relevant learning strategies [266].

Likewise, much like any learning strategy [77, 142, 121], monitoring and optimizing the technological modality-use is necessary for effective learning. Benefits from multi-device support will only go so far in enhancing engagement (as evident by high count measures for viewing discussions) as the same material is available on various devices. However, it is up to the learner to make efficient use of each modality to guarantee maximized academic output. Failure to do so poses serious threats to sustainable seamless learning, which relies substantially on a combined use of multiple device types. Having said that, we reinstates the observation reported in [142, 164, 47] suggesting that leaving the control with the learner or offering only little support is a poor pedagogical practice and instead, must be explicitly addressed.

Lastly, as a by-product from this study, we also provide partial support for the claim by existing research and statistics [151, 239, 238] that alleges a higher engagement rate when courses are delivered using the mobile format. This is true in particular for students from cluster 3 i.e. Intensive users whose substantial level of self-regulation occurred using mobile devices. According to our findings, cluster 3 students had substantially higher mean value (except *count_ReplyDiscussion* and *time_ViewDiscussion*) for counts and the time spent on reading, posting and replying to the discussion posts, compared to Cluster 2. However, the quality measures of their posts were lower than that of cluster 2 students, whose use of profiles involving mobile devices was meager. In fact, looking at Table 4.5, we see that even though cluster 2 did not post more, their contributions were larger (word count), and they posted more substantial messages, in terms of quality (except for syntactic simplicity score), compared to Cluster 3. However, according to the post-hoc tests, all these differences were non-significant. This might be due to the small group size of clusters because of which we failed to reject the null hypotheses (i.e. no differences exist between Minimalist and Intensive group) even when the true state of nature might be very different from what is stated in the null hypothesis [136]. Thus, more research using bigger participant pool is required to conclusively refute or provide support for this claim.

4.7 Limitations and Future Work

Since our methodology involved tracking user interaction with the LMS, this may raise a concern about the extent to which our results were dependent upon the learning context and the design of the LMS itself. Hence, future research should aim to replicate or extend our study and investigate the effects of instructional conditions [87] including but not limited to course design, learning activity, mode of assessment, teaching method, domain subject.

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

Regarding the validity of our significant results, given the small sample size available in our study, Royall [209] suggests that a highly attained significance level (i.e. small p-value) is greater evidence that null hypothesis is rejected when sample size is small. This is because a small sample size can only result in a small p-value when the observations are generally highly inconsistent with null hypothesis. Having said that, replications of the study with bigger dataset will benefit in solidifying the claims made by the paper.

4.8 Conclusions

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

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

Chapter 5

Temporal Analysis of Modality-usage patterns

You may delay, but time will not.
- Benjamin Franklin

5.1 Overview

This chapter addresses the following research questions:

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 a weekend compared to weekdays?

Learners' time-of-the-day preferences for engaging in learning have been studied extensively, but how these preferences are impacted when different modalities such as desktops and mobiles are available, need better understanding. In this chapter, we present a log-based exploratory study on LMS-use behaviour comparing three different modalities: desktop, 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 desktop sessions.

This study was motivated by the soar in the number of users owning smartphones which had inevitably been noticed in the general usage statistic of Canvas, our proprietary LMS. We detected a considerable chunk (over 40%) of user accesses emanating from mobiles and tablets for various learning activities. This observation poses an interesting question pertaining to the nature of modality accesses i.e. what are students doing using each platform and at what time of the day. 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 the day as opposed to the *counts* of modality-usage and time of the day, which removes it from the overall learning process. We further analyzed whether these results vary based on the technological modality strategy adopted by the learner.

Our results suggest that learning sessions from various modalities are significantly associated with the time of the day (TOD) and day of the week (weekday or weekend), and it holds true for students who made extensive use of different modalities to complete their learning activities (strategic and intensive learners) and those who sparingly used them (minimalist learners). The results also indicate strategic learners bear similarities with minimalist learners, two groups which are strikingly different in terms of their academic performances, in terms of their session-time distribution while intensive learners showed completely different patterns. For all students, sessions from mobile devices were more prominent in the afternoon while the proportion of desktop sessions was higher during night time. Upon comparison of these time-of-day preferences with respect to the modalities on weekday and weekend, they were found consistent mainly for strategic and minimalist learners only. The main contribution from this research are for designers, who can use the results to target delivery of 'right information at the right time through the right modality'.

5.2 Publication

The following sections include the verbatim copy of the following publication:

> Sher, V., Hatala, M., and Gašević, D. (2019). When do learners study?: An analysis of the Time-of-Day and Weekday-Weekend usage patterns of LMS from mobile and desktops in blended learning. Invited manuscript submitted to the Journal of Learning Analytics

5.3 Introduction

The global diffusion of smartphones and tablets, exceeding traditional desktops and laptops market share has created a unique learning environment and opportunities that span across time and space. All 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 recent report by ECAR [2] 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, students who have a few modality options at 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 [17] and even lesser attention has been paid to it with respect to various modalities in the learning environment. That is to say, the question remains as to the behavior 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 '*right information at the right time through the right modality*'. Furthermore, knowledge of any associations between time of the day and learning sessions taking place could help in implementing well-designed applications that are able to 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 [219, 233, 234]. There also exists a considerable body of literature which suggests that individual differences exist with respect to the time of the day learners prefer to work. That is to say, learners may have a unique chronotype such as morningness-eveningness preference [160] and these time preferences might even vary depending on the country one resides in [224]. Moreover, we also found evidence in literature suggesting significant associations between the learner's chronotype score and their academic achievements [193, 113]. Romero and Barbera [203] 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 a day is related to learning outcomes and modality-preference is related to learning outcomes – a discernible research question that follows is: *Does the choice of modality used by learners for their learning activities related to their preferences for particular time windows during the day, or vice versa.* This is exactly what our research aims to answer.

5.3.1 Time and modality flexibility in learning

There is consensus among researchers and educators regarding the idea that learning takes time [138, 270]. 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 [11, 172], only a limited number of papers have looked at the associations between time flexibility and the modality usage from learners' perspective, that too in very specific application domains. The results of the study by Stockwell [234] revealed that learners typically use different modalities depending on the time of a day, to partake in vocabulary activities for English language learning task. Mobile phone usage took place mostly across the morning or very late at night, typically at home, and 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 et al. [38] who studied the LMS-use behaviour and witnessed a rise in mobile activity during the night hours (8PM to 12AM) while desktop activity dropped during the same hours. Song et al. [227] 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 (8AM to 5PM), whereas mobile and tablet usages peaked during evenings (6PM to 10PM).

While much has been revealed from the aforementioned studies, associations between modality use and the 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. Researching these associations will present us with much more nuanced insights on within-session use of modalities and their distribution across different times of the day. For instance, looking at actions alone might let us make statements such as "desktop use occurs more frequently at night", whereas granular low-level interpretations of 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 desktop occur in the morning" and "shorter desktop sessions are more frequent at night time".

5.3.2 Research questions

In this paper, we look at the LMS use behaviour from different modalities across a 24-hour day. Since the LMS content (assignments, resources, course content) can be accessed at all times (i.e., 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 to say, self-regulation of learning using the LMS places the responsibility for time management on the learner themselves. The decision to work on mobile or on desktop, from home or library, in the afternoon or late at night, will depend very much on the available technological modalities, task the student wants to accomplish, 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 ways in which learners engage in learning activities. For instance, are there any differences in completion rates between sending a reminder at 9am or 9pm or what impact would a proactive intervention, such as 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 the day can shed light onto 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 a weekend compared to weekdays?

5.3.3 Significance of the study

This study contributes to several important viewpoints. *First*, “learners are perpetually in a context” [217] and there has been a growing interest in contextual profiling (i.e. context-aware recommendations) within fields akin to the likes of mobile learning [157, 246, 188, 274], 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 deluge learners have to cope with, knowledge of the temporal context of a learning session (possibly comprising of a combination of modalities), can provide valuable insights to the ‘contextual profiling’ mechanism[1] since it will capitalize on the learner’s time-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 available at their disposal, it is not necessary that they are continuously used as some might be led to believe. This is an important consideration as it questions how often and how regularly users would engage with a modality during a learning session and depending on the time of the day, would it be beneficial to display different information through a particular modality? We explore the same in our paper. *Third*, factor of time 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. *Lastly*, as pointed out by Chen and colleagues [41], not many researchers know how to combine mobile learning with web-based learning systems such that all learning processes are covered by generating a ‘ubiquitous learning environment’. To achieve this, 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 commute time for many may restrict use of desktop personal computer, while mobile phones owing to their portability may be better for use over a short span of time [200, 38].

5.4 Methods

5.4.1 Study Context

In this study, we analyzed the data produced by the second and third year undergraduate students in two programming-oriented courses at a Canadian university. The data were collected over two semesters (Fall 2017 and Spring 2018) from students who were in 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 learning management system (LMS) to support learning activities and students’ overall schoolwork. The students were experienced in using the LMS as they used it on a day-to-day basis in prior courses. The LMS hosted access to reading material, posted lecture slides, tutorial materials, general course information, weekly or bi-weekly course assignments, assignment submission, grades, and allowed participation in online discussion activities. In addition to the web-browser versions of the LMS (accessible on desktop/laptop/tablet/mobile), students had access to the mobile app version provided by the LMS vendor. Upon comparison

[1]Contextual profiling has been briefly explained in Section 3.3.1 in Chapter 3

of the features and functionalities offered by the two versions, no apparent differences were revealed.

Both courses were similar in structure, having a 2-hour face-to-face lecture per week, a 2-hour in-lab tutorial per week, and weekly 2-hour tutorials. Both courses contained assignments, quizzes and exams and the 3rd year course had an additional component of online discussions. Assignments, four in each course, were all individual, comprising of programming tasks, developed in the programming environment outside of the LMS. The assignment specifications were posted in the LMS, students submitted assignments via the LMS, and received feedback and grades as comments in the LMS. The grades for discussions were posted in the LMS as well. Students could plan their studying using LMS calendar where deadlines for all learning activities were posted.

5.4.2 Learning traces and study sessions

The study used the interaction trace data from students' engagement with the LMS. Students self-regulated their participation in the course activities, guided by the course requirements and deadlines. The use of technological modalities was a choice of each student. Each student action in the LMS was logged with the following data: student id, course id, type of learning action, action URL, session number, start time (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 [219] for details on the extraction process), they were filtered to remove any outliers which resulted in 18,895 study sessions across 120 students (1 student was deemed as an outlier).

5.4.3 Data Analysis Techniques

Pre-processing data

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

First, the modality of access associated with each event in the log data was determined from the examination of the user-agent field, and resulted in four broad categories: Desktop, Mobile, Tablet, and Unknown (for all unclear modalities). Note: the mobile and tablet category included both LMS versions that could be possibly used on cellphones (see Section 5.4.1), i.e., web browser or 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[2]: Morning (5 a.m. - 12 p.m.), Afternoon (12 - 6 p.m.), Evening (6 - 9 p.m.), and Night (9 p.m. - 5 a.m.). Time spent on the events in a session[3] was calculated using the difference between the start times of two logged events. This is a common technique used previously in many studies [142, 168, 165], 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 upon 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 5 hours, 4 hours were spent on learning actions in the afternoon.

Third, the day of week (DOW) category associated with each learning sessions was determined from the date of the learning action, which was derived from the start time of the activity. Learning sessions starting on a Saturday or Sunday were grouped under 'weekend' category or under 'weekday' if the learning occurred on Monday to Friday.

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 [83] (see [219] for details on interpretation of TraMineR sequences). Examples of the derived learning sequences are as follows: Sequence1: *mobile* – *mobile* – *desktop* and Sequence2: *desktop* – *tablet* – *desktop* – *desktop* (see Figure 4.1 for reference).

Clustering

We used agglomerative clustering based on Ward's method [249] for two kinds of clustering - sequence clustering and student clustering. For both kinds of clustering, the details on clustering algorithm, distance measures and validation of the number of clusters were the

[2]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.

[3]Time spent on the last event in a session was set at a cut-off limit measuring 15 minutes. This was done since the LMS does not have provision for recording 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.

same as reported in [219]. We summarize here the main steps how we obtained the clusters to orient the reader.

First, the modality sequences (N = 18,895), (derived in Section 5.4.3), were clustered to detect patterns in students' modality-use behaviours. The sequence clustering algorithm produced four clusters, i.e. technological-modality profiles (TMP). 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 strategies*). The student cluster assignments (representative of their technological-modality strategies) enabled us to group students and identify whether the underlying associations between the time of day (when learners engage in learning sessions) and the technological-modality profiles of these sessions varied across student clusters.

Statistical Analyses

Main effect test: To address RQ1 and examine if there was an overall significant relation between the modality-profile of learning sessions and the time of the day when these sessions took place, we performed a chi-square test of independence, after summarizing data composed of each sessions' technological modality profile cluster and the TOD category it belonged to in a two-way contingency matrix. Two-way tables were used in statistical analysis to summarize the relationship between two categorical variables, in our case technological-modality profile (TMP) cluster and time of day (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-Desktop, Desktop) for each time of day (i.e. Morning, Afternoon, Evening, Night). To further highlight how these associations changed depending upon the technological modality strategies 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 handle for possible inflation of Type 1 error from multiple comparisons.

Post-hoc test: In case of 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 [19] given that they are known to maintain Type 1 error (due to multiple comparisons) at a satisfactory level [167]. Those adjusted standardized residuals which 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 modality profiles, say mobile-oriented sessions, at night is different to that in the evening. The test uses z-tests to compare column (i.e. time of the day) proportions for each modality profile after adjusting for multiple comparisons using Bonferroni corrections.

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

5.5 Results

5.5.1 Results of clustering

The results in the following subsections are the same as reported in [219]. As they are the basis of our further analysis, they are described here at the level of details needed to give the reader the level of understanding needed to interpret our new results in Section 5.5.2.

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

The four sequence clusters, indicating the four different kinds of technological-modality profiles 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, 7.0%): This cluster constituted the smallest number of sequences. The grouping comprised learning sequences composed of actions from a wide range of modalities (desktops, mobiles, tablets, and unknown). This strategy cluster contained relatively short learning sequences (median = 3 actions in one learning session).

- TMP2 Cluster – *Mobile Oriented* (N = 2,684, 14.2%): Twice as many sequences were clustered into this cluster compared to the *Diverse* strategy cluster. Mobile constituted 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 longest number of learning actions in a session (median = 16 actions in one learning session).

- TMP3 Cluster – *Short-Desktop Oriented* (N = 9,571, 50.6%): This cluster was predominantly focused on actions from the Desktop modality. It was the biggest of all the four TMP clusters containing almost half of all learning sequences. The learning sessions (and, thus sequences) in this cluster tended to be short (median = 3 actions in one learning session) with the longest session composed of 22 actions only.

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

Clusters of students based on the adopted technological modality profiles

A three cluster solution was concluded as the optimal choice after inspection of the dendrogram and using silhouette method (see [219] for details on student clustering). Table 5.1 describes the resulting clusters. The rows *nTMP1 – nTMP4* and *seq.total* show the distribution of the values for the variables used for clustering, i.e. the number of sequences in the four TMP clusters and total number of sequences. The last row labeled *grade* shows the final course grade for students in each cluster. For all the variables the table shows the median, 25th and 75th percentiles.

Table 5.1: Summary statistics for the three student clusters: median, 25th and 75th percentiles.

	Student Cluster 1 Strategic N=47 (39.16%) Median(Q1,Q3)	Student Cluster 2 Minimalist 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-Desktop	94(80.5,113.5)	59(45.75,67)	83(72,105)
nDesktop	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 5.1, the clusters can be described as follows:

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

- Student Cluster 2 – *Minimalist users* (N = 52, 43.33%): This group of students predominantly used technology in a way consistent with TMP3 (Short-Desktop), then TMP4 (Desktop), and sparingly the other two profiles (TMP 1 and 4). The overall number of learning sequences was by far the lowest of the three student clusters. Thus, this low level of efforts, both overall and in terms of dominating short learning sessions from less-portable desktops (TMP3), may explain the group's significantly lower grades in comparison to the other two clusters (1 and 3).

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

These clusters were found capable of differentiating between students' final grade at (ϵ^2 = 0.12) power and discussion participation at (η^2 = 0.68) [219]. The pairwise comparison of clusters with respect to the final grade (i.e. percentage score) revealed that minimalist learners performed significantly lower than strategic ($p = 0.008$) and intensive learners ($p = 0.002$), even after adjustments to the p-values using the Benjamini-Hochberg (BH) procedure. However, the difference between the two high performing groups, i.e. strategic and intensive, was not statistically significant [219].

5.5.2 Associations between technological modality profiles 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 technological modality profiles, within each of these strategies, and different times of day when the learning sessions were carried out.

Figure 5.1 depicts the bubble plot for the distribution of all the learners' sessions across the four major time-of-the-day categories, with the additional dimension of size representing the counts of sessions. The figure reveals a preference for night time for carrying out learning related activities while the proportion of sessions during the morning and evening

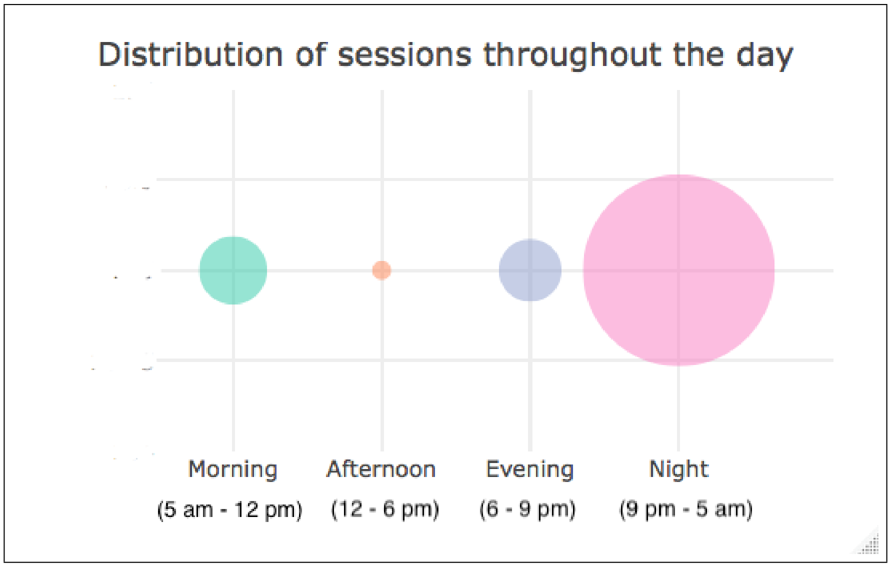


Figure 5.1: Bubble plot depicting the spread of sessions across the four major time-of-day categories. The sizes correspond to the number of sessions, the largest comprising 9,119 actions and smallest 1,984 actions.

hours were almost comparable. The lowest number of learning sessions were observed in the afternoon. Furthermore, to establish if these trends observed were consistent among students adopting different strategies for modality use (technological modality strategies identified in Section 5.5.1), we generated similar plots for each of the three student clusters identified in the previous section. Figure 5.2 depicts the distribution of the learner's sessions across time of day after stratification into each modality strategy (normalized based on the strategy cluster size). The figure shows that not only were the preferences consistent across all three modality strategies, but the ratio of *morning:afternoon:evening:night* sessions was also maintained.

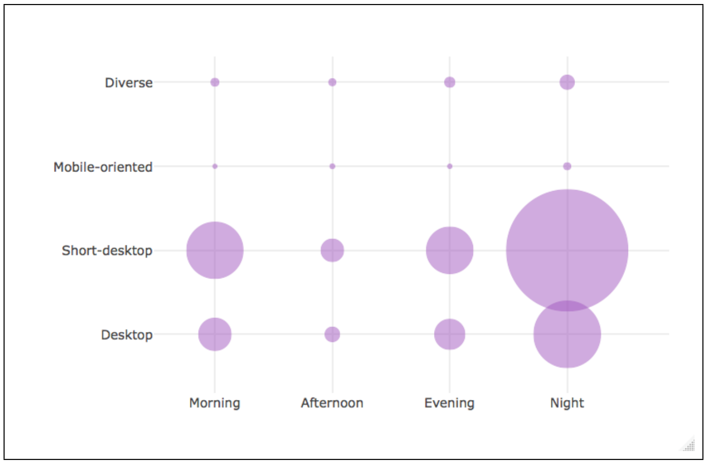
Even though the distribution of sessions across times of day was found to be consistent throughout the three modality strategies, we were interested in determining if the associations between the modality profiles (in each of these strategies) and time of the day were also replicated across the four technological modality profiles. The bubble plots in Figure 5.3 provide a visual depiction of the number of session (normalized based on the strategy cluster size) for all the different profiles across the time of day categories, within each of the three modality strategies. The figure indicates that for the majority of the TMP profiles in each of the three modality strategies, night was the dominant time of day for learning activities to take place, while afternoon time registered the lowest traffic. One possible explanation for large number of night sessions might be that the night TOD category encompasses a larger duration of the day (9 hours from 9 p.m. - 5 a.m.), hence the higher count of ses-

Figure 5.2: Bubble plot depicting spread of sessions across time of day for the three modality strategies identified in Section 5.5.1

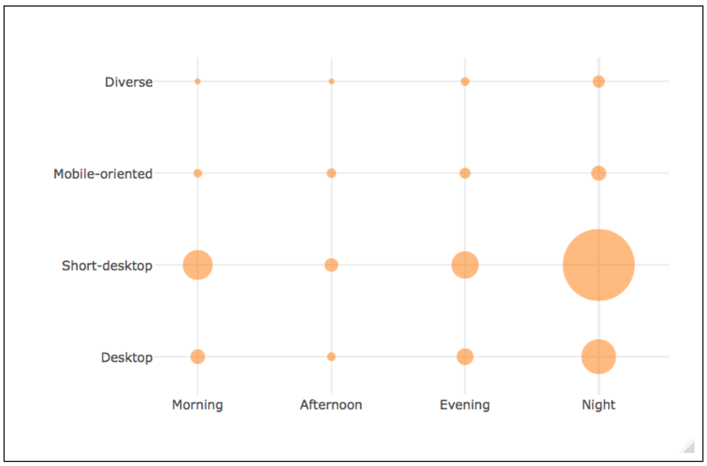
sions whereas the low session traffic during the afternoon can be attributed to the fact that learners are full-time students and therefore must be attending lectures during daytime.

Looking closely at the strategic learners in Figure 5.3a, we see differences with respect to short-desktop sessions in that there were far fewer (8.7%) short-desktop sessions in the afternoon than during morning (22.8%), evening (18.7%), and night (49.8%). Similarly, for the minimalist students (Figure 5.3b), 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 in the night (5%), 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 sessions (modality profile) and the time of the 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-desktop and desktop) 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 ($\chi^2(9) = 374.90$, $p < 0.001$).

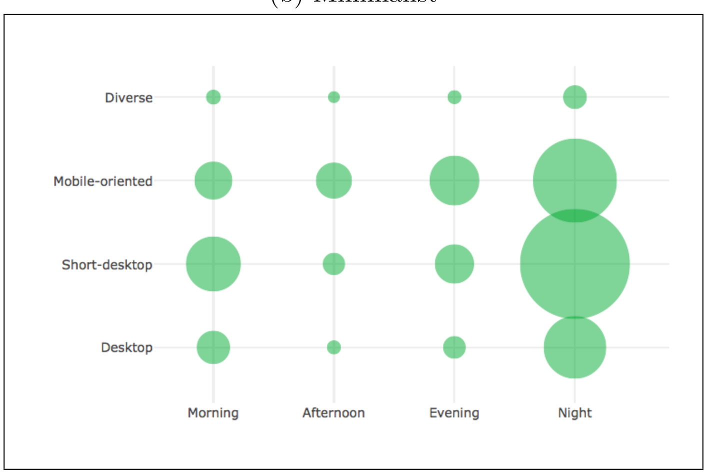
To confirm whether the aforementioned associations were consistent for all three learner modality strategies (i.e., three student clusters introduced in Section 5.5.1 - strategic, minimalist and intensive), Chi-square tests were carried out again but this time controlling for the additional layering variable, i.e. technological modality strategy. This is important since



(a) Strategic



(b) Minimalist



(c) Intensive

Figure 5.3: Bubble plot depicting distribution of modality profiles across times of day for the three modality strategies. The bubble sizes in (a), (b) and (c) have been scaled between [10,100] to allow cross-strategy comparisons.

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 provided similar results as before, when learning sessions from all students were tested collectively, and revealed significant associations between the time of day and learning sessions for all the three modality strategies; ($\chi^2(9) = 124.76$, $p < 0.001$), ($\chi^2(9) = 153.51$, $p < 0.001$), ($\chi^2(9) = 150.13$, $p < 0.001$) for Strategic, Minimalist and Intensive students, respectively.

The significant p-values indicate that technological modality profile 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, were more than expected. The observed and expected frequencies are shown for all three strategies in Table 5.2 (see row 'Count' and 'Expected count'). 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 row 'Adjusted Residual' in Table 5.2). An adjusted residual that was 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 it would be expected if the null hypothesis (i.e. the two variables – time of the day or TOD and technological modality profile or TMP – are unrelated) was true, with a significance level of .05. However, in our case, given the multiple comparisons within each strategy (four levels of TMP profiles $\times$ four levels of time of the day categories = 16 comparisons), we used an alpha value of $0.05/16 = 0.003$ to assess significance.

When examining all possible combinations of technological modality profile and time of the day, those with significant adjusted residuals are highlighted in gray in Table 5.2. As it can be seen from the highlighted cells in Table 5.2, a higher than expected number of diverse sessions from the strategic students were carried out in the afternoon and evening while a significantly lower than expected number of diverse sessions took place around night time. These patterns were entirely reversed in case of short-desktop sessions in that a lower than expected number of short-desktop sessions from the strategic students were carried out in the afternoon and evening while a significantly higher than expected number of short-desktop sessions took place around night time. For the minimalist students, a significantly larger than expected proportion of diverse, mobile-oriented and short-desktop sessions took place in the evening, afternoon and night, respectively whereas mobile sessions during the night and short-desktop sessions during the afternoon and evening were observed lower than expected. For the intensive learners, the proportion of mobile-oriented sessions in the

Table 5.2: SPSS Crosstabulation results; alpha value adjusted for multiple comparisons (p < 0.003). Adjusted residual values highlighted in gray shade represent significant differences between the expected and adjusted counts.

Student cluster				TOD			
				Morning	Afternoon	Evening	Night
Strategic	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-Desktop	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**
		Desktop	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
Minimalist	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-Desktop	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**
		Desktop	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-Desktop	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**
		Desktop	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

afternoon and evening were significant greater than expected by chance and significantly lower than expected during the morning and night. These patterns were reversed in case of short-desktop sessions in that the proportion of short-desktop sessions in the afternoon and evening were significant lower than expected by chance while they were significantly greater than expected during the morning and 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 profile in the three modality strategies. Table 5.2 (see row ‘ % within TOD’) shows the percentages of each modality profile in each TOD cluster. For instance, in case of the strategic 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 minimalist learners’ desktop 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. The results of the column proportions test 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 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.

For the strategic students, a significantly smaller proportion of diverse learning sessions occurred at night (6.2%; subscript *b*) compared to the afternoon (12.7%) and evening (10%); both subscripts *a*, while a significantly greater proportion of short-desktop learning sessions occurred at night (59.1%) compared to the afternoon (49.3%) and evening (53.2%). However, in case of the mobile-oriented sessions, the proportion of afternoon sessions were significantly larger (7.5%) than in evening (3.1%), morning (2.6%), and night (2.7%) sessions. Further, no consistent preference for time of day was visible across the desktop-oriented sessions (all subscripts *a*).

In case of the minimalist students, night time witnessed significantly smaller proportion of the diverse and mobile-oriented learning sessions than those in the evening and afternoon but greater in case of the short-desktop learning sessions. Similar to strategic students, the minimalist students displayed no consistent preference for time of day in case of the desktop-oriented sessions.

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

These results indicate that depending on the type of a learning session (technological modality profile), different time of day might be more preferable based on a learner's modality strategy. Even though the results indicate no clear choice (in terms of preference or adoption) amongst the time of day categories, the results indicate that some preferences overlap based on the the learners' modality strategies. For instance, both the strategic and intensive users were shown to have the highest proportion of the mobile-oriented sessions during the afternoon and least during the morning. Similarly, both the strategic and and minimalist users were shown to have the highest proportion of the short-desktop sessions during the night and lowest during the afternoon. Such an overlap provides opportunities for synchronizing recommendation and/or feedback delivery for different learners at the same time. This is especially useful in cases when it might not be feasible to cater to a personalized time of delivery for each individual student in the cohort due to system restrictions or inability to access enough information regarding learner's schedule.

5.5.3 Associations between technological modality profiles and weekdays/weekends

Since the literature supports claims that learning behavior may be dependent not only on time of day but also day of 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 behavioral differences that might originate depending on when learning occurred throughout the week [61]. Figure 5.4 depicts the distribution of the learning session on weekdays and weekends for students adopting varying technological modality strategies. Visual inspection revealed that the distribution of sessions across different times during the day over weekends was nearly the same as on weekends for all the strategies, with the maximum activity taking place at night time and minimum in the afternoon.

The associations between the type of day during the week (weekday vs. weekend) and time of the day when the learning sessions occur, for each modality strategy, were further confirmed by the chi-square tests which revealed significant associations for strategic ($\chi^2(3)$ = 87.48, $p < 0.001$), minimalist ($\chi^2(3) = 36.84$, $p < 0.001$) and intensive learners ($\chi^2(3)$ = 63.57, $p < 0.001$) even after adjustments were made for multiple comparisons. The post-hoc analyses using column proportion tests (see Table 5.3) 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 5.3, except in case of evening sessions for the minimalist students wherein similar propor-

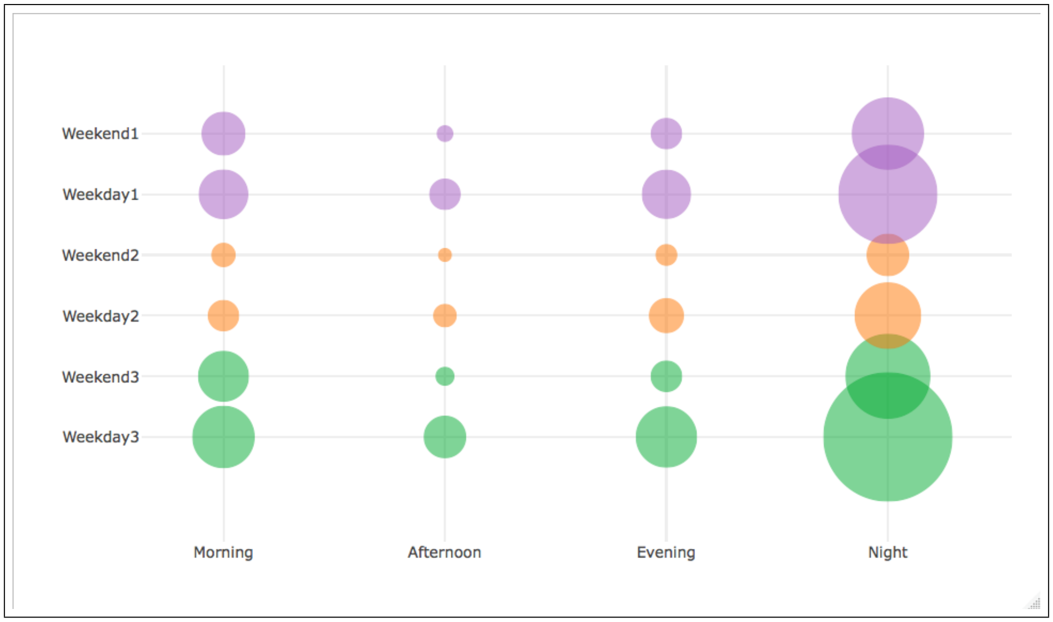


Figure 5.4: Bubble plot depicting spread of sessions across weekday and weekends for the three modality strategies: 1 = Strategic, 2 = Minimalist, 3 = Intensive.

tions 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 strategy. 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 the 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 of the four modality profiles associated with each modality strategy.

Figure 5.5 depicts the distribution of sessions across the technological modality profiles for each of the three modality strategies on weekdays (left column) and weekends (right column). The figure indicates that both weekdays and weekends, short-desktop learning sessions were the predominant modality profile, regardless of the modality strategy adopted by the learner, followed by desktop in case of the strategic and minimalist users, or the mobile-oriented sessions in case of the intensive learners. In fact, upon closer inspection of the mobile-oriented sessions of the intensive learners, we observed that on a weekday while the number of morning and afternoon sessions were almost comparable (number of

(a) Strategic weekday

(b) Strategic weekend

(c) Minimalist weekday

(d) Minimalist weekend

(e) Intensive weekday

(f) Intensive weekend

Figure 5.5: Bubble plot depicting spread of sessions on weekday and weekends for the different technological modality profiles across the three modality strategies. The bubble sizes in (a), (b), (c), (d), (e), and (f) have been scaled between [10,100] to allow cross-strategy comparisons.

Table 5.3: Crosstabulation for Time of Day (TOD) with Day of week (DOW) for each of the three technological modality strategy – Strategic, Minimalist and Intensive. The percentages depict the proportion of technological modality profiles of sessions on weekdays and weekends after stratification into each modality strategy. Column subscripts (a and b) signify the result from the comparisons of weekend and weekday proportions using z-test (after Bonferroni adjustments). Proportions with different subscripts differ significantly.

			Day of Week	
stud_cluster			Weekday	Weekend
Strategic	TOD	Morning	$20.9\%_a$	$27.3\%_b$
		Afternoon	$11.2\%_a$	$5.2\%_b$
		Evening	$20.7\%_a$	$17.2\%_b$
		Night	$47.2\%_a$	$50.4\%_b$
Minimalist	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	$46.8\%_a$	$51.4\%_b$

sessions = 220 and 253, respectively), on the weekends, the number of morning sessions (number of sessions = 76) was larger compared to sessions in the afternoon (no. of sessions = 26). Similarly, for the minimalist students on the weekends, the number of mobile-oriented sessions in the morning and night were 29 and 51, respectively whereas a fairly larger difference between the two times of the day was observed on weekdays (number 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 5.5, (after Bonferroni adjustments for multiple comparisons) to examine if the modality profiles were independent of the time of the day when the learning sessions were carried out, on both weekdays and weekends. The tests revealed high statistical significance for four of these tests – strategic weekday ($\chi^2(9)$ = 117.99, $p < 0.001$), minimalist weekday ($\chi^2(9) = 120.30$, $p < 0.001$), minimalist 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 – strategic weekend ($\chi^2(9) = 26.80$, $p =$ 0.002) and intensive weekend ($\chi^2(9) = 23.15$, $p = 0.006$). That is to say, for the learners with strategic and intensive modality strategies, there were only marginal significant associations between technological modality profiles of the learning sessions and the time of day these sessions were carried out on a weekend.

Post-hoc analyses (see Table 5.4) contradicted the visual observations we made (from the bubble plot in Figure 5.5) – i.e. the number of morning and afternoon sessions are comparable – for the intensive students' mobile-oriented sessions on the weekdays. Instead, the column proportion tests indicated that the proportion of the mobile-oriented sessions in the afternoon was significantly greater than the proportion of the mobile-oriented sessions in the morning. On the contrary, on weekends, the two proportions could not be differentiated. Similarly, the proportion of the minimalist students' mobile-oriented learning sessions in the morning and night could not be differentiated from each other on both weekdays and weekend.

Table 5.4: SPSS Crosstabulation results for technological modality profiles of the sessions with the time of the day on weekdays and weekends, across the three modality strategies. In each of the six sub-tables, column subscripts (a, b and c) signify the result from the comparisons of time of day proportions using z-test (after Bonferroni adjustments). Proportions with different subscripts differ significantly.

Panel A: Strategic

	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-Desktop	$59.3\%_b$	$48.3\%_a$	$52.9\%_a$	$58.6\%_b$
Desktop	$32.4\%_a$	$30.9\%_a$	$33.3\%_a$	$32.2\%_a$

(a) Type of Day = Weekday , Modality Strategy = Strategic

	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-Desktop	$54.7\%_a$	$57.1\%_a$	$54.3\%_a$	$60.6\%_a$
Desktop	$33.1\%_a$	$27.5\%_a$	$35.7\%_a$	$31.6\%_a$

(b) Type of Day = Weekend , Modality Strategy = Strategic

Panel B: Minimalist

	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-Desktop	$57.2\%_b$	$41.6\%_a$	$47.6\%_a$	$56\%_b$
Desktop	$25.3\%_a$	$22.9\%_a$	$26.4\%_a$	$26.4\%_a$

(c) Type of Day = Weekday , Modality Strategy = Minimalist

	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-Desktop	$56.8\%_{a,c}$	$38.6\%_{a,b}$	$43.1\%_b$	$59.3\%_c$
Desktop	$22.3\%_a$	$17.5\%_a$	$27.6\%_a$	$24.4\%_a$

(d) Type of Day = Weekend , Modality Strategy = Minimalist

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-Desktop	$42.8\%_b$	$27\%_a$	$32.1\%_a$	$40.5\%_b$
Desktop	$23.3\%_b$	$14.1\%_a$	$17\%_a$	$22.7\%_b$

(e) Type of Day = Weekday , Modality Strategy = 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-Desktop	$38\%_a$	$27.3\%_a$	$35.6\%_a$	$40.3\%_a$
Desktop	$23.6\%_a$	$9.1\%_a$	$13.3\%_a$	$19.6\%_a$

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

Post-hoc analyses for the strategic users: The proportions of the strategic learners' desktop sessions across morning, afternoon, evening, and night were non-distinguishable on the weekends (all subscripts are a). In other words, on the weekends, the proportion of the desktop sessions remained constant throughout the day. Similar trends were observed for the short-desktop sessions on weekends. However, these trends were replicated across weekdays only in case of the desktop sessions whereas in case of the short-desktop sessions, the proportion of the morning and night sessions was significantly greater than those in the afternoons and evenings. For the mobile-oriented sessions on both weekdays and weekends, the proportion in the afternoon was the highest compared to that in morning, evening and night, all three of which were non-distinguishable from each other. In case of the diverse sessions on a weekday, the proportion of afternoon and evening sessions were greater than morning and night sessions whereas the results did not hold on the weekend.

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

Post-hoc analyses for intensive users: The proportions of the intensive learners' desktop and short-desktop sessions across mornings, afternoons, evenings, and nights were non-distinguishable on a weekend (all subscripts are a). In other words, the proportion of the desktop oriented sessions on the weekends remained constant throughout days. However, these trends were not replicated on the weekdays, i.e., the proportions of the morning and night sessions for the short-desktop and desktop modality profiles were significantly greater than afternoon and evening sessions on the weekdays. An interesting observation in case of the mobile-oriented learning sessions was that the proportion of these type of sessions taking place in the afternoon was significantly greater than those occurring in the morning and at night time only on weekdays but not on weekends. On the contrary, the proportion of the diverse learning sessions remained constant throughout the day on both weekdays and weekends.

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 a weekday compared to the weekend. On the other hand, strategic and minimalist learners were quite consistent in their temporal patterns such that - 1) on both weekday and weekends, significantly greater mobile sessions took place in afternoons, and 2) on both weekday and weekends, proportion of desktop sessions remained constant throughout the day; with the only exception of short-desktop sessions whose proportion was constant throughout the day on weekends but on weekdays, morning and night time witnessed significantly more mobile sessions. In other words, different dynamics are at play depending upon whether the learning sessions took place over a weekend or weekday and thus, there is a potential for personalization of feedback pertaining to the specific technological modality profiles, not only based on time of day but also the day of week.

5.6 Discussion

5.6.1 Temporal patterns of modality usage

The setting for this work is part of a comprehensive program of research focusing on how influx of modern devices, such as desktops, tablets, smartphones, from technological advancements in learning are affecting the learning strategies, aptitudes, routines and ultimately the academic achievements of learners. The purpose of this study was to build on the earlier study by Sher et al. [219] to determine when and how learners access different modalities throughout the day (RQ1) and shed light on how these accesses on the weekends differed when compared to the weekdays (RQ2). In this exploratory study, we looked at differences in students' time flexibility (across time of day and day of week) and modality flexibility (choice of desktops, mobiles, and tablets) in individual activities related to the use of the LMS in two blended courses. All this was achieved using trace data to determine contextual time-of-day preferences from usage logs, as opposed to the current paradigm of surveys and questionnaires [203, 233, 162, 56].

While most previous studies had examined the study-time patterns at the granular level of a single modality or a single action, we established relation with the sequential patterns of using differing modalities throughout the day. Doing so helped us narrow down the time of the day (collapsed into four TOD categories – morning, evening, afternoon and night) when users are engaged intensively with the learning sessions (longer sessions such as desktop sessions) vs. when the learners are spontaneously engaged (shorter sessions such as mobile oriented sessions). Our results revealed that learning sessions from various modalities were significantly associated with the time during the day when these sessions were carried out. More interestingly, the associations held true for students with varying technological modality strategies, i.e. who made extensive use of different modalities to complete their learning activities (strategic and intensive learners) and those who sparingly used them (minimalist learners). We also revealed that the associations were similar on weekdays and weekends for strategic and minimalist learners, two groups which are strikingly different in terms of their academic performances, as reported by [219].

The temporal patterns discovered in the paper played a major role in revealing a lot more about learner's concept of utility of one modality over others. For instance, learning on a desktop usually tends to be far more meticulously planned [234] than 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 which consists of coding assignments, we saw that learners from all modality strategies gravitated towards certain slots of day, mostly nights, in order to be able to engage in learning sessions on their desktops. However, such concrete temporal patterns were visible only for the *short* desktop sessions. Engagement in the long-desktop 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 such a finding could be that unlike strategic and minimalist learners, intensive learners do not rely entirely on desktops for all their learning needs and therefore were successful in reserving the usage of a specific modality to 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 [38], were found to take place mostly in the afternoons (and relatively less during night-time) across all learners, regardless of their modality strategy. 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 evenings (when in commute on their return trip home, when desktop use would be cumbersome, if not entirely impractical). Instead, they frequently opted to use the mobile modality in the afternoons when the classes were on-going. This might suggest students use mobile phones more on campus when they experience some sort of modality restrictions, perhaps preventing them from accessing their laptops or desktops mid-lecture [154]. However, we found that a significantly higher use of mobile phones in the afternoons was prevalent on weekends too when the learners would not possibly experience any modality restrictions. This further solidifies our finding that afternoon time slot is indeed the preferred time for mobile learning sessions. This finding is also partially supported by Tabuenca et al. [242] who found that students were most active on their mobile phones during 9am to 3pm. They also found 6pm to 10pm time range (which overlaps with the evening slot defined in our study) to be highly active for student's 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 strategic and minimalist learners evenings registered comparatively low-intensity mobile learning sessions compared to morning, afternoon and evenings.

5.6.2 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 [203, 22], and by extension academic performance [98, 204]. Although learners vary in their capacity to organize quality learning times, their time allocations become particularly crucial at the post-secondary level. This is because college settings often comprise fewer hours of structured classroom time and as a result, students' academic success relies on their abilities to use time effectively.

While assessing the relation between the time of the day and academic performance was not the main aim of this study, and hence not studied in depth, we can still draw some conclusions. As Figure 5.2 suggests the learning sessions from two of the main high performing groups - strategic and intensive - were performed mostly during night time. This is in contrast to observation by Romero and Barbera [203] 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 which required them to spend fair amount of time working on their programming assignments using specific softwares on desktops. By virtue of our participants being at classes for most part of their day, evening (and late night) time undoubtedly emerged as the preferred time of the day for desktop-oriented sessions.

Considering that afternoon and post-afternoon (evening and night) are the highly preferred time for mobile and desktop activities, respectively, and the most closely related to strong academic performers (such as strategic and intensive learners), educators should consider raising awareness about these findings among students. Furthermore, since routines and time commitments on weekdays are sort of fixed, instructional interventions that promote learner's use of a greater part of their time available on the weekend to study in the time-frames observed above, have potential for improved learning outcomes. Alternatively, if leveraging temporal patterns associated with high performance fail to offer some feedback or improvement for low performing students, assessments of their routines need to be performed as they might be confronting particular challenges because of temporal orientations, defined by their professional, social activities and the digital world.

5.6.3 Implications for Research

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 random time of the day or whatever time has been hard wired in the LMS app – which might not be based on theoretical/empirical reasoning, both of which might result in undesirable learning impact [242, 233]. For instance, we observed in the Stockwell [233] study that the push mechanism was used to roll out reminders at 5pm sharp (scheduled-based notifications [241]) on to students' mobile phones justifying that evening is the commute time to home for many. However, the expected outcome was not achieved. The author found no instances of learners acting upon the activities within a six-hour period after receiving the email notification from the server. While it may have partly to do with the appropriateness of the content of the messages, as suggested by Stockwell himself, it would not be entirely unpragmatic to think that the timing or 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 favorable time for the 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 but rather one that takes into account their aptitudes, strategies, and context.

The problem experienced in the Stockwell 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 upon it. This means there is a fair possibility that they might receive it at an *inappropriate* time, say late evening when they are tired [99] or in commute [231], which in turn results in ineffective learning. Considering that we found some recurrent temporal patterns for learners with varying technological modality strategies, we urge LMS designers to consider them while designing notifications in LMS and recommender systems. The more flexible, personalized nature of notification time has the potential of shaping achievement outcomes, in ways that have yet to be clearly understood. A practical implementation of the utility of the modality-time associations worth mentioning here, was exemplified by Xu et al. [274] who used time of the day and day of the week (among other variables such as location, user type) as contextual variables (tracked from user log file) to create an information system. The information system performed context-aware delivery of application-specific information depending on which device – phone, personal digital assistant (PDA), laptop, desktop, wall display – the request was made from. Although the authors do not discuss results from the use of the system, the LA 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 vs. fixed [79, 242, 176]. Tabuenca et al. [242] studied learner perceptions regarding whether mobile notifications should be sent at random or fixed times and found that students preferred latter over former, given that it allows them to pre-plan their day ahead. While we agree to and can envision the benefits of not bombarding learners with notifications at random times, we are skeptical to the prospect of fixed time notifications. Unless modality is taken into consideration, 'fixed' time entails sending notification, 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 the time of the day and modality, we envision the potential of learning algorithms (for 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 to do so are discussed next.

Tabuenca and his colleagues [242] noted that notifications which foster participation towards studying will be acted upon the moment learners receive them. Thus, notifications which usually correspond to ongoing activities in LMS, should be delivered in a temporal context and via a modality that maximizes a learner's chances of acting upon it. 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 student are not likely engaged in other in-depth learning activity. This could be in a 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' [104], 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 desktop when the learner is likely to engage in longer study time which happens in the evenings on weekday 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 mornings on weekdays or weekends. Finally, prompts from the monitoring activities in LMS where information is mainly *consumed* rather than *created* such as tracking self progress at discussion forums or reading other's discussions, can be delivered on a desktop 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 longer duration in a study session.

The ability to share and distribute information to learners via learning systems is important for extending learning to outside of the formal classroom [44]. Based on the results of our study, learner's time-of-day preferences are linked to the sequence of their learning actions on these systems from different devices. This subsequent knowledge is paramount for help in personalizing and making 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 [91] emphasized on the need for understanding how learning activities are distributed across different contexts, especially since learners continually 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 in understanding the opportunities afforded by the incorporation of varying modalities into a learner's active learning environments as they go about their day (in classrooms, at home and outdoors), and (b) designers in understanding and conceptualizing all temporal aspects of the (mobile/desktop/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 presence of novelty devices, us exploring and finding associations in this paper is just getting one step closer to Goodyear's vision.

5.6.4 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. - 12 p.m.), afternoon (12 - 6 p.m.), evening (6 - 9 p.m.), night (9 p.m. - 5 a.m.) which usually depends upon personal life-style and culture. Therefore, it would be interesting to see this study replicated across different cultures and with diverse cohort of learners such as distance, lifelong, mature 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 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 time-of-day preferences are stable across different learning activities. This line of inquiry could also be extended to examining stability of temporal patterns in combination with other courses as course structure intricacies such as milestone definitions and submission deadlines could lead to new insights.

Third, for the analyses of this study, the learning sessions comprised of actions accumulated across the entire semester, i.e., 4 months or approximately 120 days. However, the rather low median number of total sessions, for all the three student groups, indicate students may have been working seriously on the course only couple of days a week, not everyday. 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.

5.7 Conclusion

As time acquires new meaning within the recently emergent technologically enhanced learning (TEL) environments, there is a need for a shift in the temporal framework in educational research which cannot adequately address the complexities of these environments. In this paper, we move one step beyond choronotype to study associations between time-of-day preferences (such as morning, afternoon, evening, night) and 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 desktops to identify differences between the LMS usage patterns with respect to the time of the day. Understanding how specific time 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 usage indicating that there are quite significant differences in the ways in which 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 during the day to engage with the LMS depending on whether the activity requires them to use desktop or mobiles or whether the session is a long or short one. For instance, the short desktop sessions were observed to be more prominent at night (9 p.m. – 5 a.m.) compared to other times during the day and mobile sessions were significantly higher in number in the afternoons (12 – 6 p.m.) compared to the rest of the day. Furthermore, the preferences on the weekdays were not found to be the same as those on the weekends for all students and instead depended on the session's modality profiles, learners' modality strategy, and the learning task at hand, among other contextual factors.

Being in a constantly changing environment throughout the day implies there are numerous influencing factors surrounding a learner that can impact their learning behaviour, concentration and ultimately their ability to use a specific modality at a particular time. While there is no control over these time-of-day 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 vs. desktop computers.

Chapter 6

Modality-inclusive Learner Models

Algebra is the intellectual instrument which has been created for rendering clear the quantitative aspect of the world.

- Alfred N. Whitehead

6.1 Overview

This chapter addresses the following research question:

1. **RQ**: To what extent is the predictive strength of LMS features influenced by distinguishing the modality of learner access when predicting course grade?

The research area of analyzing log file trace data to build academic performance prediction models has recognized potential for pedagogical support. Currently, these learner models are developed from logs that are composed of one intermixed stream of data, treated in the same manner regardless of which platform (mobile, desktops) the data originates from.

In this chapter, we designed a correlational study using log data from two offerings of a blended course to investigate the effects of the variables, derived from the use of varying modalities, on the prediction of students' academic success. Given that learners use a combination of devices when engaging in learning activities, it is apparent that weighing the logs based on the platform they originate from might generate different (possibly better) models, with varying priority assigned to different model features. For instance, our results show that the overall frequency of course material access is a less powerful indicator of academic performance compared to the frequency of course material access 'from mobile devices'. This and similar kind of findings have important implications for learning analytics, as they indicate that the sensitivity of models needs to be carefully considered to avoid models that do not generalize to the new context where multiple devices are used for supporting formal learning. Thus, the primary goal is to bring to light the potential for improvement of prediction power of models after considering the learner's platform of access, within the learning analytics community and the fields of user modeling and recommender systems, in general.

The main revelations from this chapter provide serious implications for research and practice. For instance, our result indicate that tracing the modality source (mobiles vs. desktops vs. tablets) of log data is helpful in improving the accuracy of learner models. We also found that some modalities are better predictors of learning outcomes than others. However, our results also highlight important effect of modality on a learning activity since the magnitude and direction of the variance in the learning outcome, explained by the modality, was found to differ based on the learning activity.

6.2 Publication

The following sections include the verbatim copy of the following publication:

> Sher, V., Hatala, M., and Gašević, D. (2019). Investigating effects of considering mobile and desktop learning data on predictive power of models of student success. Manuscript submitted to the Journal of Learning Analytics

6.3 Introduction

Predictive models play a prominent role in many fields such as health-care, finance, and risk management. They primarily make use of data mining and probabilistic modeling techniques to forecast outcomes. In particular, the fields of Education Data Mining (EDM) and Learning Analytics (LA) have recently gained widespread popularity for developing prediction models for effectively keeping track of the progress of their students – identifying at-risk students, attrition rates and achievement of academic outcomes [14, 57, 15]. As such, researchers are constantly working towards improving the accuracy and appropriateness of the interventions based on the interpretations of these models by examining the *background elements* that may 'condition the effect of predictor variables (LMS tool use) on the target variable (student performance)' [199]. These elements are considered useful for improving the understanding of learning and teaching processes, and for better prediction of the achievement of learning outcomes. The background elements comprise of contextual factors (such as institution, discipline or learning design) [78, 87], perceived contextual factors (such as overall course quality, relevance to professional practice, teacher involvement) [105, 59], and individual student characteristics (such as personality traits, prior academic performance, learning approach, or intellectual ability) [185, 102, 42, 186, 20]. However, the role of platform modalities (such as desktops, tablets) has not yet been fully explored with regards to the accuracy of these learner models.

To our knowledge, so far little research, if any, has explored the possible relationship between learner's modality usage and measures of learning outcomes. That is to say, the models rarely take into account the learner's multi-device use from various technological modalities, such as desktops, mobiles and tablets, as a viable predictor; one that can explain some amount of variance in the academic outcomes. The exploration of the impact of modalities on predictive analytics is justified and highly recommended since: (a) learning activities are often completed by students using multiple modalities, used either sequentially or simultaneously [145, 234], and (b) identification of modalities that are ill-aligned to a task is important as they could undermine knowledge construction and may lead to unintended consequences in academic outcomes [219]. This paper thus investigates the usefulness of a modality-inclusive learner model, over and above a generalized model, for predicting learner success, as operationalized by academic performance.

The review of the literature reveals that the performance prediction models draw benefits from the students' 'event-driven logs' [27] from various learning activities that are available for measurement in a web-based learning management systems (LMSs) such as logging in, reading files, viewing posts, posting discussions and accessing feedback; all of which provide early indicators of student academic performance [275, 258, 259, 37]. These logs, however, are composed of one intermixed stream of data, treated in the same manner regardless of which modality (mobile, desktops) the data came from. As a rule of thumb, the data concerning each predictor action, such as posting discussions and viewing course videos – actions that more often than not, emanate from different modalities and last for different durations – is generally pooled across all modalities. For instance, the frequency of access to course material from desktops, mobiles and tablets is typically used in the predictive model as one cumulative count measure i.e. *course_material_access*, counting all occurrences of course material access in the log file. This is done mainly due to the lack of awareness regarding the utility of technological context or merely to facilitate ease of data processing. Either way, the omission of technological modality variables in a model has potential to, at minimum, discard some useful information and as a result lower the prediction accuracy of the model, or more critically, cause serious threat to its interpretation. Thus, the primary aim of this paper is to create awareness of the role of modalities in predictive analyses of academic performance.

Research has provided evidence suggesting not all activities (features) are equally effective as predictors of outcomes [87]. More interestingly and importantly, recent studies have also suggested that not all the learning activities are performed using a single technological modality [145, 233], but are often interleaved between devices such as mobile and desktop. In other words, depending on the utility and preference for a platform (modality), the predictive power of learning indices (variable describing the frequency and/or quality of interaction with the LMS tool) in a regression model could be positively or negatively impacted. Building upon these inferences, we further posit that considering the differences in the (modality) source of the log trace data used for modeling and predicting academic success, would increase accuracy of these models and help explain anomalies. For instance, theoretically it has been established that posts from mobile devices are lower in quality compared to those from its non-mobile counterpart, i.e. desktop [106]. We hypothesize that including this information into the predictive model would make the model more accurate and explainable.

6.3.1 Contribution and Research Questions

The study is important from several viewpoints. Primarily, the modality of access and its repercussions on learning has so far not been sufficiently studied in the literature [219]. The closest the existing studies have come to assessing the impact of different modalities in a learner model for predicting academic performance is via focusing on whether or not mobile phones were used, however *not necessarily for educational purposes* [156, 123]. Secondly, with the influx of prevalent, popular and affordable modalities, the device ownership has steadily increased compared to previous years [192]. Considering that either one of these growing suite of modalities are typically readily available at everyone's disposal, it is worth considering what influence their use may have on the predictive capabilities of learning models' outcomes. Thus, the aim of the paper is to investigate the potential for improvement of prediction power of learner models after considering the modality of access for each event in the learning environment. The main research question for this study is:

RQ: To what extent is the predictive strength of LMS features influenced by distinguishing the modality of learner access when predicting course grade?

6.3.2 Theoretical Framework

The paper draws its theoretical underpinnings from two main studies and several auxiliary studies. Firstly, the Multi-Device Learning Framework proposed by Krull [145] explicates how different devices are simultaneously and/or sequentially used together. The framework suggests that patterns of use differ considerably between modalities based on three major aspects: multiple devices, learning activity, and contextual environment (location). The combined and complimentary use of modalities, for e.g., fixed desktop technologies vs. mobile technologies, serve different functions in supporting the learning process; for instance, mobile phones 'to check', tablets 'to immerse', and desktop 'to manage' ([109], as cited in [7]). Secondly, empirical support for our hypothesis is further provided by the results from Sher et al.'s recent study [219] where the researchers found a significant impact of the students' adopted modality profile, derived from patterns of modality usage for various learning activities, on the final course grade ($\epsilon^2 = .12$) and engagement and quality of participation in a discussion learning activity ($\eta^2 = .68$).

Assessing the related work regarding technological modalities, a small yet significant pool of studies has provided evidence suggesting different modalities are used based on the contextual settings, in addition to the affordances of the modalities themselves. For instance, mobile phones were found to be more preferable over other modalities for accessing academic progress information and course material [2], viewing course videos [272], and working with push notifications [242]. Some researchers, on the other hand, have argued in favour of desktops positing that desktops are better for browsing and posting activities, considering the mobile phone's 'limited bandwidth, small screen and awkward text input functions' [178]. This was empirically supported by Casany Guerrero et al. [38] who found majority of queries to the LMS (96%), for viewing assignments and resources, were performed from desktop or laptop computers. Furthermore, we found only two studies, both by Stockwell, where the pivotal aim was to compare the two dominant modalities - desktop and mobile - at an authentic learning activity, i.e. vocabulary activities for English language learning tasks. In his first study, Stockwell [233] revealed that a significant number of learners did not use the mobile phone at all and a majority used a combination of both mobile phones and desktop computers for completing vocabulary activities. Even though students' scores did not differ much, the amount of time spent by mobile phone users for completing each activity was longer by at least 1.4 minutes, a 60% increase over time spent when using desktops. Looking specifically at patterns of usage, the results of Stockwell's second study [234] revealed that learners typically use different modalities depending on the time of a day; mobile phone usage takes place mostly across the morning or very late at night, predominantly at home, and no usage at all in the afternoon or in the evening. In contrast, learners using PCs focused their usage in blocks in the afternoon or after mid-night, working primarily at home at night and at the university during the afternoon.

Even though the analysis in the aforementioned studies was simple, using descriptive statistics mostly, the variety in usage, based on the above factors, confirms that certain modalities may be used for studying more often (and for varying durations) than others depending on the type of activities, location and time of day. As a result, access to specific modalities can greatly influence study patterns. Thus, we hypothesize that considering the modality source of an activity can potentially predict the overall learning outcome better. The extent to which this is the case is exactly what we intend to explore in this study.

6.4 Methods

6.4.1 Study Context

The participants in this study were undergraduate students in a second year programming-oriented course at a Canadian university. The data was collected over two semesters (Fall 2017 and Fall 2018) from two subsequent offerings of the same course. The course duration was 13 weeks and a total of 165 students enrolled in it (83 and 82 in Fall 2017 and 2018, respectively). The course followed a blended format, utilizing the university's learning management system (LMS) to support learning activities and students' overall schoolwork. The students were familiar with the LMS as they used it on a day-to-day basis in prior courses too. The LMS hosted access to reading material, posted lecture slides, tutorial materials, general course information, instructor provided supplementary material, bi-weekly course assignments, assignment submission, and grades. In addition to the web-browser versions of the LMS (desktop/laptop/mobile), students had access to the app version provided by the LMS vendor (for use on mobile and tablets). Upon comparison of the features and functionalities offered by the two versions, no apparent differences were revealed.

The course structure consisted of a 2-hour face-to-face lecture per week and a 2-hour in-lab tutorial per week. The tutorial participation contributed 10% towards the final grade, assignments 40% of the grade, quizzes and exams 50% of the grade. There were four assignments in total, all comprising of programming tasks, and required the students to work individually in a programming environment outside of the LMS. The instructors used the LMS to post assignment specifications, while students used it for submitting assignments, and receiving feedback, grades and comments on their assignment. The grades for quizzes were posted in the LMS as well. Students could plan their studying using the LMS calendar where deadlines for all learning activities were posted.

6.4.2 Data Collection and Procedure

Learning Traces

In this study, we used the interaction trace data from students' engagement with the LMS. The traces were generated as students used the LMS to self-regulate their participation in the course activities, guided by the course requirements and deadlines. The learners had complete autonomy over the choice of the technological modality to be used for carrying out each learning-related action in the LMS. Each student action in the LMS was logged with the following data: student id, course id, type of learning action, action URL, start time, end time, and user-agent. In addition, each action was also allocated a session number to which it belongs. This was done since the notion of a session is essential for validity of the calculation of time on task.

As there does not exist a unified time-on-task estimation method within the learning analytics community [143], to group the actions into sessions, we consider a time gap of more than 30 minutes to be a new session. This delimiter was chosen because a closer analysis showed that 90th percentile of the continuous time spent on activities was 21.6 minutes, which seemed insufficiently short, while 95th percentile was 45.2 minutes, which seemed overly long. Given that the LMS serves as a content-providing host, i.e. tracking, reporting, and delivering the educational material, 30 minutes was agreed upon as an optimum threshold, based on each action requiring a reasonable number of minutes, and to allow time for quick breaks within the same session.

Finally, the data were de-identified before the analyses were performed.

Pre-processing data

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

First, the modality of access associated with each event in the log data was determined from the examination of the user-agent field, and resulted in four broad categories: Desktop, Mobile, Tablet, and Unknown (for all unclear modalities). The Desktop category included access from a web browser running on desktop computers or laptops. The Mobile category included both LMS versions that could be possibly used on cellphones (see Section 6.4.1), i.e. web browser or dedicated LMS application. The Tablet category included access from tablets. The Unknown category included access from devices where we could not categorize their modality with certainty.

Secondly, the count measures were extracted based on the number of times each learning action was performed by each student. Table 6.1 contains the types and total counts of learning actions of interest, captured by the LMS. Note that the actions contained within calendar are across all the courses that the learners took while the other categories are for the courses included in this study only.

Table 6.1: Breakdown of activities and access (in terms of the number of actions) from different modalities.

Activity	Desktop	Mobile	Tablet	Unknown
Syllabus	1,952	155	8	0
Assignments	15,929	2,474	23	0
Submission Feedback ‘	1,954	2,968	6	0
Calendar	1,734	4,687	43	10,021
Course Material	24,850	1,279	147	0

Thirdly, the time spent on an action[1] was calculated using the difference between the start times of two logged events. This is a common technique used previously in many studies, e.g. [142, 168, 165], 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.

6.4.3 Study Design

The study followed a correlational non-experimental design as it investigated the effects of the variables derived from the use of various technological modalities on the prediction of students' academic success.

Feature Engineering from LMS trace data

To investigate the effect of modality on different types of commonly included learning-related activities (Table 6.1) and their traces in the online courses, we selected 10 features (5 counts + 5 time spents for each activity) for inclusion in our analyses as predictors of academic success. Variables derived from the LMS trace data include information about the usage of the following tools/features utilized in the course under study: syllabus, course material (lecture + tutorial slides and instructor provided supplementary material), assignments, feedback on the assignments and calendar. Table 6.2 shows the extracted variables, divided into two groups: counts and time spent. For some of these predictors we find evidence in the existing literature [87, 168, 173, 225, 159, 256], while others are included in order to provide a comprehensive evaluation of possible features that students accessed frequently (see Table 6.1) and that the authors consider relevant for demonstrating impact on academic success.

[1]Time spent on the last action in a session was set at a cut-off limit measuring 20 minutes. This was done since the LMS does not have provision for recording 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.

Table 6.2: Extracted features: Predictor variables examined in the study

Type	Name	Description
Count	count_syllabus	Total number of syllabus views by the student
	count_assignment	Total number of assignment views by the student
	count_submissionFdbk	Total number of views of feedback received on the assignment submission
	count_calendar	Total number of calendar views for planning studies - adding and/or viewing deadlines
	count_courseMaterial	Total number of the times student accessed lecture slides, tutorial slides and supplementary material
Time Spent	time_syllabus	Total time spent on reading course syllabus
	time_assignment	Total time spent on viewing the assignment requirements
	time_submissionFdbk	Total time spent on viewing the feedback received on the assignment submission
	time_calendar	Total time spent on using calendar to plan the studies
	time_courseMaterial	Total time spent on accessing lecture slides, tutorial slides and supplementary material

The rationale for selecting these particular activities (or actions) is attributed to the disciplinary and course-specific needs, which explain their relevance in accordance with the instructional intentions for the use of the LMS tool. In addition, we found ample evidence in literature pointing to the usefulness of these measures for predicting course achievement [87, 275, 133, 111, 183]. Assignments are, in general, an integral part of formative assessment of student learning and have proven useful for evaluation and accountability. Since the four programming assignments built gradually on top of one another, in addition to accessing the assignments time and again, students' access to the authentic and constructive feedback, as provided to the learner on each assignment submission by the teaching staff, was necessary for student's improvement on subsequent assignments and their programming skills. Access to the course material was necessary for students to prepare for quizzes, exams and assignments, and therefore its use was mandated by the instructors for further study, after the completion of the in-class lecture. The materials were of two kinds: i) LMS content pages with list of readings in the textbook (traced) and links to material external to LMS (not traced); and ii) to lecture and tutorial slides and demo code from the tutorial (traced). There were 50-70 lecture slides per week and 20-30 tutorial slides per week, which mainly included brief introduction to (programming-related) conceptual structures and supporting coding examples. The example of an embedded LMS feature that has not been given much attention in the literature was calendar. Its usefulness, mainly for planning and self-regulatory purposes, was explicitly communicated to the students since it contained all the major assignment deadlines, quiz and exam dates. The course syllabus, comprising designated topics scheduled for each of the 13 weeks in addition to important course regulations and information such as attendance rules, assignment schedule, weekly class schedule, and the evaluation criteria, was pinned to the course home page in the LMS and provided students means to plan their studies in advance.

Next, for each student we extracted the number of times and the time spent on using a particular feature by aggregating individual operations (see Section 6.4.2). For instance, a student's assignment views across all four assignment tasks were added to compute *count_assignment* and total time spent on viewing all four assignments to compute *time_assignment*. We call these variables *LMS features*.

Each of these variables was split up further to account for the platform used to access that particular feature. For instance, in addition to having the total number of assignment views for a student, we computed three more variables – mobile views, desktop views and tablet views – which indicate the respective number of assignment views from each of the three main modalities. We call such variables *Modality features*.

The trace data for both LMS and modality features were initially collected as continuous variables. Compared to the desktop and mobile modality features, the tablet modality features were not accessed by a substantial number of students. These were, therefore, dichotomized into the *Accessed* and *Did not access* categories.

LMS features for calendar, assignment, syllabus, course material and submission feedback were accessed by many students, however, these variables were highly skewed, and so we applied Box-cox transformations [49] which transformed the variables whilst preserving the ranking order of variables. However, these transformations corrected the skewness for counts of and time spent on course material only. The remaining features were transformed into categorical variables and the cut-offs were decided arbitrarily to best represent the data, similar to the technique used by Gašević et al. [87]. For example: 15% of students did not access the calendar feature, 22% accessed the calendar for up to 30 hours, 11% were students who accessed the calendar feature for 30-60 hours, while the remaining 52% of students accessed this feature for more than 60 hours. Therefore, we divided this feature in the categories 'Did not Access', 'Accessed (0, 30] hours', 'Accessed (30, 60] hours', and 'Accessed more than 60 hours' to facilitate data analyses.

Following similar steps for *modality* features, all the variables were transformed into categorical variables except time spent on assignment viewing from desktop, counts of and time spent on course material access from desktop, and time spent on viewing submission feedback from mobile and desktop. Lastly, for all the categorical variables (with no ordinal relationship), we used one-hot encoding to perform binarization of the categories and include it as a feature to compute the model.

6.4.4 Outcome variables

For the study outcome, one main measure of students' academic success was evaluated – *course grade*, a continuous variable ranging from 0% to 100%. This is a commonly used variable to operationalize academic success, used previously in many studies (e.g. [87, 168, 170]).

6.4.5 Statistical analyses

The distribution of variables was tested for normality using the Kolmogorov-Smirnov and Shapiro-Wilk tests. Normality was further explored using the P-P plots. Table 6.3 illustrates the descriptive statistics for all the variables used to examine the data using the R statistical software package. The continuous data are presented as median median (25%, 75%) since they were skewed (non-normally distributed). Categorical data are presented as counts and percentages.

Table 6.3: Descriptive statistics of the predictor variables across different modalities – Desktop, Mobile and Tablet. Continuous but skewed variables are presented as Median along with the first and third quartiles: Md(Q1, Q3) and categorical data is presented as percentages (N = 165).

		Modality features					
Activity	Measure	Desktop		Mobile		Tablet	
Syllabus	count	Accessed up to 5 times	55 (33.3%)	Did not access	106 (64.2%)	Accessed	3 (1.9%)
		Accessed 6-15 times	59 (35.7%)	Accessed 1-2 times	39 (23.6%)	Did not access	162 (98.1%)
		Accessed more than 15 times	51 (31%)	Accessed more than 2 times	20 (12.2%)		
	time spent	Accessed up to 20 hours	99 (60%)	Did not access	106 (64.2%)	Accessed	3 (1.9%)
		Accessed (20, 40] hours	13 (7.9%)	Accessed (0, 2] hours	19 (11.6%)	Did not access	162 (98.1%)
		Accessed more than 40 hours	53 (32.1%)	Accessed more than 2 hours	40 (24.2%)		
Assignment	count	Accessed up to 50 times	14 (8.5%)	Did not access	28 (17%)	Accessed	6 (3.6%)
		Accessed 51-80 times	50 (30.3%)	Accessed 1-10 times	62 (37.6%)	Did not access	159 (96.4%)
		Accessed 81-100 times	35 (21.2%)	Accessed 11-20 times	33 (20%)		
		Accessed more than 100 times	66 (40%)	Accessed more than 20 times	42 (25.4%)		
	time spent	166.6 (107.3, 284.5)		Did not access	28 (17%)	Accessed	6 (3.6%)
				Accessed (0, 1] hour	53 (32.1%)	Did not access	159 (96.4%)
				Accessed (1, 2] hours	7 (4.2%)		
				Accessed more than 2 hours	77 (46.7%)		
Submission Feedback	count	Accessed up to 10 times	88 (53.3%)	Did not access	50 (30.3%)	Accessed	4 (2.4%)
		Accessed 11- 20 times	53 (32.1%)	Accessed 1-10 times	56 (33.9%)	Did not access	161 (97.6%)
		Accessed more than 20 times	24 (14.6%)	Accessed more than 10 times	59 (35.8%)		
	time spent*	0.3 (0.1, 4.9)		0.1 (0, 957.5)		Accessed	4 (2.4%)
						Did not access	161 (97.6%)
Calendar	count	Did not access	47 (28.5%)	Did not access	64 (38.8%)	Accessed	8 (4.8%)
		Accessed 1-10 times	68 (41.2%)	Accessed 1-10 times	37 (22.4%)	Did not access	157 (95.2%)
		Access more than 10 times	50 (30.3%)	Access more than 10 times	64 (38.8%)		
	time spent	Did not access	47 (28.5%)	Did not access	64 (38.8%)	Accessed	8 (4.8%)
		Accessed (0, 30] hours	44 (26.7%	Accessed (0, 30] hours	53 (32.1%)	Did not access	157 (95.2%)
		Accessed (30, 60] hours	12 (7.2%)	Accessed (30, 60] hours	22 (13.3%)		
		Accessed more than 60 hours	62 (37.6%)	Accessed more than 60 hours	26 (15.8%)		
Course Material	count	Accessed up to 50 times	14 (8.5%)	Did not access	54 (32.7%)	Accessed	6 (3.7%)
		Accessed 51-100 times	52 (31.5%)	Accessed 1-5 times	51 (30.9%)	Did not access	159 (96.3%)
		Accessed more than 100 times	99 (60%)	Accessed more than 5 times	60 (36.4%)		
	time spent	6.1 (3.7, 8.9)		Did not access	54 (32.7%)	Accessed	6 (3.7%)
				Accessed (0, 10] hours	63 (38.2%)	Did not access	159 (96.3%)
				Accessed more than 10 hours	48 (29.1%)		

* For ease of reading, time spent on submission feedback activity is presented in minutes. For the rest of the activities, it is in hours. For the analyses, all the time spent measures were converted into minutes.

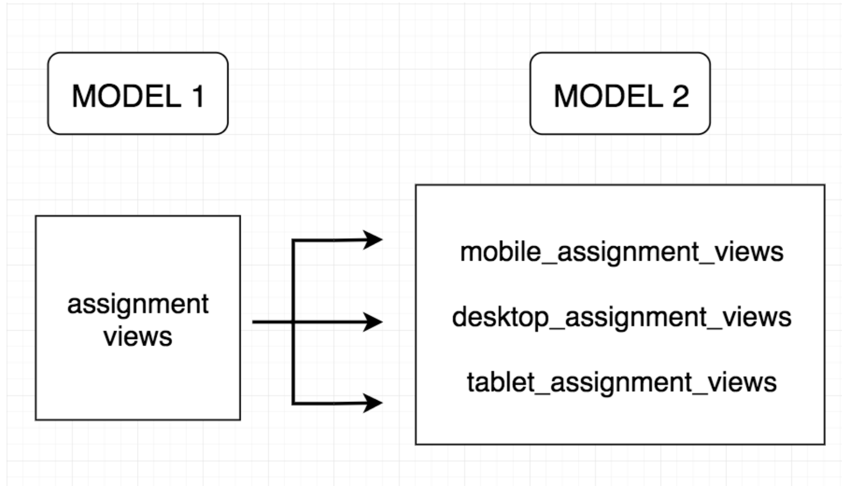


Figure 6.1: Comparison of the two regression models for the assignment activity. Model 1 comprises of assignment views aggregated across all modalities as predictors, whereas features for Model 2 are conceived by slicing the view traces into their respective modalities. Similar models can be generated for the remaining nine LMS features analyzed in this study.

To assess the importance of the modality source of the log data for predicting student course grades, we conducted a series of regression analyses, with *course grade* as the outcome variable in each. We selected this particular form of analysis due to its simplicity and robustness. Additionally, regression analyses have been widely used in different research areas, including EDM and LA [201, 143]. For each of the ten learning features introduced in Section 6.4.3, two regression models (Figure 6.1) were built using (a) LMS feature representing all counts across all modalities, and b) all three LMS modality features, i.e. desktop, mobile, and tablet. For instance, if the LMS feature in Model 1 is assignment view counts, then the corresponding modality features in Model 2 comprise of *desktop* assignment views, *mobile* assignment views, and *tablet* assignment views. The rationale for doing individual analysis for each predictor is because we were concerned more with investigating the effect of modality on the predictive power of each individual feature, rather than building the most accurate predictive model based on all available data.

Prior to running the model, the influential observations were taken into consideration in case they greatly influence the results of a regression analyses. These were detected based on Cook's distance, using the traditional cut-off of $\frac{4}{n}$ (n = number of observations) [50]. There are different ways of dealing with influential observations but for simplicity we just removed them. In our study, we consider an observation as influential which, under normal circumstances, can never be observed (for instance, count of assignment views is invalid if the time spent on viewing the assignment is 0; mere access to an assignment does not account for much if the time spent on it is under 1 second) or are exceedingly large compared to the class median. This is an important step for sieving out pseudo accesses to an LMS feature, which do not contribute much towards understanding the learner's behavioral patterns in the LMS and subsequently distort the feature's utility for predicting academic achievements.

After the aforementioned adjustments to the model, we performed regression diagnostics on it. Diagnostics are important because all regression models rely on a number of assumptions. If these assumptions are met, the model can be used with confidence. Keeping in line with this, the regression models were explored for multicollinearity. Variance inflation factors (VIFs) were well below 4, indicating no multicollinearity in the data. The independence of observations, i.e. homoscedasticity, was checked using residual plots and Durbin Watson statistic (DW). The residual plots were random and DWs between 1.5 and 2.5, indicating there was no autocorrelation (i.e. subsequent observations were unrelated). All analyses were performed using the R Statistical software and p values of ≤ 0.05 were considered statistically significant.

For each of the ten features, a change in adjusted R^2 from Model 1 to Model 2 was calculated to present the percentage of variability in student course grade explained by the *Modality features* over and above the *LMS feature*. Since an increase in number of predictors always inflates the estimated R^2 statistic of a regression model, i.e. overfitting [13], an ANOVA analysis using F-test of the statistical significance of the increase in R^2 was conducted to ascertain whether the increase was statistically significant. Finally, standardized β coefficients for the predictor variables and adjusted R^2 values are reported for the regression models. Using the adjusted R^2 is recommended over R^2 for comparing models with different numbers of terms (predictors) [207, 152].

With regards to the sample size, to have sufficient power the rule of thumb [134] and empirical reports [114] recommend an ideal sample size-to-parameters ratio of 20:1, i.e. the sample size (N) should ideally be 20 times as many cases as parameters (k). Since the proposed models for LMS features have one main independent (predictor) variable in each model, and up to three predictors in models from modality features, therefore we concluded that overall, there were more than enough participants to have sufficient power to conduct analyses.

6.5 Results

6.5.1 Prediction of student course grades: LMS vs. Modality features

In this paper, we wanted to explore the sensitivity of features, derived from the trace data, to the different modalities adopted by learners in a learner model. In essence, we compared models composed of LMS features to the models composed of the corresponding modality features derived from the three main modalities - Desktop, Mobile and Tablet. Upon inspection, the variables derived from the Tablet modality did not contribute significantly to any of the models and hence were left out of the result discussion to save space.

The results of the regression models featuring the associations between students' use of features from logged data – calculated cumulatively vs. partitioned based on the modality – and student course grades are presented in Table 6.4, along with the subsequent model comparisons using ANOVA analyses (columns F-value and p-value in Table 6.4). In each of these regressions, Model 1 corresponds to be the simple linear regression model with one of the ten predictors (defined in Table 6.2) as the independent variable and the course grade as the outcome variable. Similarly, Model 2 corresponds to the multiple linear regression model with the Modality features (corresponding to the predictor from Model 1) as independent variables and the course grade as the outcome variable.

Table 6.4: The association between the variables of students' use of the LMS and Modality features and ln (log natural) student course grades: results of multiple linear regression models.

Activity (a)	Measure (m)	Model 1 $R^2 \times 100$ (p value)	Model 2 $R^2 \times 100$ (p value)	F-value	p-value	Modality features	β Coefficients
Syllabus	count	1.4% (p = 0.12)	3.9% (p = 0.03)	3.16	**0.041**	Desktop_Accessed 6-15 times vs. up to 5 times	12.36
						Desktop_Accessed more than 15 times vs. up to 5 times	**31.86**
						Mobile_Accessed 1-2 times vs. Did not Access	**-23.11**
						Mobile_Accessed more than 2 times vs. Did not Access	-8.35
	time spent	0% (p = 0.56)	1.4% (p = 0.18)	2.59	0.078	**Desktop_Accessed (20, 40] hours vs. up to 20 hours**	**38.90**
						Desktop_Accessed more than 40 hours vs. up to 20 hours	4.90
						Mobile_Accessed (0, 2] hours vs. Did not Access	**-12.89**
						Mobile_Accessed more than 2 hours vs. Did not Access	-16.08
Assignment	count	7.3% (p <0.001)	11.5% (p <0.001)	2.92	**0.023**	**Desktop_Accessed 51-80 times vs. up to 50 times**	**40.43**
						Desktop_Accessed 81-100 times vs. up to 50 times	**66.56**
						Desktop_Accessed more than 100 times vs. up to 50 times	**73.53**
						Mobile_Accessed 1-10 times vs. Did not Access	-10.91
						Mobile_Accessed 11-20 times vs. Did not Access	6.54
						Mobile_Accessed more than 20 times vs. Did not Access	7.24
	time spent	9.5% (p <0.001)	13.4% (p <0.001)	8.20	**0.004**	**ln assignment_time_Desktop**	**0.71**
						Mobile_Accessed up to 1 hour vs. Did not Access	17.39
						Mobile_Accessed (1, 2] hour vs. Did not Access	**60.31**
						Mobile_Accessed more than 2 hours vs. Did not Access	5.13
Submission Feedback	count	2.9% (p = 0.03)	8.8% (p <0.001)	6.18	**0.002**	**Desktop_Accessed 11-20 times vs. up to 10 times**	**26.55**
						Desktop_Accessed more than 20 times vs. up to 10 times	**55.08**
						Mobile_Accessed 1-10 times vs. Did not Access	3.28
						Mobile_Accessed more than 10 times vs. Did not Access	0.66
	time spent	3.2% (p = 0.01)	5.1% (p = 0.005)	4.21	**0.041**	**ln submissionfdbk_time_Desktop**	**4.68**
						ln submissionfdbk_time_Mobile	0.98
Calendar	count	1.4% (p = 0.50)	1.9% (p = 0.92)	0.16	0.976	Desktop_Accessed 1-10 times vs. Did not Access	-8.11
						Desktop_Accessed more than 10 times vs. Did not Access	1.63
						Mobile_Accessed 1-10 times vs. Did not Access	-0.06
						Mobile_Accessed more than 10 times vs. Did not Access	1.48
	time spent	0.5% (p = 0.80)	2.1% (p = 0.74)	0.85	0.468	Desktop_Accessed (0, 30] hours vs. Did not Access	-8.35
						Desktop_Accessed (30, 60] hours vs. Did not Access	-7.79
						Desktop_Accessed more than 60 hours vs. Did not Access	-4.39
						Mobile_Accessed (0, 30] hours vs. Did not Access	12.17
						Mobile_Accessed (30, 60] hours vs. Did not Access	-13.44
						Mobile_Accessed more than 60 hours vs. Did not Access	9.91
Course Material	count	0.3% (p = 0.20)	1.6% (p = 0.18)	1.52	0.198	**Desktop_Accessed 51-100 times vs. up to 50 times**	**46.43**
						Desktop_Accessed more than 100 times vs. up to 50 times	**41.59**
						Mobile_Accessed 1-5 times vs. Did not Access	-10.24
						Mobile_Accessed more than 5 times vs. Did not Access	0.85
	time spent	1.9% (p = 0.04)	0.7% (p = 0.24)	0.01	0.989	ln material_time_Desktop	11.50
						Mobile_Accessed (0, 10] hours vs. Did not Access	0.29
						Mobile_Accessed more than 10 hours vs. Did not Access	5.74

From Table 6.4 (see columns Model-1 R^2 and Model-2 R^2), we see an increase in R^2 from Model 1 to Model 2 for each activity-measure pair (except time spent on course material), although the increase was significant only for five features. That is, the comparison of the models using ANOVA analyses revealed significant differences between the two models for counts of and time spent on assignments, counts of and time spent on submission feedback, and counts of syllabus access. These differences correspond to the improvements in predictive powers (R^2_{diff} = $R^2{}_{Model2}$ - $R^2{}_{Model1}$) and were spread over a wide range. The differences were the smallest for time spent on accessing submission feedback (R^2_{diff} = (5.1 - 3.2)% = 1.9%) and largest for the number of times submission feedback was accessed (R^2_{diff} = 5.9%). That is, the inclusion of the modality features, for the counts and time spent on the access to the submission feedback, in a learner model enhanced the predictive power by 5.9% and 1.9%, respectively, than what would have been possible if the learner model was composed of the LMS features only. Similarly, leveraging the information regarding the modality sources of the trace data improved the prediction of student course grades by 4.2%, 3.9% and 2.5% for assignment counts, assignment time spent, and syllabus counts, respectively.

For the models that were non-significant to begin with, addition of the information regarding modality sources showed no significant improvements in explaining the variability in the student course grades, such as in the case of time spent on syllabus feature, counts of course material access and counts of and time spent on calendar feature. This may be partly explained by the structure of the course included in the study, since syllabus and calendar had no direct link to the final grade, while assignments account for almost 40% of the final grade. Having said that, the inclusion of modality features seemed to have had an adverse impact too in certain cases as can be seen from the decrease in the accuracy for the model based on the amount of time spent on accessing course material. However, the decrease was non-significant (p values $>$ 0.05) and might be purely happenstance.

As demonstrated in Table 6.4, there were significant differences in the association between LMS features and Modality features and student course grades across several activities. The variability in students' course grades explained by the LMS features derived from trace data differed across learning activity measures and ranged from 0% for time spent on syllabus to 9.5% for time spent on assignment viewing. Similarly, variability in student course grades explained by the variables when considering all modalities in trace data differed across learning activities and ranged from 0.7% for time spent on course material to 13.4% for time spent on assignment viewing.

Interestingly, there was a notable difference in the extent to which trace data originating from different modalities contributed to the explanatory power in the Model 2. These were both positive and negative. For example, the results of the multiple linear regression analyses performed on the time spent on syllabus access indicated that the mobile access was a significant predictor of student learning outcome whereby course grades of students who used mobile phones for substantive duration (up to 2 hours) to access the syllabus were about 13% *lower* than those of their counterparts who did not spend any time accessing the syllabus from the mobile phone modality ($\beta = -12.9$, $p = 0.04$). On the contrary, looking at the time spent on viewing the course assignments, the mobile phone modality reflected a positive association with course grades and explained a greater amount of variance, such that the course grades of students who used mobile phones to view the assignments for 1-2 hours were about 60% *higher* than those of their counterparts who did not use the mobile phone modality at all ($\beta = 60.3$, $p = 0.01$). These results indicate that the utility of a modality for predicting student's academic progress is, among other things, highly contextual and relies heavily on the learning activity in question, operationalization of activity use, and the performance metric to be measured.

When considering the associations between separate Modality features and student course grades, we observed notable differences between the results of the analyses performed across different learning activity measures. For example, the results from the regression analyses performed on the time spent on viewing assignments indicate that desktop was a significant predictor wherein a 1% increase in the time spent on viewing assignments from desktops results in about 0.7% increase in student course grades ($\beta = 0.71$, $p < 0.001$). However, this increase was much larger in case of time spent on submission feedback wherein a 1% increase in the time spent on viewing submission feedback from desktops resulted in about 4.7% increase in student course grades ($\beta = 4.68$, $p = 0.001$). Similarly, while the course grades of students who accessed the course material from desktop frequently (more than 100 times) scored about 42% higher marks compared to those who only accessed a few times (up to 50 times) ($\beta = 41.59$, $p = 0.02$), the course grades of students who accessed the assignments from desktop frequently (more than 100 times) scored about 74% higher marks compared to those who only accessed a few times (up to 50 times) ($\beta = 73.53$, $p < 0.001$). These results indicate that in addition to the *direction* of association, the *magnitude* of the variability explained by the activity measures in a learner model changes depending on the particular activity and the modality used to carry it out.

On an activity level, while the expectation was that the students' use from all different modalities would have a significant effect on student performance, there were some contrasting results (Table 6.4, columns Modality features and β coefficients). Access to the assignments from the desktop modality consistently showed a significant positive association with student course grades. Consequently, course grades of students who accessed the assignments via desktop sparingly (up to 50 hours) were around 40%, 67% and 74% lower compared to students who accessed desktop more frequently: 51-80 times (β= 40.43, p = 0.02), 81-100 times (β= 66.56, p = 0.002) and more than 100 times (β= 73.53, p <0.001), respectively. However, access to the assignments from the mobile modality was not significantly associated with the student course grades. Similar observations were recorded for counts of and time spent on submission feedback too. A corollary to these observations is that as one modality (desktop in this case) provides greater explanation for outcome than the cumulative LMS feature, the other modality (mobile) brings in undesirable *noise* and thus, has a damping effect on the predictive power of the model that uses only the cumulative LMS feature (as can be seen from R^2 values of Model 1).

Across activities, the expectation was that some modalities might be better predictors of student outcome than other ones and we found some supporting evidence. For example, the model for syllabus activity revealed that course grades of students who used mobile phones a few (1-2) times were about 23% lower than those who did not use them (β= -23.1, p = 0.040). However, the same model also revealed a significant and much greater impact of desktop, in that the course grades of students who used desktop modalities more often (more than 15 times) were about 31% higher than those of their counterparts who only used desktop to access the syllabus a few times (up to 5 times) (β= 31.8, p = 0.008). As a result, the desktop modality induced a much greater change compared to the mobile modality in student course grades based on the counts of syllabus views. Contrasting results were obtained in case of the assignment viewing activity wherein mobile phone modality explained a greater amount of variance in the course grades compared to the desktop. That is, course grades of students who used mobile phones for a substantive duration (1-2 hours) were about 60% greater than those who did not (β= 60.3, p = 0.01), whereas for every 1% change in amount of time spent on viewing assignments from desktop only a 0.7% increase in student mark was observed (β= 0.7, p <0.001). These results indicate that depending on the learning activity (and possibly other contextual factors not investigated here) some modalities might be a better indicator of academic success than others.

6.6 Discussion

The findings in this study were based on future-work recommendations by researchers in the [219] study who hypothesized potential benefits from modality-inclusive learner models for better outcome predictions. While they were able to demonstrate the usefulness of the technological modality profiles in explaining some differences in students' engagement at discussion tasks and learning outcomes; the main aim of this study was to enrich the existing learner models by demonstrating the potential of technological modalities as an important predictor for academic achievements. We wanted to show that modality-inclusive features were more powerful in explaining variance in academic achievement than modality-agnostic predictor variables.

Based on our results of the multiple regression models – investigating the effect of trace data from different modality sources on the learning outcome – we can confirm that the *choice of modality for a particular activity in a learning environment plays an important role in the overall model fit and subsequent model interpretation.* The significant ANOVA results imply that an increased proportion of variability in student course grades can be explained if the activity measures are calculated across modalities (Model 2) instead of using one cumulative measure (Model 1). The observed differences in the predictive power of the two models, conceivably have two main implications for research and practice. First, incorporating modalities into the model is warranted, so as to increase its accuracy. Second, there must be careful consideration while designing interventions based off of interpretations from predictive models of academic success, if these models do not incorporate modality features. In such cases, several threats to the validity of the results may emerge if numerous patterns of direct importance of a modality, for the practice of learning and teaching, remain undetected.

More importantly, the *impact of these modalities in explaining the overall fit was not consistent across activities in the course deployed in the learning environment*, both in their presence and magnitude. That is to say, some modalities may or may not play a role in determining student's course grade depending upon the activity performed using the modality. For instance, the duration of time spent on a desktop for viewing the assignments was a significant predictor of student course grades whereby a 10% increase in time spent resulted in around 7% increase in student course grades. On the contrary, the same modality was not significant at all when the activity involved engaging with the course material. However, the desktop modality was again found significant for the submission feedback activity where this effect was seven times larger compared to assignment viewing i.e. a 10% increase in time spent on engaging with the feedbacks on assignment submissions on a desktop resulted in around 47% increase in student course grades.

A caveat of these results is that extraction of higher number of modality features does not guarantee better accuracy of the prediction of academic performance. Our results indicate that within a learning activity, *not all modalities might be equally relevant in terms of associations with the course grade*, as seen in case of submission feedback activity. In our study, it was necessary for students to reflect on the feedback, as assignments were built on top of each other, and to do so students had to work in the programming environments on *desktops*. So, we speculate that *mobiles* were less favorable because even if students looked at the feedback on them, they could not act on it directly and thus it was preferred less or had limited impact on assignment scores[2]; ergo, the significant and non-significant associations with desktop and mobile, respectively. Thus, we can imply only some modalities contribute in explaining the overall fit which is quite intuitive as students adapt a modality according to its affordances, availability and the learning task at hand [234, 219]. From a research implication perspective, this means when generating learner models, the calculation of modality features from all different modalities might not be necessary. From a practical implication perspective, it seems appropriate to recommend that an instructor in our case should advise their students to engage with the feedback received on assignments from desktop. Another option is to have the learning system to prompt students to view the feedback when they are accessing the LMS from the desktop, rather than when they are accessing it from the mobile device.

Looking at all the different modalities investigated in this study, we observed only a minority of students used tablets, which isn't surprising since the survey results from the 2017 ECAR study [30] revealed a combination of Mobiles and Desktops as the most common device ownership combination. If we compare the two main modalities – Desktop and Mobiles – across all the activities investigated here, we can see that neither one was the clear 'winner' in terms of explaining variance in course grade. However, the coefficients of the desktop modality features in Table 6.4 reveal why desktops continue to be the predominantly used modality in learning environments [194], given that they were found to be positively associated with student course grades (except for the calendar activity, although the associations were found to be insignificant).

While these initial analyses may tempt readers to gravitate towards the other end of the spectrum wherein use of mobile phone modalities are discouraged for any learning activity, one should be wary of it. The connotations associated with mobile phones has led many researchers to imprudently critique the use of mobile phones in education, mainly due to their tendency to cause distraction among students [257, 147]. However, we found evidence for

[2]However, for other type of assignments or where feedback is provided at a meta-cognitive level, such as change in ways students approach or plan their studies, it might be conceivable that feedback on mobile will be equally effective as desktops.

both positive *and* negative influence of the use of mobile phones for a learning activity, such as in the case of syllabus vs. assignments. These results are therefore suggestive of the fact that *contextual factors such as course design, activity type and the measured performance metric, collectively play a major role in determining whether a modality will positively or negatively influence the learning outcome.* This interpretation further accentuates the need for building knowledge regarding how students approach and regulate their learning in the presence of mobile technology, which so far has been largely contained within a black box and studied only cursorily.

It is evident in the literature that the idea of a one-size-fit all learner model is at best inadequate, and at worst a threat to the potential of learning analytics to improve the quality of learning. That is to say, the outcomes of prediction models depend upon a number of contextual factors such as instructional conditions [87], student's learning approaches [186], and their personality traits [42], which if ignored could result in flawed inferences. Drawing on similar lines, we posit that a modality-inclusive learner model, one that accounts for the modality-source of the logged trace data, has a better potential for explaining the variability in student learning outcome compared to a generalized linear model, one that uses cumulative measures of predictor variables. These results are important in order to augment the discussion first put forth by Finnegan et al. [78] and later empirically supported by Gasevic et al. [87] which highlighted the inherent risks linked to the pooling of LMS data across pedagogical contexts. Consequently, we conclude that a learner's modality-use context must be accounted for too, for predictive analytics to yield enriched models that helps gain additional insights.

Lastly, in our analyses prior to the selection of the activity measures (for which the corresponding learner models were developed), scatter plots were generated for each of the LMS tracking variables as a useful initial approach to identifying potential correlational trends between variables under investigation [76]. Although future studies may choose to pick only those variables that have high correlation with the academic success based on a pre-determined cutoff, we did not conduct any such filtering in our study, since (a) the aim of this paper was not to select the most optimal (or the best) predictors of student outcome, but to reflect how these predictors might be useful for further enhancing the predictions when the modalities the predictors originate from are accounted for, and more importantly (b) it is possible that a variable with relatively lower correlation can prove significant and valuable in regression models when their modality source is captured, even if they are of overall 'lower' importance. The latter was indeed reflected in our results as well. For example, we found support for the benefits of modality-inclusive model for the 'course syllabus' feature even though there is limited evidence in the literature regarding learner interaction with the curriculum structure as having significant associations with academic success. On the other hand, modality variables from time spent on interacting with the 'course material' – an intuitive and logical predictor of success, whose usefulness is deep rooted in literature [173, 225] – were unable to prove any associations with academic success. Thus, we can conclude that the benefits of modality-inclusive models are independent of the 'pre-established' utility of the predictor variable used to build the model. If anything, modality variables might even transform a previously non-significant learner model, into a significant one as was observed in case of syllabus counts, or vice versa, as was observed in case of time spent on engaging with course material!

6.7 Limitations and Future Work

In our analyses, we observed rather low R^2 values regardless of whether it belongs to Model 1 or Model 2. This is because in our models we were testing individual activities for improvements in course grade, whereas several variables are included in typical learner models as the course performance is usually determined as a combination of student's characteristics (for e.g. prior GPA) and performance on multiple learning activities. Nonetheless, our results suffice in making claims regarding the usefulness of the modality features over and above the LMS features. Future studies would benefit from looking at the interaction effects between these independent variables, and their corresponding modality features too, to infer if the associations with academic outcome are still valid. It would also be beneficial to incorporate student characteristics (for e.g. prior GPA, deep learners vs. surface learners) and course characteristics (fully online vs. blended) to the model to assess their impact on final results.

To further broaden the discussion, there are in fact many features that are computed from trace data and that are used in the prediction models. As we saw improvements in the 'crude' features that we investigated, it is conceivable that we can see improvement in other derived features and therefore improve fidelity of the models. Furthermore, it would also be interesting to devise, using a bigger participant pool and diverse activity pool, the most optimal learner model comprising a combination of highly explanatory LMS and Modality features from various learning activities as predictors. A wider pool would also allow for cross validations (using separate training and testing dataset), to prevent underfitting/overfitting of this optimal model, which is a limitation of the current paper.

Our methodology involved tracking user interaction with the LMS and this may raise a concern about the extent to which our results were dependent upon the activities targeted in the LMS and the design of the LMS (both browser and app) itself. The types of activities included in our study are quite common in instructional design and usually captured in the same way, thereby rendering good generic results. However, there might be variances in how learning activities are structured and presented in LMS and some LMS can offer even more fine grained tracking to see the influence of modality features from various other activities on the learning outcomes. Even thought the LMS design in our study was relatively simple, it would also be interesting to see any impact of student's familiarity with the LMS (freshman vs. senior) on the results.

Our methodology involving pre-processing of skewed continuous variables into discrete groups was inevitable and done as best suited to our data and keeping in mind the course design. Therefore, the categories produced might have had an undesirable impact (both positive or negative) on the predictive power of the variables and the model. Thus, replication of the study by future researchers in very similar contexts is necessary to solidify the claims made in this paper.

Lastly, even though we analyzed data from only one course, it does not undermine the results generated in our study. This is because different models will and should be generated for different courses, given the previously established inadequacies of models generalized at the course level [87]. Having said that, care must be taken when generalizing the interpretation of our results beyond programming-oriented courses. This is because these courses have certain requirements necessitating specific modality use, such as desktops for coding tasks, where mobile use would be cumbersome if not entirely impractical. Hence, it would be interesting to see the results from replicating the study across courses from different disciplines, say social sciences, to see if benefits from modality-inclusive learner models persist.

6.8 Conclusion

Taking up the research on use of mobile and desktop devices in learning environments and its ramifications on learning outcomes one step further, in this paper we looked at how modalities used by students for carrying out learning activities in the LMS, could act as powerful indicators of academic success. To test the influence of modality from which the trace data originates, we created two separate prediction models using measures (e.g., counts and time spent) of activities in the learning environment aggregated across (a) all log data and (b) each individual modality in the log data. We observed that considering how learners use different devices to carry out different activities in the course led to improvements in the accuracy of models.

To further illustrate the significance of these improvements, statistical analyses confirmed the improvements to be significant for most of the predictor measures assessed in this study. While the magnitude of improvements may not be of particular interest, the major take away from the study is that interpretations and subsequent interventions based off of generalized learner models may be improved by utilizing modality-inclusive models, since modalities may contribute differently to the learning process depending on the activity they are used for. Further, the significance of this research lies in the simplicity of the method by which the modality of access for a learning action/activity can be readily available through capturing the 'user-agent' from the students' log data and the potential improvement it has on the prediction process.

The aim of the study was not to make concrete statements regarding a clear 'winner' amongst modalities that could explain the maximum variance in a learner model. The overall idea was to generate awareness within the research community of the potential of modalities when building and interpreting learning analytics models, particularly for blended and seamless learning environments where use of multiple modalities is prevalent. We argue that in addition to capturing cumulative measures of predictor variables from the log data, as has been the norm in the literature to date, future research should also focus on incorporating the modality source of the students' activity in the learning environment. Additionally, we envision that this will prove useful for gaining a fuller insight into the way different modalities support learning and self-regulative activities.

Chapter 7

Consistency in learning in presence of multiple modalities

I can predict the long-term outcome of your success if you show me your daily habits.
- John Maxwell

7.1 Overview

This chapter addresses the following research questions:

1. **RQ1**: How consistent are students' work patterns across subsequent activities of the same type, when engaging with them from multiple modalities? That is, can we identify conceptually and practically meaningful clusters of students with distinct consistency patterns?

2. **RQ2**: Is there an association of the identified patterns with students' academic performance?

Consistency, or persistence in work patterns, has been previously primarily studied at semester, year or degree level. However, these studies were done in contexts where use of multiple devices for learning were not prevalent and as a result, we are unaware of how exactly, if at all, learners' preferences for particular technological modalities (say desktop, tablets, mobiles) evolve over the course of their studies.

In this paper, we consider an analysis of the within-activity consistency in online work habits using a time series approach. Of particular importance for this study is the examination of how engagement with various modalities fluctuate as the learner participates in different phases of a learning activity. We used the Dynamic Time Warping (DTW) measure for quantifying the similarity between pairs of temporal sequences over 11 day timeline up to the submission date. The overall aim was not to detect good time distributions from bad ones, but to focus more on the consistency with which each time series, (composed of engagement with learning activities on desktops or mobiles) or work habits were adopted across similar activities. We analyze consistency of modality-use at two learning activities - discussions and assignments[1], separately, to investigate if patterns of usage repeat across learning activities. Finally, we examine any underlying associations of consistency patterns with academic performance.

The results of our study provide one of the first insights into the ways in which multiple devices are (in)coherently used for various phases of a learning activity. Our findings revealed that the use of desktop modality varied during subsequent assignment/discussion activities whereas mobile phone usage was constant throughout the course. To study the consistency in desktop patterns in depth, we obtained meaningful clusters of students exhibiting similar behavior and we use these to identify three distinct consistency patterns: *highly consistent*, *incrementally consistent*, and *inconsistent users*. We also found evidence of significant associations between these patterns and learner's academic performance.

7.2 Publication

The following sections include the verbatim copy of the following publication:

> Sher, V., Hatala, M., and Gašević, D. (2019). Analyzing the consistency in within-activity learning patterns in blended learning. Manuscript submitted to the Tenth International Learning Analytics and Knowledge (LAK) Conference

7.3 Introduction

An interesting topic of ongoing research in higher education context has been how different learning approaches relate to academic achievement [25]. These learning approaches are generally part of the cyclic processes involved in self-regulated learning (SRL) (i.e. planning a task, monitoring the performance and reflecting on the outcomes and on the learning process) [281] and educational psychologists affirmed that these processes are a key contributor to the academic success of students. Of the many self-initiated actions involved in SRL such as goal setting, self-monitoring, metacognition, physical and social environment management, and effort regulation, time management is known to be a strong predictor of student grades [25, 198]. Time management as a key self-regulatory skill involves scheduling,

[1] The assignment and discussion tasks for each week are available in Appendix A.

planning, and managing one's study time, to allocate efforts depending on intensity of work [191].

Although less frequently highlighted, the *consistency* of our study habits that controls regulation of effort, setting specific work load for the week, and behavioral adjustments is also a key dimension of time management. Despite research suggesting time management and effort regulation, i.e. perseverance, positively predict academic grades significantly [24, 55], the analysis of student's work-pattern changes across individual activities has so far only been sparsely studied, in the context of blended and technology-enhanced learning. Our aim in this study is to observe how stable these patterns of work habits (or procrastination, as an extreme) are when students are given the opportunity to acknowledge differences that may arise from considerable variation in successions of the same type of learning activity in a blended learning environment.

Students' learning patterns are dynamically changing entities. Unlike students' demographics or their prior academic record, learning patterns reflect students' current unique engagement levels and learning processes [72]. Analyzing the within-activity variance in online learning-patterns for a student allows us to challenge most 'traditional aggregated evaluation and analysis methods' [112] (say, prediction models), which utilize data aggregated across the entire semester. As a result of the aggregation, these methods fails to consider the variances in course-activity patterns. For instance, a student's aggregated time spent per week in two different weekly assignments might be identical. However, during week 1 the student might have evenly allocated their learning time in the days leading up to the deadline; whereas in week 2, activities might be concentrated in the last two days before the deadline. Although considered equivalent in total performance efforts, the student's varying patterns might be indicative of success or failure at a finer level. While there could be plenty of reasons (which are outside the scope of this paper) for the observed inconsistencies in behaviors, such as active procrastination [271] or excess workload from other courses, it is nonetheless worthwhile to assess if, and when, the course-activity patterns start to deviate from patterns known to be *favorable* for academic success [107].

Our study is motivated by existing research on engagement, which suggests that academic success is highly likely in case of students adopting habit-inducing behavior [62, 182]. Analysis of consistency can allow us to further understand if the student behavior remains constant throughout the semester, visible only in the beginning of a course or converges as one progresses in their course. In this paper, consistency is analyzed from two viewpoints – (a) through periodic participation in the discussion forums, mainly reviewing the course-related discussion topics, and (b) recurring engagement with the assignment tasks. These two learning activities were chosen because of the course design that made use of these two main activities in the online setting. Further, since it has been already established that learners make sequential and simultaneous use of various technological modalities such as desktops, mobiles and tablets for learning activities [145, 234] and that these have potential for an impact on their academic achievements [219], we posit that the preferences for a modality may also evolve over time. Therefore, we include modalities in our analysis of students' activity changes across assignments and discussions when the students are given the opportunity to use multiple devices for participating in a learning activity.

In particular, this paper answers the following research questions:

- **RQ1**: How consistent are students' work patterns across subsequent activities of the same type, when engaging with them from multiple modalities? That is, can we identify conceptually and practically meaningful clusters of students with distinct consistency patterns?
- **RQ2**: Is there an association of the identified patterns with students' academic performance?

7.3.1 Time series analyses of work patterns

This research was designed to evaluate the issue of consistency in learning patterns as the term progresses, i.e whether similar work patterns persist across *all* assignments or discussions. This required the analyses of time series of LMS usage for particular course activity (discussion or assignment) in the days leading up to the task deadline. In the recent years, there has been a dramatically increasing amount of interest in time series analyses in various fields for making predictions [9], finding similar series [131] and supervised [179] or unsupervised learning [149].

In recent years, several implementations of time series analysis have also been reported in the field of education and learning analytics. Time-series clustering was applied by Młynarska et al. [174] to identify distinct activity patterns among students, in order to tackle the issue of difficulty in keeping up with deadlines. Based on high activity levels within a three-week timeline, they identified seven groups of students - Procrastinators, Strugglers, Unmotivated, Steady, Hard-workers, Strategists and Experts. Hung et al. [112] demonstrated that time series models (time series data points aggregated daily) were better than traditional data aggregation models (frequencies over the whole semester) at identifying at-risk online students, both earlier and with greater accuracy (misclassification rate below 10%). Brooks et al. [28] employed features created as n-grams (n = 2 to 5) over different time periods, from logs of learner interactions with educational resources. They chose four different granularities of timeframes: accesses within a calendar day, a three-calendar day period, a calendar week, and a calendar month; such that 'an *n*-gram with the pattern (*false*, *true*, *false*), the label of *week*, and count of 2 would indicate that a student had two occurrences of the pattern of not watching lectures in one week, watching in the next week, and then not watching again in the third week' [28]. By detecting similar patterns of interaction that lead to learners achieving a passing grade for a course, their designed models were highly accurate (with a misclassification rate below 5%) and generalizable to new real-world dataset with highly accurate results by third week of the course.

Some empirical investigations have also been carried out to elucidate the theoretical mechanisms that link certain activity patterns (extracted from student time-series) to academic success. For instance, Hung et al. [112] exemplified successful learning patterns as *stable and consistent* engagement levels on all basic learning behaviors, and at-risk patterns as unstable engagement levels with high peaks and gaps during the semester. According to Młynarska et al. [174], the most common patterns for students achieving high grades were regular, relatively higher spikes in activity levels or low-level frequent activity with no high spikes around deadline. Unsurprisingly, students achieving low grades exhibited minimal overall effort but larger activity levels closer to the deadline. Hensley et al. [107] identified six time-use patterns from weekly time logs with late-start studying and Sunday cramming indicative of ineffective time use and consistent weekday studying, Saturday studying, consistent bedtime, and consistent wake time indicative of effective time use.

Altogether, the findings suggest the academic relevance of how students manage their learning time. More nuance in future research is necessary, particularly through studies that address consistency of time use patterns thereby providing a detailed view of how students routinely engage with a learning task – whether they are piecing together a routine or simply engaging in a one-off task.

7.3.2 Consistency in Learning Behaviours

How stable are learning patterns? A systematic review of the seminal works on learning consistency by Vermunt and Vermetten [254] revealed that these studies were conducted from a longitudinal perspective. That is, questionnaires were typically administered at a suitable gap of time to explore students learning patterns in a pre-post test design. For instance, Svensson [240] studied the ways students process learning material using three measurement points over a period of five weeks and found that ways of processing the learning material were rather stable across the three occasions. In a series of studies by another group of researchers, similar questionnaires were administered twice to the same group of students at a gap of 3 months [253] and 6 months [252]. Overall, the results indicated high stability of learning strategies, learning orientations and conceptions of learning on the two occasions.

The aspect of consistency has also been analyzed, albeit briefly, under different contextual conditions and at varying levels of granularity. In the study by Thomas and Bain [244], a 7-item questionnaire was administered to determine whether the students' learning strategies (deep vs. surface) were consistent in tests vs. essays comparison. High level of consistency in the strategies was found; also high levels of achievement on both tests and essays were associated with use of deep strategies.

A general shift in learning approaches (from surface to deep or vice-versa) was researched by [70, 279] who studied whether learner's approaches to learning develop during studies in higher education. Contrary to popular belief, their results reflected that students' approaches to learning were relatively stable during studies and overtime, there were come consistent changes.

At course-specific levels, Vermetten et al. [251] assessed strategy use by the same group of students in four different courses. They found not only that students vary their learning strategies for different courses, but also that the learning strategies differed from each other in their degree of variability across courses. For instance, a high variance in concrete-processing strategy was visible across courses but a low degree of variability with regard to a memorizing strategy was observed.

As evidenced by the aforementioned studies, existing research on learning consistency in students has been investigated mainly using questionnaires, measuring consistency in the way users respond about their learning strategies. A large majority of studies have made use of the Inventory of Learning Styles (ILS) questionnaire to measure consistency and variability in students' use of learning strategies (for an in-depth review, see Vermunt and Vermetten [254]). More recently, there have been attempts at empirically investigating the aspects of consistency in everyday learning. Jo et al. [117] studied the impact of login consistency on academic performance and found significant associations between (ir)regularity of learning interval in LMS and final grades, where regularity was calculated using the standard deviation of the login intervals (i.e. the average login time into the LMS). Thus, a higher value indicated highly irregular logins.

Similarly, Dvorak and Jia [66] studied the relationship between consistency of time of study and found regular work on assignments to be associated with high grades in course work. They defined regularity as the degree to which the student tends to work at the same time of the day, i.e. whether he or she would start each assignment at the same time of day throughout the term, and operationalized it as the inverse of the standard deviation of the hours before the assignment deadline. Młynarska et al. [174] studied consistency at the activity-specific level by comparing the time series signatures of activity patterns between successive assignments. They found activity patterns were more similar for the same student than those for different students, and moreover, students who changed their behaviour from one assignment to another, exhibited a change in grade too, i.e. the two were positively correlated.

To the best of our knowledge, only Młynarska et al. [174] have attempted to evaluate consistency in learning patterns at an activity-specific level and as such, the topic warrants ongoing attention from the learning analytics community. Additionally, we noticed a distinct lack of studies that assess how the use of multiple devices is associated with consistency of activity and learner success. Analysis of the use of multiple devices is necessary in this digital era since learners are making sequential and simultaneous use of a combination of devices (like mobiles and tablets) to support formal learning [145]. Further, most previous studies have investigated either variation or consistency in learning processes by looking at variability and consistency of *self-reported* strategies at the same time. In the present paper, however, a different position was taken by looking at variability and consistency in work patterns using log data, which does not suffer from the shortcomings of survey or questionnaire data [267, 280] and thus reflects actual students' behaviours.

7.4 Method

7.4.1 Study Context

The data analyzed in the current study was gathered from the second and third year undergraduate students in two subsequent offerings (2017 and 2018) of two information technology courses (C1 - Multimedia Programming and C2 - Internet Computing Technologies) at a Canadian university. Both courses were similar in structure, having a 2-hour face-to-face lecture per week, a 2-hour in-lab tutorial per week. Tutorial participation contributed 10% towards the final grade, assignments 40% of the grade, quizzes and exams 50% in course C1 and 35% in course C2, and course C2 had three online discussions 5% each for a total of 15%. C1 was used for collecting data related to assignment activity whereas C2 provided the discussion activity data. The activity topics and grading structure for both assignment and discussion activities remained constant over the two offerings (in 2017 and 2018) and were taught by same instructors too. Both courses used blended delivery, utilizing the university's learning management system (LMS) to support learning activities and students' overall schoolwork. The students were experienced in using the LMS as they used it on a day-to-day basis in prior courses. In addition to the web-browser versions of the LMS (desktop/laptop/mobile), students had access to the mobile app version provided by the LMS vendor. There was no apparent difference between the features and functionalities offered by the two versions. The log data from the LMS was the main source of data for analyses.

Prior to the analyses, student records were anonymized and assignment reviewing and discussion participation records were extracted from C1 and C2, respectively. Assignments in C1, eight in total, were all individual, comprising of programming tasks of increasing complexity, and developed in the programming environment outside of the LMS. The assignment specifications were posted in the LMS; students submitted assignments via the LMS, and received feedback and grades with comments in the LMS. The discussion activities in C2, three in total and unrelated to one another, were 10-14 days long, in small groups of 6-8 students, and required conducting research and developing a group statement to an open ended question. Quality of post content, building on ideas of others and quality of the group final statement were marked. A minimum of four posts was required for a student to get the full mark. The grades for discussions were posted in the LMS as well.

7.4.2 Learning traces and time series

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 device modalities was a choice of each student. Each student action in the LMS was logged with the following data: student id, course id, type of learning action, user-agent (used for extracting the type of device used for the action), action URL, session number, start time, and end time.

The log data was transformed into a series of equispaced points in time. In our case, a time series is a 11-day timeline – from 10th day before a deadline until the day of submission. Each bucket in these timeline corresponds to activity counts on the (i-1)th day before the deadline (i = 1:11). The count measures were extracted based on the number of times each learning action was performed by each student (i.e., discussion views in case of discussion activity and assignment views in case of assignment activity). A 10-day limit was chosen because even though each assignment was released at least 14 days in advance, most students did not start working 10 days prior to the deadline. Similar observations were made for discussion activity too. The day of deadline (0th day) was included in the timeline since a majority of students (96%) submitted the assignment on the day of the deadline (of these, 73% submitted less than 6 hours before the deadline), meaning they were working very close to the deadline on their assignment tasks. Further, to account for the simultaneous use of multiple modalities in these activities, we created multi-dimensional time series. Thus, for each student, we generate two time series per assignment or discussion task: T1 = x_{10}, x_9, ... x_0 and T2 = y_{10}, y_9, ... y_0, where x_i is the count of (assignment/discussion) views from desktop on the i-th day before the deadline and y_i is the count of views from mobile on the i-th day before the deadline.

In order to assess consistency between a student's temporal patterns during a learning activity, we first addressed the challenge of appropriately measuring the similarity/distance between pairs of series. Euclidean distance was ruled out since it misses similarity between time series if the activity peaks are offset in time, a common occurrence especially since learners work according to their own time availability. Instead, we used the dynamic time warping (DTW) measure which has been proposed for quantifying similarity between pairs of temporal sequences [80, 3]. DTW, using stretching or compressing segments of temporal data, determines an optimal match between any two time series. That is, two series that exhibit similar peaks (or troughs) are considered similar even if they are slightly displaced in time. The extent of warping allowed can be maintained using global constraints [89] in a way that provides more intuitive warpings. For instance, the series with the peak in actions on 10th day before the deadline will be distinguished from a peak in actions one day before the deadline, since the two represent quite different time scheduling patterns from an SRL perspective. For calculating the DTW measure in our study, we implement the *sakoechiba window* [210] for enforcing a global constraint on the envelope of the warping path with the *window size* set to 2. The window size was intuitively and carefully chosen since a very small size makes the warping impossible whereas an unnecessarily large size will introduce impossible mappings (or pathological warping). Finally, the computed DTW distances were normalized for warping path length.

7.4.3 Data Analysis Techniques

To find recurring patterns in the consistency of work habits, for each student we first calculated the similarity between subsequent activities. That is, for a student participating in three discussion activities, we calculate three corresponding distance measures ($D_{i,j}$), one for each pair of discussion task, such that $D_{i,j}$ is the DTW measure between the bi-variate time series obtained from work habits in discussion i and discussion j. Thus, we obtained $D_{1,2}$, $D_{1,3}$ and $D_{2,3}$ measures for each student participating in discussion activity. For the eight assignment activities, we obtained 28 corresponding measures, one for each pair of assignment tasks.

The distance measures computed for each student were used in the cluster analysis (agglomerative clustering based on Ward's method) to group students (N = 55 for discussion activity and N = 162 for assignment activity). All the DTW measures were normalized prior to the clustering; the Euclidean metric was used to compute the distance between vectors. The optimal number of student clusters was obtained from (a) inspection of the resulting dendrogram, and (b) using the "Silhouette statistic" proposed by Rousseeuw [124, 208] and computed using the clValid R package [26]. The Silhouette value measures the degree of confidence in a particular clustering assignment and lies in the interval [-1,1], with well-clustered observations having values near 1 and poorly clustered observations having values near -1.

Each student cluster was summarized by calculating its centroid, which represented the mean value of all cluster members across all clustering variables. The student cluster assignments (representative of their work pattern consistencies) enabled us to group students and identify whether different consistency patterns relate to differences in overall academic performance (operationalized by discussion grades in discussion activity and assignment grades in assignment activity).

To examine if there was a significant difference between the identified student groups, we performed two separate analysis of variance (ANOVA) tests. The student cluster assignment was treated as the single, independent variable in each test, along with the respective dependent variables: final discussion grade and final assignment score.

Before running the ANOVA, we checked the homogeneity of variance using Levene's test. The Shapiro-Wilk test was performed to check for normality. In our case, we found significant Levene's test (i.e., the homogeneity of variance assumption was violated), thus, the non-parametric Kruskal-Wallis test was used. Finally, the measure of epsilon-squared (ϵ^2) were used to report the effect sizes for Kruskal-Wallis tests, and interpretations were done using Cohen's primer [48], the most commonly used primer for effect size interpretation. The significant Kruskal-Wallis tests were followed up by pairwise Wilcox test to calculate pairwise comparisons between group levels with Benjamini-Hochberg (BH) corrections for multiple testing.

7.5 Results

In Section 7.5.1 and 7.5.2, we present the results from the clustering of students based on their consistency in assignment activities and assess the impact of consistency on academic achievement. In Section 7.5.3 and 7.5.4, we do the same for the discussion activities.

7.5.1 Clustering of students based on consistency in assignment activities

The solution with five clusters was found as optimal. The resulting clusters indicate five different patterns of consistency in temporal patterns that students tended to display when engaging with the assignment material whilst working towards a deadline, and self-regulating their studies through the LMS.

Figure 7.1 presents the box-plots for each of the five consistency clusters. The y-axis represents all possible assignment-assignment pairs (starting from assg1-assg2, assg1-assg3, and so on at the bottom, to assg7-assg8 at the very top) and the x-axis denotes the corresponding DTW measures for each pair. The DTW measures were scaled between [0,1] for cross-cluster comparisons, with values closer to 0 representing almost similar time series and values closer to 1 representing highly dissimilar time series. For all the clusters, the box plots denote the five-number summary - whiskers going from (1) minimum to (2) maximum DTW value, middle box representing middle 50% of DTW scores for the group i.e. left and right box-edge representing (3) Q1 (first quartile) and (4) Q3 (third quartile), respectively, and (5) median DTW measure represented by the vertical line going through the box. As can be observed from Figure 7.1, except for Cluster 5, students in all other clusters had median DTW measures for all 28 assignment-assignment pairs well below the half of the maximum threshold.

From the perspective of the pairwise DTW measures described in Section 7.4.3, the clusters can be described as follows:

- Student Cluster 1 – *Highly Consistent* (N = 62, 38.27%): This cluster constitutes the largest group of students. This group of students had the least variation in their work patterns in going from one assignment to the other, as exhibited by the low DTW measures.

- Student Cluster 2 – *Delayed Consistent* (N = 25, 15.43%): This group of students' approach in first two assignments was quite different from the six remaining assignments. However, assignment 3 onward their work patterns steadily got more consistent.

- Student Cluster 3 – *Incrementally Consistent* (N = 19, 11.73%): This cluster represents the group of students whose time-series, reflecting engagement with assignment material, became more and more similar as the assignments progressed.

- Student Cluster 4 – *Early Consistent* (N = 48, 29.63%): This cluster is similar to Cluster 2 in that the students' engagement patterns with assignment materials in the very first assignment were less similar to the subsequent assignments but assignment

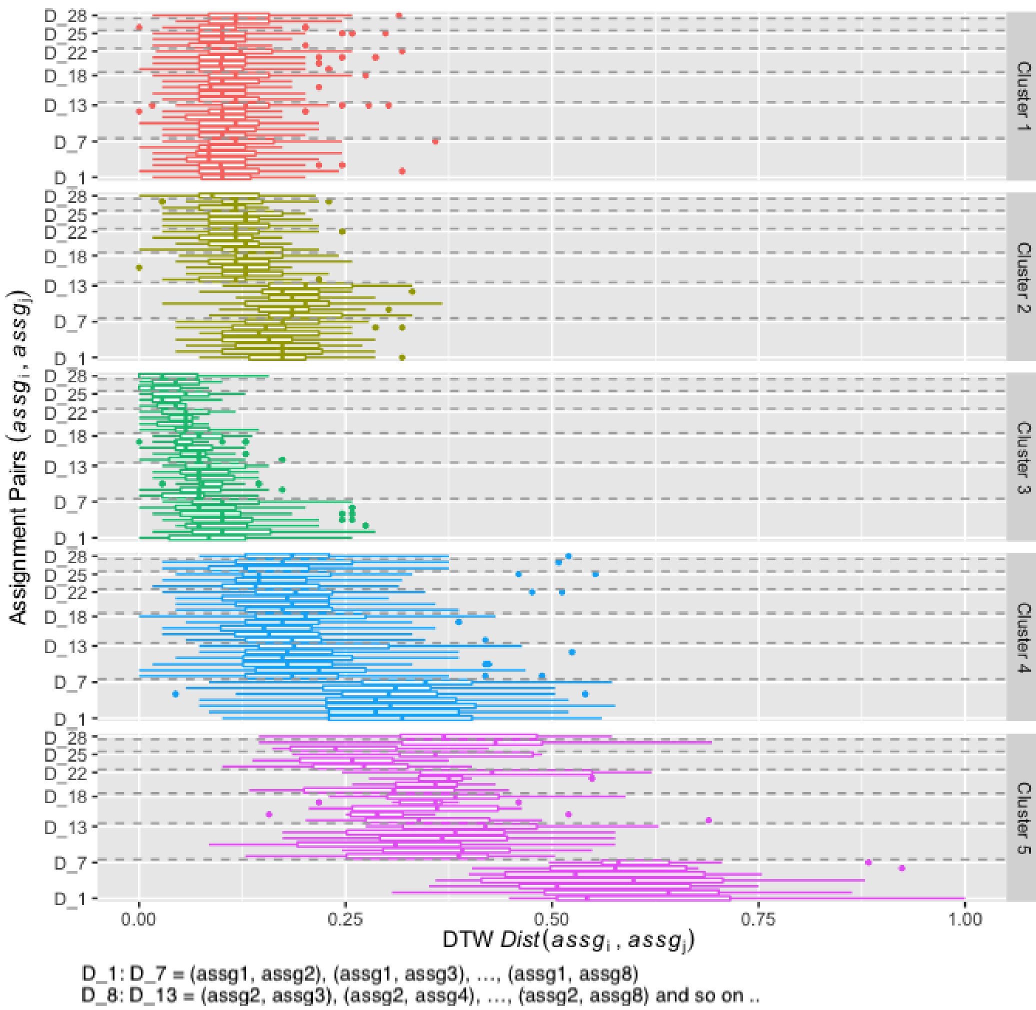


Figure 7.1: Box plots representing five number summary for the five student clusters. The box plots are color-coded by the student cluster they belong to. The y-axis represents all possible assignment-assignment pairs and the x-axis denotes the corresponding DTW measures for each pair.

2 onward, their work patterns steadily became more consistent. However, it never reached the level of consistency of Cluster 2.

- Student Cluster 5 – *Inconsistent Users* (N = 8, 4.94%): This cluster constitutes the smallest group of students. These students exhibited remarkably different temporal work patterns and even though the similarity increased (i.e., DTW measures start getting smaller) as the assignments progressed, they were still relatively large compared to the DTW measures from the previous four clusters.

Analysis of cluster differences based on overall grade

Since we found a high degree of correlation between assignment score and final grades ($r = .85$), we decided to test any underlying cluster differences on the overall student grades before proceeding to check for differences with respect to assignment grades in particular. In order to do so, we used the ANOVA test due to their robustness to mild violations of normality [90], with cluster assignments as the independent variable and final academic grade as the dependent variable. The analyses of the degree of variation in adopted temporal consistency patterns was found to be significantly associated with the overall academic performance score, with a moderate effect size ($F(4{,}157) = 5.943$, $p < 0.001$, $\eta^2 = .13$). The pairwise comparison of clusters with respect to the final grade (i.e. *percentage*) revealed that Cluster 3 performed significantly lower than all the other clusters (all $ps < 0.005$), even after adjustments to the p-values using the Tukey HSD procedure. However, the difference between the two highly contrasting groups, i.e. Cluster 1 and 5, was not statistically significant.

Transitions in work patterns at activity-specific level

To inspect whether the transitions in temporal work-pattern were because of switching to different modality (from desktop to mobile, or vice versa), variations in intensity of peaks (higher or lower activity peaks due to procrastination) or a combination of the two, we examined the prototype[2] time-series of the clusters. Since the computation of the optimal prototype poses some challenges, we used DTW Barycenter Averaging (DBA) algorithm [190] to determine the cluster centroids (prototypes). This approach computes an 'average' sequence, called barycenter, such that the sum of squared DTW between the barycenter and the set of considered sequences is minimum. Upon observing the prototypes, we found almost no contribution of varying modalities to the varying consistency patterns within assignment phases. This is because students relied mostly on desktops for all assignments and the use of mobiles for this learning activity was sparse, with under 10% of the class using it at most 2-3 times in the 11-day timeline (in conjunction with desktops) in any given assignment.

Table 7.1 sheds further light on the shift in work pattern timeseries from one assignment to the other for each of the five clusters described above, with the black trend-line representing the prototype time series. We graphed the number of times assignments were

[2] A prototype effectively summarizes the most important characteristics of all series in a given cluster [213].

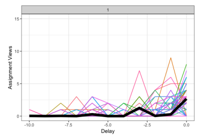
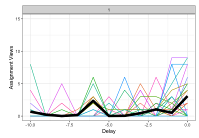
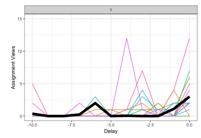
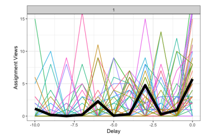
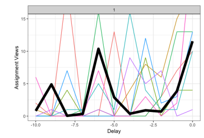
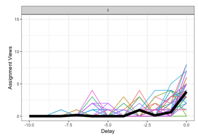
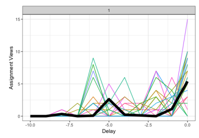
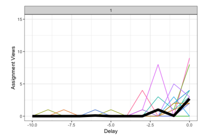
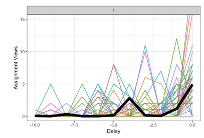
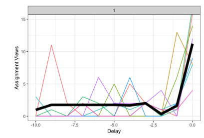
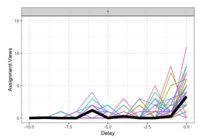
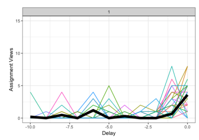
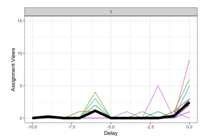
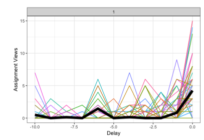
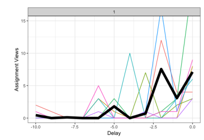
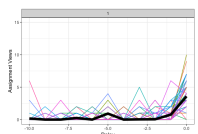
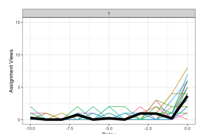
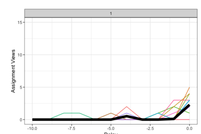
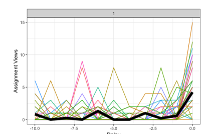
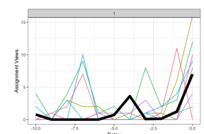
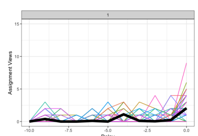
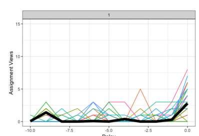
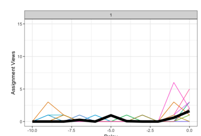
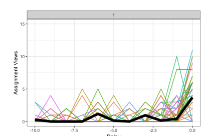
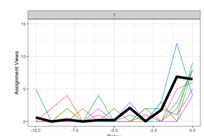
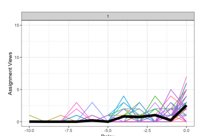
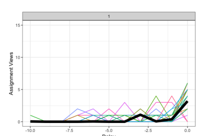
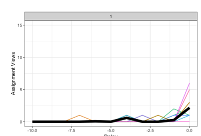
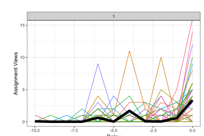
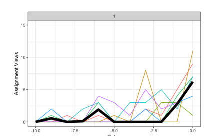
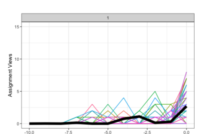
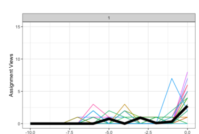
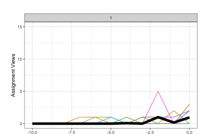
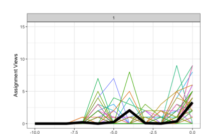
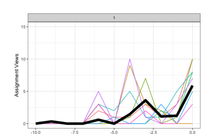
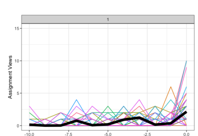
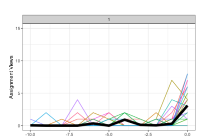
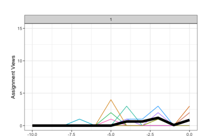
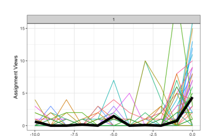
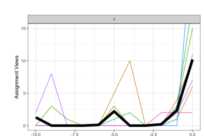
.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
A1					
A2					
A3					
A4					
A5					
A6					
A7					
A8					

Table 7.1: Prototype activity patterns for the five student clusters (Cluster1 : Cluster5) at the eight assignment tasks (A1 : A8). The x-axis represents number of days before the assignment, starting from 10th day before the deadline up to the day of submission and the y-axis represents the number of assignment views. To allow cross graph comparison, all graphs have been plotted with x-axis scale [-10,0] and y-axis [0,15].

accessed on each day (until the deadline) to demonstrate changing patterns of access over the course. Since, it was observed that the use of mobile modality for this learning activity was sparse, only desktop accesses are plotted. Based on Table 7.1, we can draw some inferences regarding frequently-occurring patterns which were present across multiple assignments. (Note: Each column in Table 7.1, representing a cluster, has the same number of time series in each of the 8 corresponding assignments; however, some time-series were composed of all zeroes, i.e. zero-engagement level on any given day in timeline, and hence may have been obscured by each other at the bottom of the graph.)

For most assignments, students in cluster 1 were active quite early on (five or six days before the deadline) but their level of engagement with the assignment was low (less than 5 views) and infrequent (at most two peaks in 11 day time-frame). The Cluster 2 students' engagement with the first two assignments differed compared to the later six assignments. While the level of engagement in assignments A1 and A2 was high (5 or more views in a day) and evenly spaced out in the days leading up to the deadline, assignment A3 onward the engagement levels dropped immensely and a high level of activity was witnessed closer to the deadline. The Cluster 3 students were barely active with the assignment activity on the LMS (except for the first two assignments, which were relatively easier in terms of task difficulty). Any engagement with assignment activities was witnessed much closer to the deadline only, thus explaining their incrementally consistent (but rather poor) approach observed. The level of activity revealed in all the assignments in Cluster 4 was higher than that of any other group. Except for assignment A1 where exceptionally large peaks in activity levels (7 or more views in a day) were present throughout the 11-day timeline, the Cluster 4 students were steady in their approach, with preparations starting quite in advance and small peaks in engagement (5 or less views) observed around four-five days before the deadline. The students belonging to the smallest group, Cluster 5, demonstrated unique activity patterns with each assignment. There were some instances (for example assignment A2 and A8) where exceedingly high spikes in activity levels (more than 10 views) were found on the day of submission whereas in other cases (for example assignments A3, A5, and A7) the engagement was regular before the deadline and even higher compared to those found in other groups.

7.5.2 Analysis of cluster differences based on assignment grade

After examining the differences between clusters based on final grade, we proceeded to further check for the differences between the discovered clusters with respect to their performance in the assignments, per se. In total, scores obtained in the eight assignment submissions represented the main data source for analyzing cluster differences.

A non-parametric one-way analysis of variance was conduced with the students' cluster assignment and the final assignment score (average of the eight assignments) as the single independent and dependent variable, respectively. The main effect analyses from the test revealed that the final assignment scores were statistically significantly associated with the learners' consistency profile, with a small-medium effect size ($\chi^2(5) = 17.463$, $p = 0.001$, $\epsilon^2 = .11$). The pairwise comparison of clusters with respect to the assignment grade (i.e. assignment percentage) revealed that Cluster 3 (52.44 ± 32.14) performed significantly lower than all other clusters (all $ps < 0.01$), even after adjustments to the p-values using the Benjamini-Hochberg (BH) procedure. Additionally, performance was significantly better for students in Cluster 5 (92.45 ± 5.86) compared to Cluster 1 (74.72 ± 17.66, $p < 0.01$) and Cluster 4 (75.04 ± 18.67, $p < 0.01$). For completeness, the Cluster 2 percentages were (76.57 ± 21.48).

7.5.3 Clustering of students based on consistency in discussion activities

The solution with 6 clusters was found as optimal. The resulting clusters indicating the six different patterns of consistency in temporal patterns that students tended to display, when reviewing the discussions in the forum whilst working towards a deadline. Figure 7.2 presents the box-plots for each of the six consistency profiles (with the interpretation of the several plot elements same as in Figure 7.1).

As can be observed from Figure 7.2, except Cluster 2 and 5, the median DTW measures for all three discussion-discussion pairs were well below the half of the maximum threshold. From the perspective of the pairwise DTW measures described in Section 7.4.3, the clusters can be described as follows:

- Student Cluster 1 – *Highly Consistent* (N = 9, 16.36%): This group of students had the least variation in their work patterns in going from one discussion to the other, as exhibited by the low DTW measures.
- Student Cluster 2 – *Incrementally Inconsistent (high DTW)* (N = 6, 10.91%): This group of students' patterns became increasingly dissimilar with each successive discussion.
- Student Cluster 3 – *Early Consistent* (N = 12, 21.82%): This cluster constitutes the second largest group of students wherein engagement patterns in the first discussion are less similar to the other two discussions tasks. However, discussion 2 onward, their

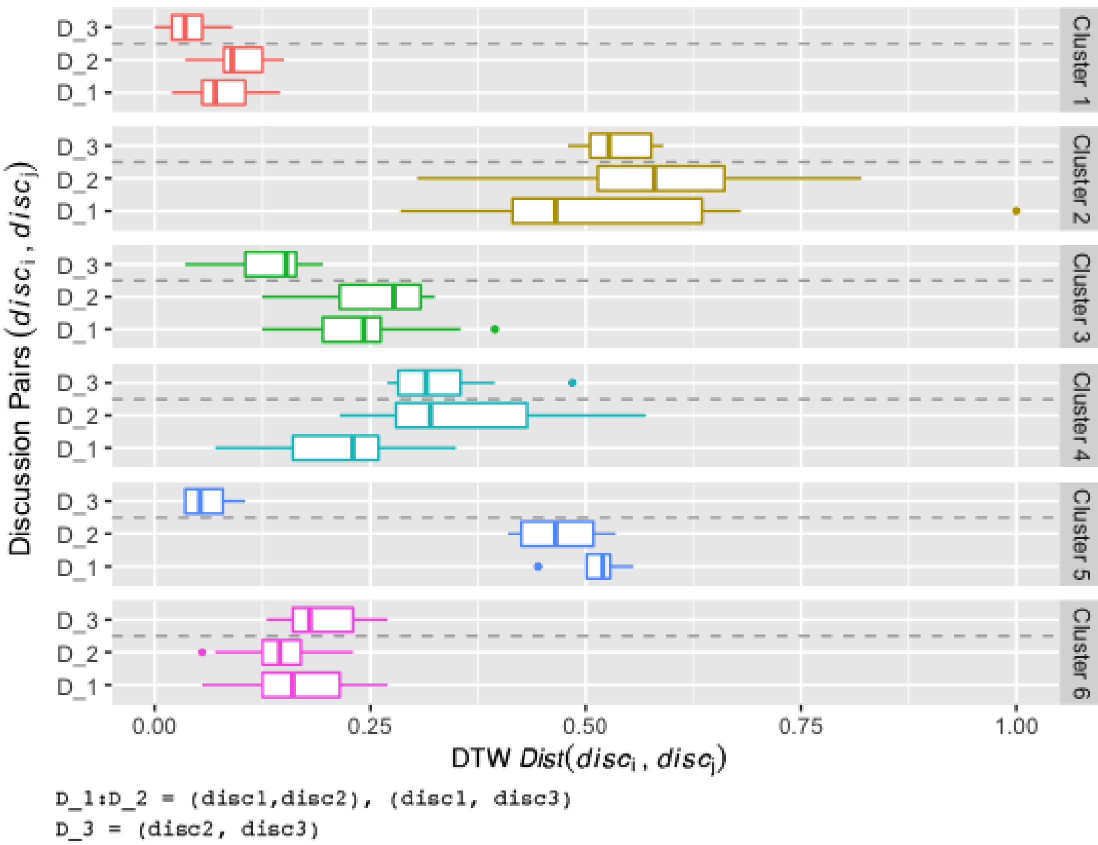


Figure 7.2: Box plots representing five number summary for the six student clusters. The box plots are color-coded by the student cluster they belong to. The y-axis represents all possible discussion-discussion pairs and the x-axis denotes the corresponding DTW measures for each pair.

work patterns became more similar, although it never reached the level of consistency of Cluster 1.

- Student Cluster 4 – *Incrementally Inconsistent (low DTW)* (N = 11, 20%): This cluster is similar to cluster 2 in that the patterns become increasingly dissimilar discussion 2 onward. However, it never reached the level of inconsistency of Cluster 2.

- Student Cluster 5 – *Steep Consistent* (N = 4, 7.27%): In this cluster, students' engagement patterns with discussion posts in the very first discussion were highly dissimilar to those in the subsequent discussions. However, a remarkable level of consistency between timeseries patterns of discussion 2 and 3 was seen (low *D_3* DTW measure) such that Cluster 1's level of consistency was achieved.

- Student Cluster 6 – *Fairly Consistent* (N = 13, 23.64%): This cluster constitutes the largest group of students wherein least variation in their work patterns were observed between subsequent discussion tasks but the overall consistency was slightly lower than that observed in Cluster 1.

Analysis of cluster differences based on overall grade

The analyses of the degree of variation in adopted temporal consistency patterns was found to be significantly associated with the overall academic performance score, with a large effect size ($F(5{,}49) = 3.381$, $p < 0.01$, $\eta^2 = .32$). The pairwise comparison of clusters with respect to the final grade (i.e. *percentage*) revealed that Cluster 1 performed significantly lower than Clusters 2 and 4 (both $ps < 0.01$) while Cluster 2 performed better than Cluster 3 ($p = 0.04$), even after adjustments to the p-values using the Tukey HSD procedure.

Transitions in work patterns at activity-specific level

Table 7.2 depicts the shift in work pattern timeseries between discussion tasks for each of the six clusters described above, with the black trend-line representing the prototype time series. Much like the assignment activity, the use of mobile phone modality was sparse for the discussion activity as well and the variations in work patterns are mainly attributed to the change in intensity of engagement levels (from desktops).

For Cluster 1, the high consistency was a result of almost no discussion-viewing activity throughout the 11-day timeline. On the contrary, the consistency achieved by Cluster 6 was achieved as a result of regular evenly spaced out work patterns, with a majority of viewing activity occurring from 3-4 days before the deadline. The work patterns for both Cluster 2 and 4 went from consistent in first two discussions (D1 and D2) to inconsistent in last two discussions (D2 and D3), although the change for Cluster 4 was not that extreme. For Cluster 2, the majority of the discussion-viewing activity in D1 and D2 took place in the middle of the timeline (approximately 10 views in a day) whereas the strategy for the third assignment included preparations starting much in advance (almost 10 days before the deadline) and finishing with another peak in discussion activities just a day before the deadline. For Cluster 4, work patterns in D1 and D2 were fairly consistent but in D3, the students performed discussion-viewing activity on the deadline only. Both Cluster 3 and 5 achieved higher consistency in work patterns as the discussion tasks progressed. However, the extremely high consistency levels witnessed in D2 and D3 in Cluster 5 were a result of students doing minimal work, whereas in Cluster 3 it was due to the similar activity levels (approx 3 views in a day) with students showing larger activity 2-3 days before the deadline.

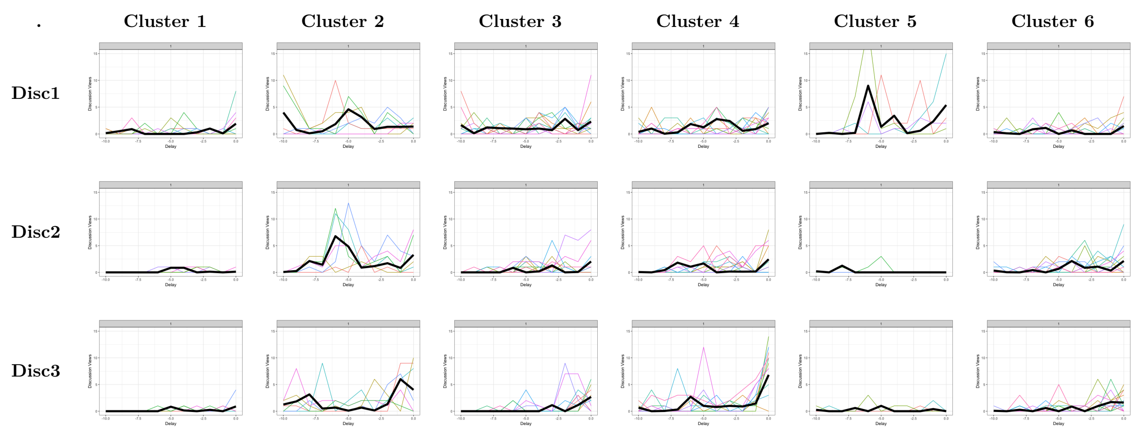


Table 7.2: Prototype activity patterns for the six student clusters (Cluster1 : Cluster6) at the three discussions tasks (Disc1 : Disc3). The x-axis represents the number of days before the discussion, starting from 10th day before the deadline up to the day of submission and the y-axis represents the number of discussion views. To allow cross graph comparison, all graphs have been plotted with x-axis scale [-10,0] and y-axis [0,15].

7.5.4 Analysis of cluster differences based on discussion grade

The ANOVA analyses revealed statistically significant associations between final discussion scores (average of the three discussions) and learners' consistency cluster, with a large effect size ($\chi^2(5) = 22.73$, $p < 0.001$, $\epsilon^2 = .40$). The pairwise comparison of clusters revealed that performance of Cluster 1 (28.15 $\pm$ 32.05) was significantly lower than all other clusters (Cluster 2 = 82.48 $\pm$ 14.06, Cluster 4 = 85.45 $\pm$ 19.22, Cluster 6 = 64.79 $\pm$ 30.3; all ps < .05) except Cluster 3 (54.99 $\pm$ 24.03) and Cluster 5 (29.67 $\pm$ 15.49) where the differences were non-significant. The differences between the two incrementally inconsistent groups – i.e. Cluster 2 and 4 – were non-significant although the former performed significantly better than Cluster 5 and latter performed significantly better than Cluster 3 and 5. The differences between the two incrementally consistent groups, i.e. Cluster 3 and 5, were again non-significant. Overall, it seems that students who drastically changed their work patterns in the later discussions were more bound to be successful compared to those whose performance remained constant throughout.

7.6 Discussion

It may be regarded with fair certainty that academic progress is non-linear and so are students' learning approaches [175, 36]. Changes in student behaviour are inevitable and so, in this paper we focus on examining within-activity consistency of online work habits in a blended learning environment. We investigated consistency in two different learning contexts – assignment-reviewing and discussion-reading behaviour – and the subsequent impact on academic achievements. Since the assignments in this study were multimedia programming activities requiring various design and logic features to be implemented in the code, it was necessary to refer to the assignment specifications time and again. Similarly, the discussion activity was a collaborative process wherein arguments had to be built upon other students' post and thus, regularly keeping up with the discussion forum and reading through the discussions posted by others was essential if one wanted to make a contribution to it.

Upon observing the consistency profiles obtained from each of the two activities - discussions and assignments, we found some commonalities. First, for both the learning activities, the preferred technological modality for engaging was primarily desktop. It was initially hypothesized that for discussion activity at least, mobile use would be prominent in the early days to "keep-in-touch" with the forum, followed by a switch to desktop modality as the deadline approached for creating stronger arguments requiring deeper knowledge construction. However, this was not found to be true (as seen in Section 7.5.1 & 7.5.3) and thus, it is safe to assume choice of technological modality remains consistent throughout the learning activity phases. Therefore, we agree with Sher et al. [219]'s recommendation that it is imperative for instructors to educate their students on the benefits of choosing a modality which has been theoretically-established as appropriate for a particular learning activity, as it is likely that once a modality is adopted, it will be continually used.

Second, overall student performance decrease throughout the course, as exemplified by the decline in non-zero time-series from A1 to A8 (in Figure 7.1) and D1 to D3 (in Figure 7.2), although the pattern was more prominently visible in assignment activity. This is consistent with recent research findings by Ahadi et al. [5] who found a noticeable decline in the number of students who belong to the high-performing quantile as the semester progresses, partially explainable by the incremental nature of programming.

Third, contrary to the trend in the recent literature implying a far greater degree of time management skills as learners progress in their course [97], the notion of increased consistency in temporal work patterns across subsequent learning tasks was unrelated to improvement in deadline management. In our study, we found a substantial number of students in each activity (12% (Cluster 3) and 24% (Cluster 1 and 5 combined) in assignment and discussion activity, respectively) who maintained high consistency profiles, meaning there was little to no change in their work patterns throughout the semester. However, these were often students performing bare minimal activity in each (assignment or discussion) task or performing activity on the deadline only. In fact, these students scored the lowest in terms of academic achievement in both final grade and activity-specific grades, and qualify for those needing interventions and support the most. This data suggests that high consistency is not always a sign of excellence in learning and relying entirely upon students to ensure good time management practice is not a sign of sound pedagogical practice. Consequently, it is necessary for instructors to carefully sieve out learners with habits of effort and participation that are too similar to detrimental work patterns as identified in the literature [112, 107].

Much like lecture-specific traits are known to be associated with student persistence and engagement [72], we found possibility of some activity-specific traits to be associated with student consistency after comparing the work patterns in the two contexts – discussion and assignment. This is because the profiles obtained from assignment activity all seemed to converge (decreasing DTW measures from A1 to A8 in each of the five profiles in Figure 7.1). i.e. the engagement patterns in a specific assignment were more or less similar to the next subsequent assignments. The degree of sameness varied depending on the profile as some converged after the very first assignment (Cluster 2) whereas others after the second one (Clusters 4 and 5). On the other hand, the discussion activity witnessed instances where instead of converging, the work patterns turned excessively varied (increase in DTW measure from D1 to D3 for Cluster 2 and 4 in Figure 7.2). For instance, the top two high performing groups in discussion activity (Clusters 2 and 4) demonstrated very varied consistency in work patterns between the three discussion tasks as seen in Table 7.2. In discussions D1 and D2, Cluster 4 demonstrated patterns conventionally associated with good performance such as stable participation throughout the 11-day timeline and non-reliance on the day of the deadline to complete task and Cluster 2 showed consistency in terms of when in the 11-day timeline majority of the coursework would take place. However, for discussion D3, both clusters experimented with temporal patterns that did not match the patterns from the preceding discussion tasks, but instead were indicative of active procrastination [271], i.e. their time management strategies involved deliberately delaying task participation until the deadline. These findings suggest a continuing need to understand the nature of consistency, including when and why learners break patterns to opt for widely varied work habits and whether activity-specific traits such as inherent group dynamics, assessment methods and instructional conditions play a role in it.

In summary, for the assignment activity learners' engagement patterns were incrementally consistent with each of the eight assignment tasks. However, for the discussion activity, evidence suggested one third of the class deviated from consistent patterns towards the end (RQ1).

In the discussions surrounding aspects of consistency in learning, question of variability versus consistency does not yield an 'either-or answer' [254], since empirical support for this presumed conceptual structure is limited and conflicting. On the one hand, we can argue sticking to a routine is better while on other assert that strategies must evolve with time and needs. To give some perspective to this discussion on utility of a consistent vs. evolving learning approach, the results show that most successful group of students in terms of academic performance were those who were able to adapt their work patterns to each individual task, as a result of which their weekly patterns were unable to follow consistency (high DTW measures for each activity pair). These results partially contradict the claims by Du et al. [60] that students who study at consistent times outperform those with more varied time patterns. In fact, in our study, students whose consistency levels increased incrementally throughout the course scored lower in academic achievement than those whose consistency levels dropped. This also serves as a cautionary note to researchers using entropy [122, 60] or standard deviation [117, 66] of LMS activity measures (counts and time spent) as a measure of consistency since it could be the case that high consistency could be attributed to series of bad engagement patterns which the learner is not correcting. Thus, achieving consistency is not always analogous to excellence in learning and while time management and effort regulation may positively predicts academic grade [24], time-management skills need not be consistent but evolved enough to stabilize these efforts.

In summary, there is an association between identified patterns of consistency with student's academic performance for both assignment and discussion learning activity, although the associations are not always positive (RQ2).

Lastly, as a by-product from this study we were able to confirm claims by existing research that link certain activity patterns to academic success. The study confirmed that consistent participation is more important than high frequency [112]. Cluster 6 in discussion activities was perhaps the only cluster wherein engagement patterns were highly symmetrical in all activity phases and the high consistency in work patterns was not a result of near-zero activity. Their strategy involved studying a little bit every day which is usually associated with a 'willingness to pursue longer-term academic goals over immediate gratification' ([21], as cited in [107]), thereby explaining highest grade amongst all clusters. We also found evidence of poor academic performance linked to students working minimally on the assigned tasks or working only on deadline, in accordance with claims by Młynarska et al. [174], as exemplified by Cluster 3 in assignment and Cluster 1 and 5 in discussion activity.

7.7 Conclusions

The current study analyzed consistency, or persistence in work patterns on an activity-specific level, in the presence of multiple modalities. The Dynamic Time Warping (DTW) measure was proposed for quantifying the similarity between pairs of temporal sequences (representing work patterns). We found that the use of mobile modality is constantly minimal (almost negligible) throughout the semester whereas its counterpart i.e. desktop, experiences some fluctuations.

The results showed that students were incrementally consistent in their work habits using desktops over different assignments up to some extent, although students do vary in their consistency of work patterns during the discussion activity. Further, there were significant associations between identified patterns of consistency with student's academic performance for both assignment and discussion learning activity, although the associations were not always positive.

While we acknowledge that time scheduling patterns may be impacted by external factors relevant to a student – e.g., heavy course-load, freshman vs. senior time-management skills, personal commitments – in the current study we assumed that learners render equal importance to the courses used in this study (since these were mandatory and important pre-requisites to future courses) and to any other courses they may be simultaneously enrolled in. In future research, we aim to consider whether external factors are at play which may hamper or promote consistency in work patterns.

Chapter 8

Discussions of Cumulative Results

If you can't explain it simply, you don't understand it well enough.
- Albert Einstein

8.1 Context of Interpretation of Thesis

Like most studies in the field of learning analytics, this research made use of post-hoc data to assess and make claims. Thus, it is important to keep in mind any claims of causality, indirect or otherwise, were not intended, especially given the lack of experimental manipulation possible with post-hoc data. To establish causality, one needs to satisfy three main criteria: (1) *association*, (2) *time ordering* (or temporal precedence) and (3) *non-spuriousness* [39]. So far, this thesis has set the stage for establishing causality by focusing on the association stage. In future, we need experimental manipulation for the remaining two stages and also testing any confounding "third variable" such as digital literacy skills, study-life balance, socio-economic status, etc that might impact their access to and usage of modalities in TEL environments.

It is also important to note that the post-hoc data helped us analyze learner behavior with respect to multiple devices in a *naturalistic* setting, one where students engage with LMS like they normally would on a daily basis under normal classroom conditions. Drawing on the benefits of naturalistic setting for providing "quite different insights into people's perceptions and their experience of using, interacting, or communicating through the new technologies in the context of their everyday and working lives" [235] , this method gave us a good starting point to produce some novel findings about student learning in presence of multiple devices. The naturalistic environment also provided an ideal setting to answer the research problems posed at the beginning of thesis (see Section 3.6.3) as we were interested in understanding modality-use without any instructor intervention.

8.2 Physical affordances of learning tools

Depending on the learning context, certain devices offer better opportunities for learning [145, 169]. Mobile technologies afford real-time information based on when and where learner needs it [148], desktop PCs afford high computational power and their dedicated keyboards allow easy inputs [45], and finally tablets with their virtual keyboards, larger screens and specialized softwares support specialized tasks such as graphic designing and academic writing [155]. In this thesis, analyses of the affordances of multiple modalities in blended learning environment were assessed from the viewpoint of the physical size of the modality itself (detailed description and reasoning in Section 3.6.1). In this regard, desktop PCs and laptops are comparable in that both allow easy navigation between LMS pages, opening multiple windows as opposed to mobile phones that support a simple LMS view and where screens are smaller and navigation is cumbersome, if not entirely problematic. For instance, even reviewing written text (say during discussion activity or reading the course material) requires considerable scrolling on a mobile phone, as compared to desktops or tablets. Hence, interpretations of the learning behaviors of students using multiple devices was done keeping in mind that choice of screen size might impact the results obtained in our research.

Perhaps, this physical affordance of size can partially explain the supportive role that mobile phones were found to play in our research results. That is, even though we found a small yet substantive group of students in Chapter 4 (Cluster 3: Intensive) that engaged in learning sessions using mobile modality, further inspections revealed that mainstream use of mobiles was mainly for 'course planning and management' kind of activities, such as calendar, announcements and notification settings (as seen in Table 4.1 in Chapter 4). Although we observed 20% of accesses to the assignments page in the LMS from mobile phone modality (see Table 4.1), these accesses were distributed in a certain way such that Intensive learners accounted for majority of those accesses (approximately 51%). Further, mobile modality's supportive role was reaffirmed in Chapter 7 wherein mobile use was found almost negligent for two main learning activities i.e. assignments and discussions. While we found majority of students used mobile phones at least once to access the LMS, only few of them (less than 10% of the class) used mobile phones in the studied activities (assignments and discussions), and even then their prolonged usage over the semester (through the eight assignment phases) was not visible, not even for reading assignment specification on the mobile phones. Collectively, these point towards the fact that mobile phones are still not being used up to their maximum potential for learning activities. This might suggest limitations of mobile phones for *targeted* activities that we tend to overlook, especially given that they are widely used for several other activities.

These results further solidify our initially noted gap in literature regarding a higher usage of mobile phones only when they are being used for dedicated purposes, as in mobile apps. As a result, we agree with some of the ideas put forth by Krull [145] who suggested academic and technological support needs for students such as provision of 'audio-visual materials' and advice regarding 'specific devices and device configurations for specific learning activities'. We consider this will help students create a more seamless learning environment making use of all available modalities. These support guidance will also help us identify instances where mobile modality may be unsuitable for learning processes, contrary to common assumptions that mobile phones can be effectively used for all activities simply because students are using them for social, leisure and personal activities.

Finally, the results obtained in this thesis with respect to the device affordances are, to some extent, context-dependent. For the same modalities and similar activities we investigated, their assessment in a different context would possibly yield different results. For instance, discussions are an essential component of Massive Open Online Courses (MOOCs) and are vital for deepening the understanding of the course content [216]. The same can be said about watching lecture videos as being a common MOOC behaviour. Within the context of these activities and owing to the online nature of MOOCs, mobile use is much more probable compared to desktops. Furthermore, given the inability to gauge a modality's mobility affordances i.e. collect location-specific information in logged data due to privacy concerns, we were not able to depict a richer picture of our learners' actions on-the-move. The lack of location or GPS data for user actions with respect to each modality has some implications for synthesis of our results. For instance, knowing about the location information is helpful in thoroughly understanding how feasible the actionable interventions (see Implications for Research in Section 5.6.3) based off of time-of-day and modality associations are, as desktop accesses could be scrutinized to know if actions were undertaken on a laptop from lecture or laptop from lab or on a desktop PC from home.

8.3 Implications of the Research

We established early on in the thesis a gap in literature, stemming from the dearth of studies assessing how multiple devices are used for common learning activities. The main theoretical framework by Krull [145] (discussed in Section 3.5.2) does contribute substantially towards bridging that gap, however, the claims made by him were based mainly on survey and semi-structured interview data. Though useful, the shortcomings associated with such data are well known within the learning analytics community [280, 267]. Thus, this thesis adopted a data-driven approach to assess how multiple devices are used in blended learning environments whilst simultaneously corroborating some of the claims made in Krull's theory.

The results in Chapter 4 were able to not only confirm Krull's claims that students make use of multiple modalities in learning environments separately (Strategic and Minimalist) and together (Intensive), but also that how frequently these modalities will be used for learning is associated with their academic outcomes and performance at online discussion activities. Further, we used trace data to confirm Krull's claims regarding desktop and handheld devices' use in learning as being central and supplementary, respectively. That is, we found in Chapter 4 that desktops were the main modality used for engaging in studied activities, i.e. assignments and discussions, whereas mobile modality was rarely used for this purpose. Instead, students used mobile devices for housekeeping activities like course management and planning. Finally, in Chapter 6, we saw the role of device affordances, which Krull hypothesized as an important factor for influencing how frequently a modality will be utilized for learning. That is, we were able to observe a variance in not only the magnitude of impact but also the direction of impact of a modality on a learning activity. This has an important implication for good practices for instructional strategies, that is, *considering modality should become part of what we recommend to students as successful learning strategies.*

In addition to corroborating some of Krull's claims using data-centric approaches, the findings in this thesis were also able to contribute to the literature by providing new lens to advance Krull's theory for future researchers and designers. For instance, the theory includes time availability (with respect to task complexity) as an important factor in deciding whether or not a modality will be used [145, p. 62]. By introducing the associations between the concept of time of day and technological modalities, as done in Study 2, we were able to observe in our context that time availability, in addition to *when* that time is available in the 24-hour day has significant bearing on whether students have an increased tendency to use the modality or not. This has implications for the way *LMS designers can customize and personalize the delivery of notifications/reminders in a way that fits learner's schedule and available modalities*, although with caveat that the impact on learning still needs to be confirmed. For instructors, this knowledge has implications for creation of new learning designs. For instance, the knowledge that students do most of their LMS accessing from computers (PCs or laptops) in the evening (see Results in Chapter 5), at times in quite short sessions, can be used for *re-design of activities such that the new activities are char-*

acterized by short time cycle of analyzing-strategizing-completion of task. As a result, this would prompt more active participation from student's end, even at the end of a regular school day.

From a practical perspective, the most significant implication of our work is for (re)design and implementation of learner models. The 'one-size-fit-all' theory [87] claims generalized models of learner success are not effective since they tend to over/under estimate effect of predictors. Hence, we were able to *improve upon the prediction power of the models developed for each course by directing attention towards the modality* through which the access occurred and thus presenting a more nuanced view of how technological modality may matter for learning.

The field of learning analytics, though equipped with ample research on designing and evaluating mobile LMSs (learning management systems) and desktop-based LADs (learning analytics dashboards), still lacks a decent framework for assessing how learning unfolds in the presence of multiple devices. In this regard, the present thesis serves as one of the first examples on how the development of learning analytics can be linked with the existing literature on technological modality use in learning environments. We see a potential for getting the conversation surrounding usefulness of modalities started within the LA community. Given the ability to mine and analyze large amount of educational data, it was surprising to find so few LA researchers recording and developing analytics surrounding modalities. Even the immensely popular Moodle learning platform used all over the world, which stores huge amount of data related to learning processes, does not store the information about 'user-agent' (informing the modality/browser used) for each action in the stored event-logs. As students increasingly rely on multiple devices for learning, it may be beneficial to track the modality sources of their accesses. By simply logging the user-agent field in trace analysis, researchers (and instructors) can unlock potentially useful analytics, which has implications for educational practitioners. That is, through analysis of the learners' modality support throughout different activities, they have more means to strategically design more nuanced recommendations and instructor interventions.

The seminal exploratory work on technological modalities included in this thesis provides necessary first steps to formulate more precise research questions and hypotheses. From hereon, LA researchers can advance their research in multiple directions, most important of which involves assessing how soon into the course, can the technological modality strategy of a student be detected. There is also a potential line of enquiry into analyzing whether the accesses to learning activities from multiple modalities is done as part of conscious decision-making or not. With the proliferation of online learning context like MOOcs, it is essential to scale up existing analyses to fully online learning contexts where modality use is not just a medium that helps facilitate the learning process but rather the central entity used for delivering complete learning programs.

8.4 Critical Reflection

The four main studies introduced in this thesis (Chapter 4-7) were conducted and published over period of one and a half year. Since then, we have gained a deeper understanding of the domain and in this section would like to take the opportunity to reflect on some decisions and interpretations made at the time when work was done.

In the very first study introduced in Chapter 4, we opted for hierarchical clustering of the sequences (learning sessions) to determine patterns of modality usage, even though 95% of the sequences were mono-modal i.e. composed of single modality use. Instead, we could have opted for a much simpler grouping of sessions (after elimination of the remaining 5% of mixed sessions) based on two criteria: *modality used* (desktop, mobile, tablet) and *session length* (short, long) based on the number of actions in the session, to create six technological modality profiles (short-desktop, long-desktop, short-mobile, .. and so on). There was trade-off between computational time (for performing computationally complex optimal matching of sequences) and quality of clusters, and our chosen clustering strategy allowed us to avoid some of the spurious groupings like 'long-mobile' use.

Furthermore, discussion surrounding the naming of clusters in this study was left out of the main text in published paper due to space constraints. To shed some light on it, the naming of the three technological modality strategies was done with the intent of showing how modalities were used: intensive users 'intensively' used all available modalities, minimalist users made 'minimal' use of mobile modality and strategic users 'strategically' used desktops mainly for advancing their learning and outperformed all other students. In hindsight, better nomenclature could have been adopted for strategic group as the current name suggests intent, for which there isn't enough evidence. Similarly, the term minimalist reflects the amount of modality used as opposed to the type of modality used, and is inconsistent with how intensive cluster was named.

Within the same study, we saw a significantly large amount of variance in quality of discussion messages (calculated using Coh-Metrix analysis) explained by the student's technological modality strategy. It was interesting to see that while variance in the measures of meaningfulness (*concreteness*), degree to which ideas overlapped across sentences (*referential cohesion*) and use of simple and familiar structures in the discussion messages (*syntactic simplicity*) was explained by the modality strategy, two important Coh-Metrix aspects were unaffected. That is, how deeply the ideas in the discussion messages (posted or replied) were coherently connected (*deep cohesion*) and whether the text inside those messages conveyed a story (*narrativity*) were similar for all modality strategies. These two aspects are directly relevant to a deeper understanding of the text per se (rather than the structure of the sentences). It was our initial understanding that those using desktop modalities would perform significantly better than others given the ability to create richer content doing research on multiple tabs of a PC or laptop. Consequently, even though the strategic users were found to outperform the other groups on these two measures, the differences were non-significant. Additionally, we observed a large effect size (68%) from the MANOVA analysis in this study, quantifying the important relationship between modality strategies and performance at online discussions. Though quite optimistic, this high percentage must be interpreted with necessary precautions as it reflects the multivariate eta-squared which can be substantially higher than the eta-square for any of the individual outcome variables (Kline [135, pp.4-5] discussed this effect size in detail). In our case, we had a large pool of dependent (outcome) variables, such as word count, quality measures, counts and time spents, some potentially correlating with each other and thus 68% is the multivariate proportion of explained variance in the total data set (i.e. all the outcome variables considered together).

In the second study introduced in Chapter 5, the 24 hours available to the learner during the day were binned into four discrete categories (morning, afternoon, evening and night) prior to the analyses. While the bins reflect how students might organize their day based on their general activities, some bins occupied a larger duration of the day (for instance, night) while others retained smaller number of hours (evening). We took necessary precautions for normalizing results based on the number of hours in each bin, although it would be interesting to investigate these results with varying distribution of time of day clusters, perhaps in an exceedingly different learning context of part-time learners. Additionally, it may be of use to extend the discussion beyond time-modality associations by looking into what elements in a course are accessed at certain hours of the day. This in turn would help formalize more solid hypothesis for modality-inclusive learner models (like those introduced in the third study in Chapter 6), especially if a course material access has been recorded at multiple times throughout the day from the same modality.

As part of the fourth study in Chapter 7, we study the variations in modality use patterns across assignments and discussion tasks to see if the patterns in week 1 are more or less similar to the ones from week 2 and so on. We consider this as an important area of study to see how coherence and consistent usage can explain certain criteria for approaching the task (and ultimately the quality of the academic artefact produced). For example, do students always choose to begin the planning phase of an assignment on their mobile phones, then follow it up with detailed engagement via a desktop in later days. Given the lack of time series data from mobile phones, the aimed objective was only partially achieved. Furthermore, the consistency patterns of modality-usage were obtained from the viewing (reading) patterns of the messages in online discussion forum. However, we did not consider the effect, if any, of the timing of these discussion messages. This is necessary since the reading activity is highly influenced by the posting activity of the group members. Thus, student belonging to a highly active discussion group would have registered more viewing on the LMS as opposed to another highly motivated student belonging to a less active discussion group. We conducted the research, however, with an assumption that regardless of the posting intensity the student would still regularly monitor the forum by visiting it. Similarly, in case of assignments, if some students decided to take printouts i.e. hard-copy of the assignment requirements, then their 'actual' assignment-view patterns were not registered by the LMS. Such limitations are widespread and inevitable in research using post-hoc data but which must nonetheless be explicitly stated out for future researchers.

Chapter 9

Conclusions and Future Directions

To raise new questions, new possibilities, to regard old problems from a new angle, requires creative imagination and marks real advance in science.

- *Einstein*

The overarching idea of this thesis is to use data collected by learning environments to provide assessment and better understanding of students' learning processes and strategies in presence of multiple modalities. Using techniques from the field of learning analytics and educational data mining, we provide valuable insights into the multi-device use in technology-enhanced learning environments from several view points.

In this chapter, we first briefly summarize the main findings of our work and dedicate special attention to the impact of the present work and its implications, both for research and practice. Finally, we conclude the thesis with fruitful avenues for future work.

9.1 Summary of the present work

The present thesis serves as one of the first examples on how the techniques from learning analytics can be leveraged to gain insights on learning processes of students adopting various technological modalities.

In Chapter 4, we present the sequential and simultaneous patterns of usage of multiple modalities together for engaging with the learning management system for self-regulatory activities. We found distinct patterns of usage such as *short-desktop* and *mobile-oriented* and based on the usage of such patterns, we were able to derive meaningful clusters of students, representing their unique technological modality strategy. We also demonstrate how learner's choice of modality, and by extension his/her modality strategy, has a significant impact on their learning outcomes and performance at discussion activities. There are important implications of such results since so far only limited attention has been paid to the role of modality in formal learning [219]. Our results provide strong theoretical foundation for the need for educators to be aware of what modalities students have access to and how they use them. In particular, being aware of the nuances associated with using each modality will allow educators to provide better support to their students and design appropriate learning experiences. For instance, exploitation of the potential of different modalities for personalization of learning experiences, and seamless integrated within everyday activities.

In Chapter 5, we analyze the aspect of time, associated with use of multiple modalities i.e. *when* do learners utilize a modality to engage in learning activities. Given that learners possess unique time-management strategies [271] and chronotype i.e. morningness-eveningness preference [160], it is pragmatic to speculate that there exists some associations between modality-usage and temporal preferences. The results presented in this chapter offer support for this hypothesis as significant associations between modality-usage patterns and specific times during the day were observed. For instance, mobile and short-desktop sessions were more prominent during afternoon and night time, respectively. Not only that, depending on whether the learning session took place on a weekend or weekday, specific modality usage was more prominent than others. These and similar observations are extremely useful from a design perspective as they provide LMS designers with the understanding of how learning activities are distributed across different contexts. By understanding the temporal aspect associated with a modality, not only can they design systems which send learners their notifications and reminders on their preferred modality, but more importantly, it improves the *accessibility* of these prompts i.e. a learner's chances of acting upon them are maximized.

In Chapter 6, we highlight the usefulness of capturing a learning action's modality in learner models for improving the prediction accuracy. Most conventional learner models are modality-agnostic, meaning they are generated from logs that do not take into account the modality utilized by the learner to perform a learning action. Our results confirm that models where predictor measures were partitioned based on the modality (desktop, mobile and tablet) were significantly better at predicting student's course grade, compared to the null model wherein predictors were generated from cumulative measure. From a practical standpoint, these results indicate that much like contextual factors such as instructional conditions [87], student's learning approaches [185], and their personality traits [42] are known to influence the outcome of prediction models, similarly, modality-source of the logged trace data, has a better potential for explaining the variability in student learning outcome compared to a generalized linear model, one that uses cumulative measures of predictor variables. Moreover, our study also identified important differences with respect to the learning activity since the magnitude and direction of the variance in the learning outcome, explained by the modality, was found to differ based on the learning activity.

In Chapter 7, we reveal the consistency with which different modalities are used for subsequent phases of a learning activity and their impact on the academic outcomes. We derived consistency profiles to conduct an exploratory analysis into the habits or effort and participation using various modalities. Contrary to our initial hypothesis that mobile modality would be utilized more for initial phases of an activity, their use was constant throughout the semester. Desktops, on the other hand varied considerably during subsequent learning activities. The results render some perspective to the discussion surrounding utility of a consistent vs. evolving learning approach, and provide evidence suggesting that an increment in the consistency levels of modality-usage is not always an indicator of academic success, given that some of the most consistent learners were also found to be the worst academic performers. These findings have important research implications for researchers using entropy or standard deviation of LMS activity measures (counts and time spent) as a measure of consistency, and subsequently high academic achievement, since it could be the case that high consistency has been achieved as result of series of bad engagement patterns from a modality which the learner is failing to correct.

9.2 Impact of the present Work

In this section, we revisit some of the higher level research goals introduced at the beginning of the thesis (in Section 3.6.3)

9.2.1 Research Goal I: Access to and use of multiple devices

The findings show that students in blended learning environments engage with both stationary and handheld devices in order to access learning material on the LMS. However, the use of desktop PCs, laptops and mobile phones was predominant while fewer tablet use was observed. These findings are similar to the results of the 2016 ECAR study [29] that found desktop-mobile combination as the most common modality combination that learners own.

We detected a very small overlap in terms of usage of different modalities within the same learning session (5% of sessions were of types *mixed* i.e. composed of two or more modalities). We also found that usage of the desktop modality differed based on the number of actions completed on them. That is, students engaged in both short and long sessions on the desktop modality whereas sessions on the mobile modality were mostly uniform (see Figure 4.2).

9.2.2 Research Goal II: Learning activities and Modality affordances

Given the blended nature of learning, the use of modalities was observed for a range of learning-related tasks within the LMS environment such as accessing assignments, quizzes, discussions, course-related material and participating in online discussions (see Table 4.1). All these activities witnessed greater use of desktop modality as compared to mobiles, except course management and planning where the reverse was true. The latter can be explained by the small screen of mobiles conducive to performing management tasks on-the-go like accessing calendar or checking notifications. In fact, our results revealed that mobile phones are being used in supportive roles mainly since their use was almost non-existent for two main learning activities i.e. assignment and discussions. Our results resonate with those of [145] who revealed that 'handheld devices such as tablets and smartphones are seen as supplementary by students in online learning contexts. As a result, the large screen desktop and laptops still continue to dominate the learning environments.

9.2.3 Research Goal III: Temporal associations with modalities

The findings revealed some significant associations, not only between patterns of modality usage and time of the day (TOD), but also with day of the week. In brief, mobile sessions were found more prominent in the afternoon whereas short-desktop sessions at night. More interestingly, the modality-TOD associations were similar on weekdays and weekends for strategic and minimalist learners, two groups which are strikingly different in terms of their academic performances. From a practical perspective, these associations can be leveraged for customizing recommender systems such that notifications and feedbacks are delivered on appropriate modalities, not at random or inappropriate times, but when the learner can act upon them.

9.2.4 Research Goal IV: Modalities and Academic Success

The findings revealed significant associations not only between the learner's modality strategies and their overall course grade but also between these strategies and their performance at specific learning tasks, such as online discussions. Surprisingly, and contrary to what was expected, learners with heavy use of mobile phones (intensive learners) were not able to outperform those who made limited use of mobile phones (strategic learners) and in fact there were instances where quality (referential cohesion and syntactic simplicity) of intensive students' discussion messages was significantly lower than strategic learners'.

Leveraging these associations, we were also able to prove the usefulness of metrics based on the modalities for modeling learner achievements. That is, we were able to improve upon the course-specific learner models by accounting for the modality through which a learner accesses elements of LMS. In the process of doing so, we unveiled how impact of a modality on a learning task can either positively or negatively impact predictions, thus presenting a more nuanced view of how technological modality may matter for learning.

9.3 Directions for future work

There are many promising directions for future work to expand the findings from this thesis. Apart from the ones mentioned in the four main chapters (Chapter 4 - Chapter 7), we discuss here a few general research findings that would benefit from further exploration and research.

Our research was focused exclusively in a blended learning context. Given the importance of learning contexts on students' learning behaviours [24, 87], an important direction for future research is an examination of the extent to which findings from this study are replicated in other contexts. For instance, similar research assessing multi-device use in learning settings could be designed and conducted in online institutions, where much of the coursework and learner-learner interactions happen online. Additionally, much of the analyses in our research was conducted using data from undergraduate level STEM courses. While the use of different modalities was prevalent in these courses, it might be the case that modality-use strategies identified in Chapter 4 differ in courses from other domains with a different course organization and structure, for example, a graduate psychology class.

In addition to understanding the role of course context on the patterns of modality usage, an important area of future work relates to the role of instructor autonomy/guidance on use of modalities. Our research was based in a context where the learning experiences were designed such that the extent of modality-usage was entirely under learner autonomy. That is, the usage was unstructured as opposed to structured use wherein technology is embedded within a learning tasks so as to enhance the overall learning process (for instance, short lectures followed by extensive practice on the laptop [127]). In future, it would be interesting to see variations in the behavior, mainly time-of-day preferences of modality-usage presented in Chapter 5, once *structured* modality-use is introduced as a pedagogical intervention. We hypothesize that structured use may significantly impact the time-management strategies i.e. how time is spent for on-task activities from various modalities, and also peculiarities surrounding their preferences for day of the week for learning.

From the analysis of the user-agents in our trace data, we identified desktop, smartphones and also tablets (to some extent) as the main modalities used by students. However, in future, there is a possibility that with emergence of newer technologies, student preferences as well as associated patterns of usage of these contemporary modalities might be impacted. Thus, a consideration for future research is a systematic review of the newer technologies such as wearables and their influence on work habits. The recognition of new technologies in learning arena would also prove beneficial for improving the modality-inclusive learner models presented in Chapter 6, since the newer modalities might prove more relevant for explaining the variance in academic outcomes.

Finally, key findings surrounding the consistency of modality usage in Chapter 7 focused on within-activity patterns mainly. A suggestion for future research is to track students longitudinally over the course of their studies to determine how patterns of use are developed and change over time (especially with the introduction of new modalities). Though difficult to administer, such studies would help in revealing modalities that are conducive or detrimental to learning activities, after assessing learning trends and outcomes over time.

Bibliography

[1] Call for papers, 1st international conference on learning analytics and knowledge 2011, 2011. URL `https://tekri.athabascau.ca/analytics/`.

[2] Ecar study of undergraduate students and information technology, 2012. URL `https://library.educause.edu/resources/2012/9/ecar-study-of-\undergraduate-students-and-information-technology-2012`.

[3] Saeed Aghabozorgi, Ali Seyed Shirkhorshidi, and Teh Ying Wah. Time-series clustering–a decade review. *Information Systems*, 53:16–38, 2015.

[4] Nancy M Aguilar-Roca, Adrienne E Williams, and Diane K O'Dowd. The impact of laptop-free zones on student performance and attitudes in large lectures. *Computers & Education*, 59(4):1300–1308, 2012.

[5] Alireza Ahadi, Raymond Lister, Shahil Lal, Juho Leinonen, and Arto Hellas. Performance and consistency in learning to program. In *ACM International Conference Proceeding Series*, 2017.

[6] Mohamed Ally and Josep Prieto-Blázquez. What is the future of mobile learning in education? *International Journal of Educational Technology in Higher Education*, 11 (1):142–151, 2014.

[7] Mohamed Ally and Avgoustos Tsinakos. Increasing access through mobile learning, 2014.

[8] Wafaa Alsaggaf, Margaret Hamilton, James Harland, and Daryl D'Souza. The use of laptop computers in programming lectures. In *ACIS 2012: Location, location, location: Proceedings of the 23rd Australasian Conference on Information Systems 2012*, pages 1–11. ACIS, 2012.

[9] Oren Anava, Elad Hazan, Shie Mannor, and Ohad Shamir. Online learning for time series prediction. In *Conference on learning theory*, pages 172–184, 2013.

[10] Muhammad Anshari, Mohammad Nabil Almunawar, Masitah Shahrill, Danang Kuncoro Wicaksono, and Miftachul Huda. Smartphones usage in the classrooms: Learning aid or interference? *Education and Information Technologies*, 22(6):3063–3079, 2017.

[11] Per Arneberg, Lourdes Guardia, Desmond Keegan, Jüri Lõssenko, Ildikó Mázár, P Michels, and Torstein Rekkedal. Analyses of european megaproviders of e-learning. *Megatrends Project*, 2007.

[12] Kimberly E Arnold and Matthew D Pistilli. Course signals at purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd international conference on learning analytics and knowledge*, pages 267–270. ACM, 2012.

[13] Michael A Babyak. What you see may not be what you get: a brief, nontechnical introduction to overfitting in regression-type models. *Psychosomatic medicine*, 66(3): 411–421, 2004.

[14] Ryan Shaun Baker and Paul Salvador Inventado. Educational data mining and learning analytics. In *Learning analytics*, pages 61–75. Springer, 2014.

[15] Ryan SJD Baker and Kalina Yacef. The state of educational data mining in 2009: A review and future visions. *JEDM| Journal of Educational Data Mining*, 1(1):3–17, 2009.

[16] Miri Barak, Alberta Lipson, and Steven Lerman. Wireless laptops as means for promoting active learning in large lecture halls. *Journal of Research on Technology in Education*, 38(3):245–263, 2006.

[17] E Barbera, B Gros, and PA Kirschner. Paradox of time in research on educational technology. *Time & Society*, 24(1):96–108, 2015.

[18] Owen Barden and Mark Bygroves. 'i wouldn't be able to graduate if it wasn't for my mobile phone.'the affordances of mobile devices in the construction of complex academic texts. *Innovations in Education and Teaching International*, 55(5):555–565, 2018.

[19] T Mark Beasley and Randall E Schumacker. Multiple regression approach to analyzing contingency tables: Post hoc and planned comparison procedures. *The Journal of Experimental Education*, 64(1):79–93, 1995.

[20] Sanam Shirazi Beheshitha, Marek Hatala, Dragan Gašević, and Srećko Joksimović. The role of achievement goal orientations when studying effect of learning analytics visualizations. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*, pages 54–63. ACM, 2016.

[21] Héfer Bembenutty. Academic delay of gratification, self-efficacy, and time management among academically unprepared college students. *Psychological Reports*, 104(2):613–623, 2009.

[22] MJF Blake. Relationship between circadian rhythm of body temperature and introversion–extraversion. *Nature*, 215(5103):896, 1967.

[23] James H Bray, Scott E Maxwell, and Scott E Maxwell. *Multivariate analysis of variance*. Number 54. Sage, 1985.

[24] Jaclyn Broadbent. Comparing online and blended learner's self-regulated learning strategies and academic performance. *The Internet and Higher Education*, 33:24–32, 2017.

[25] Jim Broadbent and Walter L Poon. Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, 27:1–13, 2015.

[26] Guy Brock, Vasyl Pihur, Susmita Datta, Somnath Datta, et al. clvalid, an r package for cluster validation. *J. of Statistical Software*, 25(4), 2011.

[27] Christopher Brooks and Craig Thompson. Predictive Modelling in Teaching and Learning. In Charles Lang, George Siemens, Alyssa Friend Wise, and Dragan Gašević, editors, *The Handbook of Learning Analytics*, pages 61–68. Society for Learning Analytics Research (SoLAR), Alberta, Canada, 1 edition, 2017. ISBN 978-0-9952408-0-3. URL `http://solaresearch.org/hla-17/hla17-chapter1`.

[28] Christopher Brooks, Craig Thompson, and Stephanie Teasley. A time series interaction analysis method for building predictive models of learners using log data. In *Proceedings of the fifth international conference on learning analytics and knowledge*, pages 126–135. ACM, 2015.

[29] D Christopher Brooks. Ecar study of undergraduate students and information technology. Technical report, 2016, 2016.

[30] D Christopher Brooks and Jeffrey Pomerantz. Ecar study of undergraduate students and information technology, 2017. *EDUCAUSE*, 2017. URL `https://library.educause.edu/resources/2017/10/ecar-study-of-undergraduate-students-and-information-technology-2017`.

[31] Abbie Brown and Tim Green. Issues and trends in instructional technology: Growth and maturation of web-based tools in a challenging climate; social networks gain educators' attention. In *Educational media and technology yearbook*, pages 29–43. Springer, 2010.

[32] Abbie Brown and Tim Green. Issues and trends in instructional technology: Lean times, shifts in online learning, and increased attention to mobile devices. In *Educational media and technology yearbook*, pages 67–80. Springer, 2012.

[33] Aaron T Brubaker. Faculty perceptions of the impact of student laptop use in a wireless internet environment on the classroom learning environment and teaching. 2006.

[34] Peter Brusilovsky, I-Han Hsiao, and Yetunde Folajimi. Quizmap: open social student modeling and adaptive navigation support with treemaps. In *European Conference on Technology Enhanced Learning*, pages 71–82. Springer, 2011.

[35] Susan Bull, Adam Thomas McEVOY, and Eileen Reid. Learner models to promote reflection in combined desktop pc/mobile intelligent learning environments. In *Proceedings of Workshop on Learner Modelling for Reflection, Supplementary Proceedings of the 11th International Conference*, volume 5, pages 199–208. Citeseer, 2003.

[36] Dave Burnapp. Trajectories of adjustment of international students: U-curve, learning curve, or third space. *Intercultural Education*, 17(1):81–93, 2006.

[37] John P Campbell, Peter B DeBlois, and Diana G Oblinger. Academic analytics: A new tool for a new era. *Educause Review*, 42(4):40, 2007.

[38] María José Casany Guerrero, Marc Alier Forment, Nikolaos Galanis, Enric Mayol Sarroca, and Jordi Piguillem Poch. Analyzing moodle/lms logs to measure mobile access. In *UBICOMM 2012: The Sixth International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies*, pages 35–40, 2012.

[39] Daniel F Chambliss and Russell K Schutt. Making sense of the social world: Methods of investigation. chapter 5. Sage Publications, 2018. URL `https://www.sagepub.com/sites/default/files/upm-binaries/23639_Chapter_5___Causation_and_Experimental_Design.pdf`.

[40] Mohamed Amine Chatti, Vlatko Lukarov, Hendrik Thüs, Arham Muslim, Ahmed Mohamed Fahmy Yousef, Usman Wahid, Christoph Greven, Arnab Chakrabarti, and Ulrik Schroeder. Learning analytics: Challenges and future research directions. *eleed*, 10(1), 2014.

[41] Gwo-Dong Chen, Chih-Kai Chang, and Chih-Yeh Wang. Ubiquitous learning website: Scaffold learners by mobile devices with information-aware techniques. *Computers & education*, 50(1):77–90, 2008.

[42] Sue-Jen Chen and Edward J Caropreso. Influence of personality on online discussion. *Journal of Interactive Online Learning*, 3(2):1–17, 2004.

[43] Xiao-Bin Chen. Tablets for informal language learning: Student usage and attitudes. *Language learning & technology*, 17(1):20–36, 2013.

[44] Jongpil Cheon, Sangno Lee, Steven M Crooks, and Jaeki Song. An investigation of mobile learning readiness in higher education based on the theory of planned behavior. *Computers & education*, 59(3):1054–1064, 2012.

[45] Simon KS Cheung. A study on the use of mobile devices for distance learning. In *International Conference on Hybrid Learning*, pages 89–98. Springer, 2012.

[46] Tosti HC Chiang, Stephen JH Yang, and Gwo-Jen Hwang. Students' online interactive patterns in augmented reality-based inquiry activities. *Computers & Education*, 78: 97–108, 2014.

[47] Geraldine Clarebout, Jan Elen, Norma A Juarez Collazo, Griet Lust, and Lai Jiang. Metacognition and the use of tools. In *International handbook of metacognition and learning technologies*, pages 187–195. Springer, 2013.

[48] Jacob Cohen. A power primer. *Psychological bulletin*, 112(1):155, 1992.

[49] Sean Collins. Prediction techniques for box–cox regression models. *Journal of Business & Economic Statistics*, 9(3):267–277, 1991.

[50] R Dennis Cook. Influential observations in linear regression. *Journal of the American Statistical Association*, 74(365):169–174, 1979.

[51] Tarsem Singh Cooner. Creating opportunities for students in large cohorts to reflect in and on practice: Lessons learnt from a formative evaluation of students' experiences of a technology-enhanced blended learning design. *British Journal of Educational Technology*, 41(2):271–286, 2010.

[52] Jonathan Copley. Audio and video podcasts of lectures for campus-based students: production and evaluation of student use. *Innovations in education and teaching international*, 44(4):387–399, 2007.

[53] Simon Cross, Mike Sharples, and Graham Healing. Learning with mobile devices: the changing place and space of distance learners' study. 2016.

[54] Eden Dahlstrom, JD Walker, and Charles Dziuban. Ecar study of undergraduate students and information technology. Technical report, 2013, 2013.

[55] Jesus Alfonso D Datu, Jana Patricia M Valdez, and Ronnel B King. Perseverance counts but consistency does not! validating the short grit scale in a collectivist setting. *Current Psychology*, 35(1):121–130, 2016.

[56] Alexandra Davidson and Kerry Lynn Ritchie. The early bird catches the worm! the impact of chronotype and learning style on academic success in university students. *Teaching and Learning Innovations*, 18, 2016.

[57] Shane Dawson, Dragan Gašević, George Siemens, and Srećko Joksimović. Current state and future trends: A citation network analysis of the learning analytics field. In *Proceedings of the fourth international conference on learning analytics and knowledge*, pages 231–240. ACM, 2014.

[58] Beth Dietz-Uhler and Janet E Hurn. Using learning analytics to predict (and improve) student success: A faculty perspective. *Journal of interactive online learning*, 12(1): 17–26, 2013.

[59] Åge Diseth. Approaches to learning, course experience and examination grade among undergraduate psychology students: Testing of mediator effects and construct validity. *Studies in Higher Education*, 32(3):373–388, 2007.

[60] Xu Du, Mingyan Zhang, Brett E Shelton, and Jui-Long Hung. Learning anytime, anywhere: a spatio-temporal analysis for online learning. *Interactive Learning Environments*, pages 1–15, 2019.

[61] Steve Duck, Deborah J Rutt, Margaret Hoy, and Hurst Heather Strejc. Some evident truths about conversations in everyday relationships all communications are not created equal. *Human communication research*, 18(2):228–267, 1991.

[62] Charles Duhigg. *The Power of Habit: Why we do what we do and how to change.* Random House, 2013.

[63] Hakan Dündar and Murat Akçayır. Tablet vs. paper: The effect on learners' reading performance. *International Electronic Journal of Elementary Education*, 4(3):441–450, 2017.

[64] Joseph C Dunn. Well-separated clusters and optimal fuzzy partitions. *J. of cybernetics*, 4(1):95–104, 1974.

[65] Muharrem Duran and Tufan Aytaç. Students' opinions on the use of tablet computers in education. *European Journal of Contemporary Education*, 15(1):65–75, 2016.

[66] Tomas Dvorak and Miaoqing Jia. Do the timeliness, regularity, and intensity of online work habits predict academic performance?. *J. of Learning Analytics*, 3(3):318–330, 2016.

[67] Susan Dynarski. Laptops are great. but not during a lecture or a meeting. *The New York Times*, 2017.

[68] The Economist. Beyond the pc, Oct 2011. URL `https://www.economist.com/node/21531109`.

[69] Bradford Lee Eden, Alexandros Koulouris, and Angelos Anagnostopoulos. Theses e-submission tool at the national technical university of athens. *OCLC Systems & Services: International digital library perspectives*, 2010.

[70] Robert Edmunds and John TE Richardson. Conceptions of learning, approaches to studying and personal development in uk higher education. *Br. J. Educ. Psychol.*, 79 (2):295–309, 2009.

[71] Rachel H Ellaway, Patricia Fink, Lisa Graves, and Alanna Campbell. Left to their own devices: medical learners' use of mobile technologies. *Medical teacher*, 36(2):130–138, 2014.

[72] Brent J Evans, Rachel B Baker, and Thomas S Dee. Persistence patterns in massive open online courses (moocs). *The J. of Higher Education*, 87(2):206–242, 2016.

[73] Helen Farley, Angela Murphy, Chris Johnson, Brad Carter, Michael Lane, Warren Midgley, Abdul Hafeez-Baig, Stijn Dekeyser, and Andy Koronios. How do students use their mobile devices to support learning? a case study from an australian regional university. *J. of Interactive Media in Education*, 2015(1), 2015.

[74] Janet M Ferguson. Middle school students' reactions to a 1: 1 ipad initiative and a paperless curriculum. *Education and Information Technologies*, 22(3):1149–1162, 2017.

[75] Rebecca Ferguson. Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, 4(5):304–317, 2012.

[76] Andy Field. *Discovering statistics using SPSS*. Sage publications, 2009.

[77] Oliver Edmund Fincham, Dragan V Gasevic, Jelena M Jovanovic, and Abelardo Pardo. From study tactics to learning strategies: An analytical method for extracting interpretable representations. *IEEE Transactions on Learning Technologies*, 2018.

[78] Catherine Finnegan, Libby V Morris, and Kangjoo Lee. Differences by course discipline on student behavior, persistence, and achievement in online courses of undergraduate general education. *Journal of College Student Retention: Research, Theory & Practice*, 10(1):39–54, 2008.

[79] Joel E Fischer, Nick Yee, Victoria Bellotti, Nathan Good, Steve Benford, and Chris Greenhalgh. Effects of content and time of delivery on receptivity to mobile interruptions. In *Proceedings of the 12th international conference on Human computer interaction with mobile devices and services*, pages 103–112. ACM, 2010.

[80] Tak-chung Fu. A review on time series data mining. *Engineering Applications of Artificial Intelligence*, 24(1):164–181, 2011.

[81] Giovanni Fulantelli, Davide Taibi, and Marco Arrigo. A semantic approach to mobile learning analytics. In *Proceedings of the First International Conference on Technological Ecosystem for Enhancing Multiculturality*, pages 287–292. ACM, 2013.

[82] Giovanni Fulantelli, Davide Taibi, and Marco Arrigo. A framework to support educational decision making in mobile learning. *Computers in Human Behavior*, 47:50–59, 2015.

[83] Alexis Gabadinho, Gilbert Ritschard, Nicolas Séverin Mueller, and Matthias Studer. Analyzing and visualizing state sequences in r with traminer. *J. of Statistical Software*, 40(4):1–37, 2011.

[84] Dana C. Gierdowski Galanek, Joseph D. and D. Christopher Brooks. Ecar study of undergraduate students and information technology, 2018. URL `https://library.educause.edu/resources/2018/10/2018-students-and-technology-research-study`.

[85] D Randy Garrison and Norman D Vaughan. *Blended learning in higher education: Framework, principles, and guidelines*. John Wiley & Sons, 2008.

[86] Dragan Gašević, Shane Dawson, and George Siemens. Let's not forget: Learning analytics are about learning. *TechTrends*, 59(1):64–71, 2015.

[87] Dragan Gašević, Shane Dawson, Tim Rogers, and Danijela Gasevic. Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, 28:68–84, 2016.

[88] Patrick Gaudreau, Dave Miranda, and Alexandre Gareau. Canadian university students in wireless classrooms: What do they do on their laptops and does it really matter? *Computers & Education*, 70:245–255, 2014.

[89] Toni Giorgino et al. Computing and visualizing dynamic time warping alignments in r: the dtw package. *J. of Statistical Software*, 31(7):1–24, 2009.

[90] Gene V Glass, Percy D Peckham, and James R Sanders. Consequences of failure to meet assumptions underlying the fixed effects analyses of variance and covariance. *Review of educational research*, 42(3):237–288, 1972.

[91] Peter Goodyear. Emerging methodological challenges for educational research. In *Methodological choice and design*, pages 253–266. Springer, 2011.

[92] Sten Govaerts, Katrien Verbert, Erik Duval, and Abelardo Pardo. The student activity meter for awareness and self-reflection. In *CHI'12 Extended Abstracts on Human Factors in Computing Systems*, pages 869–884. ACM, 2012.

[93] Arthur C Graesser, Danielle S McNamara, Max M Louwerse, and Zhiqiang Cai. Coh-metrix: Analysis of text on cohesion and language. *Behavior research methods, instruments, & computers*, 36(2):193–202, 2004.

[94] Arthur C Graesser, Danielle S McNamara, and Jonna M Kulikowich. Coh-metrix: Providing multilevel analyses of text characteristics. *Educational researcher*, 40(5): 223–234, 2011.

[95] David Green, Essendran Naidoo, Caroline Olminkhof, and Laurel Evelyn Dyson. Tablets@ university: The ownership and use of tablet devices by students. *Australasian Journal of Educational Technology*, 32(3), 2016.

[96] Scott W Greenwald, Mina Khan, Christian D Vazquez, and Pattie Maes. Tagalong: Informal learning from a remote companion with mobile perspective sharing. 2015.

[97] Keith Gregory and Sue Morón-García. Assignment submission, student behaviour and experience. *Engineering Education*, 4(1):16–28, 2009.

[98] Anna Gromada and Claire Shewbridge. Student learning time. 2016.

[99] Janis Grundspenkis, Jurijs Lavendels, L Novitsky, and Vjaceslavs Sitikovs. Compatibility of the principles of computer-based and classical teachings. In *Proceeding of IADIS International Conference "Web Based Communities 2006*, pages 335–339, 2006.

[100] James Cengiz Gulek and Hakan Demirtas. Learning with technology: The impact of laptop use on student achievement. *The journal of technology, learning and assessment*, 3(2), 2005.

[101] Chad Habel and Matthew Stubbs. Mobile phone voting for participation and engagement in a large compulsory law course. *Research in Learning Technology*, 22, 2014.

[102] Alyse C Hachey, Claire W Wladis, and Katherine M Conway. Do prior online course outcomes provide more information than gpa alone in predicting subsequent online course grades and retention? an observational study at an urban community college. *Computers & Education*, 72:59–67, 2014.

[103] Allyson F Hadwin, John C Nesbit, Dianne Jamieson-Noel, Jillianne Code, and Philip H Winne. Examining trace data to explore self-regulated learning. *Metacognition and Learning*, 2(2-3):107–124, 2007.

[104] John Hattie and Helen Timperley. The power of feedback. *Review of educational research*, 77(1):81–112, 2007.

[105] Abigail Hawkins, Charles R Graham, Richard R Sudweeks, and Michael K Barbour. Academic performance, course completion rates, and student perception of the quality and frequency of interaction in a virtual high school. *Distance Education*, 34(1):64–83, 2013.

[106] Houston Heflin, Jennifer Shewmaker, and Jessica Nguyen. Impact of mobile technology on student attitudes, engagement, and learning. *Computers & Education*, 107: 91–99, 2017.

[107] Lauren C Hensley, Christopher A Wolters, Sungjun Won, and Anna C Brady. Academic probation, time management, and time use in a college success course. *J. of College Reading and Learning*, 48(2):105–123, 2018.

[108] Danielle Herro, Derick Kiger, and Carl Owens. Mobile technology: Case-based suggestions for classroom integration and teacher educators. *Journal of Digital Learning in Teacher Education*, 30(1):30–40, 2013.

[109] Whitney Hess. Location agnostic, context specific, Oct 2015. URL `https://whitneyhess.com/blog/2012/02/07/location-agnostic-context-specific/`.

[110] Matissa Hollister. Is optimal matching suboptimal? *Sociological Methods & Research*, 38(2):235–264, 2009.

[111] Jui-Long Hung and Ke Zhang. Revealing online learning behaviors and activity patterns and making predictions with data mining techniques in online teaching. *MERLOT Journal of Online Learning and Teaching*, 2008.

[112] Jui-Long Hung, Morgan C Wang, Shuyan Wang, Maha Abdelrasoul, Yaohang Li, and Wu He. Identifying at-risk students for early interventions - a time-series clustering approach. *IEEE TECT*, 5(1):45–55, 2015.

[113] Heike Itzek-Greulich, Christoph Randler, and Christian Vollmer. The interaction of chronotype and time of day in a science course: Adolescent evening types learn more and are more motivated in the afternoon. *Learning and Individual Differences*, 51: 189–198, 2016.

[114] Dennis L Jackson. Revisiting sample size and number of parameter estimates: Some support for the n: q hypothesis. *Structural equation modeling*, 10(1):128–141, 2003.

[115] Martin Jenkins. Unfulfilled promise: formative assessment using computer-aided assessment. *Learning and teaching in higher education*, (1):67–80, 2005.

[116] Lai Jiang, Jan Elen, and Geraldine Clarebout. Learner variables, tool-usage behaviour and performance in an open learning environment. In *Beyond Knowledge: The Legacy of Competence*, pages 257–266. Springer, 2008.

[117] Il-Hyun Jo, Taeho Yu, Hyeyun Lee, and Yeonjoo Kim. Relations between student online learning behavior and academic achievement in higher education: A learning analytics approach. In *Emerging issues in smart learning*, pages 275–287. Springer, 2015.

[118] Srećko Joksimović, Dragan Gašević, Thomas M Loughin, Vitomir Kovanović, and Marek Hatala. Learning at distance: Effects of interaction traces on academic achievement. *Computers & Education*, 87:204–217, 2015.

[119] Srećko Joksimović, Nia Dowell, Oleksandra Poquet, Vitomir Kovanović, Dragan Gašević, Shane Dawson, and Arthur C Graesser. Exploring development of social capital in a cmooc through language and discourse. *The Internet and Higher Education*, 36: 54–64, 2018.

[120] Jelena Jovanović, Dragan Gašević, Shane Dawson, Abelardo Pardo, and Negin Mirriahi. Learning analytics to unveil learning strategies in a flipped classroom. *The Internet and Higher Education*, 33(4):74–85, 2017.

[121] Jelena Jovanovic, Dragan Gasevic, Shane Dawson, Abelardo Pardo, and Negin Mirriahi. Learning analytics to unveil learning strategies in a flipped classroom. 33, 02 2017.

[122] Jelena Jovanovic, Negin Mirriahi, Dragan Gašević, Shane Dawson, and Abelardo Pardo. Predictive power of regularity of pre-class activities in a flipped classroom. *Computers & Education*, 134:156–168, 2019.

[123] Reynol Junco and Shelia R Cotten. No a 4 u: The relationship between multitasking and academic performance. *Computers & Education*, 59(2):505–514, 2012.

[124] Leonard Kaufman and Peter Rousseeuw. *Finding Groups in Data: An Introduction To Cluster Analysis*. 01 1990. ISBN 0-471-87876-6.

[125] Robin Kay. Addressing gender differences in computer ability, attitudes and use: The laptop effect. *Journal of Educational Computing Research*, 34(2):187–211, 2006.

[126] Robin Kay and Sharon Lauricella. Assessing laptop use in higher education: The laptop use scale. *Journal of Computing in Higher Education*, 28(1):18–44, 2016.

[127] Robin H Kay and Sharon Lauricella. Unstructured vs. structured use of laptops in higher education. *Journal of Information Technology Education*, 10(1):33–42, 2011.

[128] Robin Holding Kay and Sharon Lauricella. Investigating the benefits and challenges of using laptop computers in higher education classrooms. *Canadian Journal of Learning and Technology/La revue canadienne de l'apprentissage et de la technologie*, 40(2), 2014.

[129] Derick Kiger, Dani Herro, and Deb Prunty. Examining the influence of a mobile learning intervention on third grade math achievement. *Journal of Research on Technology in Education*, 45(1):61–82, 2012.

[130] Dongho Kim, Yeonjeong Park, Meehyun Yoon, and Il-Hyun Jo. Toward evidence-based learning analytics: Using proxy variables to improve asynchronous online discussion environments. *The Internet and Higher Education*, 30:30–43, 2016.

[131] Sang-Wook Kim, Sanghyun Park, and Wesley W Chu. An index-based approach for similarity search supporting time warping in large sequence databases. In *Proceedings 17th International Conference on Data Engineering*, pages 607–614. IEEE, 2001.

[132] René F Kizilcec, Chris Piech, and Emily Schneider. Deconstructing disengagement: analyzing learner subpopulations in massive open online courses. In *Proceedings of the third international conference on learning analytics and knowledge*, pages 170–179. ACM, 2013.

[133] René F Kizilcec, Mar Pérez-Sanagustín, and Jorge J Maldonado. Self-regulated learning strategies predict learner behavior and goal attainment in massive open online courses. *Computers & education*, 104:18–33, 2017.

[134] Rex B Kline. *Principles and practice of structural equation modeling*. Guilford publications, 2015.

[135] Rex Bryan Kline. Supplemental chapter on multivariate effect size estimation multivariate effect size estimation in two-group designs. URL https://www.semanticscholar.org/paper/Supplemental-Chapter-on-Multivariate-Effect-Size-in-Kline/0807834e67e569302252bf6a1e554fb477dd807c#citing-papers.

[136] James Knaub. Practical interpretation of hypothesis tests - letter to the editor - tas. 41:246–247, 08 1987.

[137] Jasper Knight. Distinguishing the learning approaches adopted by undergraduates in their use of online resources. *Active Learning in Higher Education*, 11(1):67–76, 2010.

[138] S Kolari, C Savander-Ranne, and E-L Viskari. Learning needs time and effort: a time-use study of engineering students. *European Journal of Engineering Education*, 33(5-6):483–498, 2008.

[139] Marguerite Koole and Mohamed Ally. Framework for the rational analysis of mobile education (frame): A model for evaluating mobile learning devices. In *MDE thesis. Athabasca University, Athabasca.* Citeseer, 2006.

[140] Marguerite L Koole. A model for framing mobile learning. *Mobile learning: Transforming the delivery of education and training*, 1(2):25–47, 2009.

[141] Vitomir Kovanović, Dragan Gašević, Shane Dawson, Srećko Joksimović, Ryan S Baker, and Marek Hatala. Penetrating the black box of time-on-task estimation. In *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge*, pages 184–193. ACM, 2015.

[142] Vitomir Kovanović, Dragan Gašević, Srećko Joksimović, Marek Hatala, and Olusola Adesope. Analytics of communities of inquiry: Effects of learning technology use on cognitive presence in asynchronous online discussions. *The Internet and Higher Education*, 27:74–89, 2015.

[143] Vitomir Kovanović, Dragan Gašević, Shane Dawson, Srećko Joksimović, and Ryan Baker. Does time-on-task estimation matter? implications on validity of learning analytics findings. *J. of Learning Analytics*, 2(3):81–110, 2016.

[144] Vitomir Kovanović, Srećko Joksimović, Zak Waters, Dragan Gašević, Kirsty Kitto, Marek Hatala, and George Siemens. Towards automated content analysis of discussion transcripts: A cognitive presence case. In *Proceedings of the sixth international conference on learning analytics & knowledge*, pages 15–24. ACM, 2016.

[145] Greig Emil Krull. *Supporting seamless learning: Students' use of multiple devices in open and distance learning universities.* PhD thesis, Universitat Oberta de Catalunya, 2017.

[146] Agnes Kukulska-Hulme. Learning cultures on the move: Where are we heading? *Journal of Educational Technology & Society*, 13(4):4–14, 2010.

[147] Jeffrey H Kuznekoff and Scott Titsworth. The impact of mobile phone usage on student learning. *Communication Education*, 62(3):233–252, 2013.

[148] C-H Lai, J-C Yang, F-C Chen, C-W Ho, and T-W Chan. Affordances of mobile technologies for experiential learning: the interplay of technology and pedagogical practices. *Journal of Computer Assisted Learning*, 23(4):326–337, 2007.

[149] Cheng-Ping Lai, Pau-Choo Chung, and Vincent S Tseng. A novel two-level clustering method for time series data analysis. *Expert Systems with Applications*, 37(9):6319–6326, 2010.

[150] Sawsen Lakhal and Hager Khechine. Student intention to use desktop web-conferencing according to course delivery modes in higher education. *The International Journal of Management Education*, 14(2):146–160, 2016.

[151] Yu-Ju Lan, Yao-tin Sung, and Kuo-En Chang. A mobile-device-supported peer-assisted learning system for collaborative early efl reading. 2007.

[152] Lesley F Leach and Robin K Henson. The use and impact of adjusted r2 effects in published regression research. *Multiple Linear Regression Viewpoints*, 33(1):1–11, 2007.

[153] Chwee Beng Lee. Exploring the relationship between intention to use mobile phone as a visualization tool and regulation of cognition. *Computers & Education*, 60(1): 138–147, 2013.

[154] Heyoung Lee, Heejune Ahn, Trung Giang Nguyen, Sam-Wook Choi, and Dae Jin Kim. Comparing the self-report and measured smartphone usage of college students: a pilot study. *Psychiatry investigation*, 14(2):198, 2017.

[155] Jang Ho Lee. Development and usability assessment of tablet-based synchronous mobile learning system. In *Ubiquitous information technologies and applications*, pages 301–306. Springer, 2014.

[156] Andrew Lepp, Jacob E Barkley, and Aryn C Karpinski. The relationship between cell phone use, academic performance, anxiety, and satisfaction with life in college students. *Computers in Human Behavior*, 31:343–350, 2014.

[157] Renan HP Lima, Moushir M El-Bishouty, and Sabine Graf. A framework for automatic identification and visualization of mobile device functionalities and usage. In *Human-Computer Interaction and Knowledge Discovery in Complex, Unstructured, Big Data*, pages 148–159. Springer, 2013.

[158] Chen-Chung Liu, Pin-Ching Wang, and Shu-Ju Diana Tai. An analysis of student engagement patterns in language learning facilitated by web 2.0 technologies. *ReCALL*, 28(2):104–122, 2016.

[159] Alf Lizzio and Keithia Wilson. Feedback on assessment: students' perceptions of quality and effectiveness. *Assessment & evaluation in higher education*, 33(3):263–275, 2008.

[160] Filipe Loureiro and Teresa Garcia-Marques. Morning or evening person? which type are you? self-assessment of chronotype. *Personality and Individual Differences*, 86: 168–171, 2015.

[161] M Lu. Effectiveness of vocabulary learning via mobile phone. *Journal of computer assisted learning*, 24(6):515–525, 2008.

[162] Yi Luo, Rui Pan, Jea H Choi, and Johannes Strobel. Effects of chronotypes on students' choice, participation, and performance in online learning. *Journal of Educational Computing Research*, 55(8):1069–1087, 2018.

[163] Griet Lust, Mieke Vandewaetere, Eva Ceulemans, Jan Elen, and Geraldine Clarebout. Tool-use in a blended undergraduate course: In search of user profiles. *Computers & Education*, 57(3):2135–2144, 2011.

[164] Griet Lust, Norma A Juarez Collazo, Jan Elen, and Geraldine Clarebout. Content management systems: Enriched learning opportunities for all? *Computers in Human Behavior*, 28(3):795–808, 2012.

[165] Griet Lust, Jan Elen, and Geraldine Clarebout. Regulation of tool-use within a blended course: Student differences and performance effects. *Computers & Education*, 60(1):385–395, 2013.

[166] Griet Lust, Jan Elen, and Geraldine Clarebout. Students' tool-use within a web enhanced course: Explanatory mechanisms of students' tool-use pattern. *Computers in Human Behavior*, 29(5), 2013.

[167] Paul L MacDonald and Robert C Gardner. Type i error rate comparisons of post hoc procedures for i j chi-square tables. *Educational and Psychological Measurement*, 60 (5):735–754, 2000.

[168] Leah P Macfadyen and Shane Dawson. Mining lms data to develop an "early warning system" for educators: A proof of concept. *Computers & education*, 54(2):588–599, 2010.

[169] Louis Major, Bjoern Haßler, and Sara Hennessy. Tablet use in schools: impact, affordances and considerations. In *Handbook on digital learning for K-12 schools*, pages 115–128. Springer, 2017.

[170] Farshid Marbouti, Heidi A Diefes-Dux, and Krishna Madhavan. Models for early prediction of at-risk students in a course using standards-based grading. *Computers & Education*, 103:1–15, 2016.

[171] Riccardo Mazza and Christian Milani. Gismo: a graphical interactive student monitoring tool for course management systems. In *International Conference on Technology Enhanced Learning, Milan*, pages 1–8, 2004.

[172] Susan Y McGorry. Measuring quality in online programs. *The Internet and Higher Education*, 6(2):159–177, 2003.

[173] Behrouz Minaei-Bidgoli, Deborah A Kashy, Gerd Kortemeyer, and William F Punch. Predicting student performance: an application of data mining methods with an educational web-based system. In *Frontiers in education, 2003. FIE 2003 33rd annual*, volume 1, pages T2A–13. IEEE, 2003.

[174] Ewa Młynarska, Derek Greene, and Pádraig Cunningham. Time series clustering of moodle activity data. In *24th Irish Conference on Artificial Intelligence and Cognitive Science (AICS'16)*, 2016.

[175] Magdalena MC Mok, Dennis M McInerney, Jinxin Zhu, and Anthony Or. Growth trajectories of mathematics achievement: Longitudinal tracking of student academic progress. *British Journal of Educational Psychology*, 85(2):154–171, 2015.

[176] Leanne G Morrison, Charlie Hargood, Veljko Pejovic, Adam WA Geraghty, Scott Lloyd, Natalie Goodman, Danius T Michaelides, Anna Weston, Mirco Musolesi, Mark J Weal, et al. The effect of timing and frequency of push notifications on usage of a smartphone-based stress management intervention: an exploratory trial. *PloS one*, 12(1):e0169162, 2017.

[177] Angela Murphy, Helen Farley, Michael Lane, Abdul Hafeez-Baig, and Brad Carter. Mobile learning anytime, anywhere: What are our students doing? *Australasian Journal of Information Systems*, 18(3), 2014.

[178] Jun Nakahara, Shinichi Hisamatsu, Kazaru Yaegashi, and Yuhei Yamauchi. itree: Does the mobile phone encourage learners to be more involved in collaborative learning? In *Proceedings of th 2005 conference on Computer support for collaborative learning: learning 2005: the next 10 years!*, pages 470–478. International Society of the Learning Sciences, 2005.

[179] Alex Nanopoulos, Rob Alcock, and Yannis Manolopoulos. Feature-based classification of time-series data. *International J. of Computer Research*, 10(3):49–61, 2001.

[180] Lemai Nguyen, Siew Mee Barton, and Linh Thuy Nguyen. ip ads in higher education—hype and hope. *British Journal of Educational Technology*, 46(1):190–203, 2015.

[181] Kleopatra Nikolopoulou. Mobile learning usage and acceptance: perceptions of secondary school students. *Journal of Computers in Education*, 5(4):499–519, 2018.

[182] Suzanne Nolte et al. *The comparison of behavioural patterns of top achievers from diverse work environments: an analysis of Shadowmatch database benchmarks*. PhD thesis, University of Pretoria, 2016.

[183] José Carlos Núñez, Natalia Suárez, Pedro Rosário, Guillermo Vallejo, Rebeca Cerezo, and António Valle. Teachers' feedback on homework, homework-related behaviors, and academic achievement. *the Journal of Educational research*, 108(3):204–216, 2015.

[184] James O'donovan and Mahiben Maruthappu. Distant peer-tutoring of clinical skills, using tablets with instructional videos and skype: A pilot study in the uk and malaysia. *Medical teacher*, 37(5):463–469, 2015.

[185] Stuart Palmer. Modelling engineering student academic performance using academic analytics. *International journal of engineering education*, 29(1):132–138, 2013.

[186] Abelardo Pardo, Robert A Ellis, and Rafael A Calvo. Combining observational and experiential data to inform the redesign of learning activities. In *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge*, pages 305–309. ACM, 2015.

[187] Abelardo Pardo, Negin Mirriahi, Shane Dawson, Yu Zhao, An Zhao, and Dragan Gašević. Identifying learning strategies associated with active use of video annotation software. In *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge*, pages 255–259. ACM, 2015.

[188] David Parsons. The future of mobile learning and implications for education and training. *Increasing Access*, 217, 2014.

[189] David Parsons, Herbert Thomas, and Jocelyn Wishart. Exploring mobile affordances in the digital classroom. *International Association for Development of the Information Society*, 2016.

[190] François Petitjean, Alain Ketterlin, and Pierre Gançarski. A global averaging method for dynamic time warping, with applications to clustering. *Pattern Recognition*, 44 (3):678–693, 2011.

[191] Paul R Pintrich. A conceptual framework for assessing motivation and self-regulated learning in college students. *Educ. Psychol. Rev*, 16(4):385–407, 2004.

[192] Jeffrey Pomerantz and D. Christopher Brooks. Ecar study of faculty and information technology, 2017, 2017. URL `https://library.educause.edu/resources/2017/10/ecar-study-of-faculty-and-information-technology-2017`.

[193] Christoph Randler and Daniela Frech. Correlation between morningness–eveningness and final school leaving exams. *Biological Rhythm Research*, 37(3):233–239, 2006.

[194] Emanuele Rapetti, Anna Picco-Schwendener, and Sara Vannini. Is mobile learning a resource in higher education? data evidence from an empirical research in ticino (switzerland). *Journal of e-learning and knowledge society*, 7(2):47–57, 2011.

[195] Susan M Ravizza, Mitchell G Uitvlugt, and Kimberly M Fenn. Logged in and zoned out: How laptop internet use relates to classroom learning. *Psychological science*, 28 (2):171–180, 2017.

[196] Stephanie M Reich, Joanna C Yau, and Mark Warschauer. Tablet-based ebooks for young children: What does the research say? *Journal of Developmental & Behavioral Pediatrics*, 37(7):585–591, 2016.

[197] David Reid and Ekaterina Pechenkina. Bring-your-own-device or prescribed mobile technology? investigating student device preferences for mobile learning. *Mobile learning futures: Sustaining quality research and practice in mobile learning*, 2016.

[198] Michelle Richardson, Charles Abraham, and Rod Bond. Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological bulletin*, 138(2):353, 2012.

[199] Tim Rogers, D Gašević, and S Dawson. Learning analytics and the imperative for theory driven research. *The SAGE Handbook of E-Learning Research,*, pages 232–250, 2016.

[200] Yvonne Rogers, Kay Connelly, William Hazlewood, and Lenore Tedesco. Enhancing learning: a study of how mobile devices can facilitate sensemaking. *Personal and Ubiquitous Computing*, 14(2):111–124, 2010.

[201] Cristóbal Romero and Sebastián Ventura. Educational data mining: a review of the state of the art. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 40(6):601–618, 2010.

[202] Cristóbal Romero, Sebastián Ventura, and Enrique García. Data mining in course management systems: Moodle case study and tutorial. *Computers & Education*, 51 (1):368–384, 2008.

[203] Margarida Romero and Elena Barbera. Quality of e-learners' time and learning performance beyond quantitative time-on-task. *The International Review of Research in Open and Distributed Learning*, 12(5):125–137, 2011.

[204] Margarida Romero and Elena Barberà. Lifelong learners and teachers' time-management competency in e-learning. *International Handbook of E-Learning Volume 2: Implementation and Case Studies*, page 135, 2015.

[205] Jeremy Roschelle, Deborah Tatar, S Raj Chaudhury, Yannis Dimitriadis, Charles Patton, and Chris DiGiano. Ink, improvisation, and interactive engagement: Learning with tablets. *Computer*, 40(9):42–48, 2007.

[206] Jonathan P Rossing, Willie Miller, Amanda K Cecil, and Suzan E Stamper. ilearning: The future of higher education? student perceptions on learning with mobile tablets. 2012.

[207] DG Rossiter. Tutorial: An example of statistical data analysis using the r environment for statistical computing. 2008.

[208] Peter J Rousseeuw. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *J. Comput. Appl. Math.*, 20:53–65, 1987.

[209] Richard M Royall. The effect of sample size on the meaning of significance tests. *The American Statistician*, 40(4):313–315, 1986.

[210] Hiroaki Sakoe and Seibi Chiba. Dynamic programming algorithm optimization for spoken word recognition. *IEEE transactions on acoustics, speech, and signal processing*, 26(1):43–49, 1978.

[211] Ieda M Santos and Nagla Ali. Exploring the uses of mobile phones to support informal learning. *Education and Information Technologies*, 17(2):187–203, 2012.

[212] Jose Luis Santos, Sten Govaerts, Katrien Verbert, and Erik Duval. Goal-oriented visualizations of activity tracking: a case study with engineering students. In *Proceedings of the 2nd international conference on learning analytics and knowledge*, pages 143–152. ACM, 2012.

[213] Alexis Sardá-Espinosa. Comparing time-series clustering algorithms in r using the dtwclust package, 01 2018.

[214] Cornelia Schoor and Maria Bannert. Exploring regulatory processes during a computer-supported collaborative learning task using process mining. *Computers in Human Behavior*, 28(4):1321–1331, 2012.

[215] Dolores R Serrano, Maria Auxiliadora Dea-Ayuela, Elena Gonzalez-Burgos, Alfonso Serrano-Gil, and Aikaterini Lalatsa. Technology-enhanced learning in higher education: How to enhance student engagement through blended learning. *European Journal of Education*.

[216] Afsaneh Sharif and Barry Magrill. Discussion forums in moocs. *International Journal of Learning, Teaching and Educational Research*, 12(1), 2015.

[217] Mike Sharples. Making sense of context for mobile learning. In *Mobile Learning*, pages 154–167. Routledge, 2015.

[218] Ruimin Shen, Minjuan Wang, and Xiaoyan Pan. Increasing interactivity in blended classrooms through a cutting-edge mobile learning system. *British Journal of Educational Technology*, 39(6):1073–1086, 2008.

[219] Varshita Sher, Marek Hatala, and Dragan Gašević. On multi-device use: Using technological modality profiles to explain differences in students' learning. In *Proceedings of the Ninth International Conference on Learning Analytics & Knowledge*. ACM, 2019. URL `https://dl.acm.org/citation.cfm?id=3303790`.

[220] Ru-Chu Shih. Can web 2.0 technology assist college students in learning english writing? integrating facebook and peer assessment with blended learning. *Australasian Journal of Educational Technology*, 27(5), 2011.

[221] Simon Buckingham Shum and Rebecca Ferguson. Social learning analytics. *Journal of educational technology & society*, 15(3):3–26, 2012.

[222] Valerie J Shute and S Rahimi. Review of computer-based assessment for learning in elementary and secondary education. *Journal of Computer Assisted Learning*, 33(1): 1–19, 2017.

[223] Melody Siadaty, Dragan Gašević, and Marek Hatala. Measuring the impact of technological scaffolding interventions on micro-level processes of self-regulated workplace learning. *Computers in Human Behavior*, 59:469–482, 2016.

[224] Carlla S Smith, Simon Folkard, Robert A Schmieder, Luis F Parra, Evelien Spelten, Helena Almiral, RN Sen, S Sahu, Lisa M Perez, and John Tisak. Investigation of morning–evening orientation in six countries using the preferences scale. *Personality and Individual Differences*, 32(6):949–968, 2002.

[225] Vernon C Smith, Adam Lange, and Daniel R Huston. Predictive modeling to forecast student outcomes and drive effective interventions in online community college courses. *Journal of Asynchronous Learning Networks*, 16(3):51–61, 2012.

[226] Tal Soffer and Efrat Yaron. Perceived learning and students' perceptions toward using tablets for learning: The mediating role of perceived engagement among high school students. *Journal of Educational Computing Research*, 55(7):951–973, 2017.

[227] Yang Song, Hao Ma, Hongning Wang, and Kuansan Wang. Exploring and exploiting user search behavior on mobile and tablet devices to improve search relevance. In *Proceedings of the 22nd international conference on World Wide Web*, pages 1201–1212. ACM, 2013.

[228] Yanjie Song and Siu Chueng Kong. Affordances and constraints of byod (bring your own device) for learning and teaching in higher education: Teachers' perspectives. *The Internet and Higher Education*, 32(1):39–46, 2017.

[229] Emrah Soykan. Views of students', teachers' and parents' on the tablet computer usage in education. *Cypriot Journal of Educational Sciences*, 10(3):228–244, 2015.

[230] J Michael Spector, Dirk Ifenthaler, Demetrios Sampson, Joy Lan Yang, Evode Mukama, Amali Warusavitarana, Kulari Lokuge Dona, Koos Eichhorn, Andrew Fluck, Ronghuai Huang, et al. Technology enhanced formative assessment for 21st century learning. 2016.

[231] Vijay Srinivasan, Christian Koehler, and Hongxia Jin. Ruleselector: Selecting conditional action rules from user behavior patterns. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 2(1):35, 2018.

[232] Niwat Srisawasdi and Patcharin Panjaburee. Technology-enhanced learning in science, technology, and mathematics education: results on supporting student learning. *Procedia-Social and Behavioral Sciences*, 116:946–950, 2014.

[233] Glenn Stockwell. Using mobile phones for vocabulary activities: Examining the effect of platform. 2010.

[234] Glenn Stockwell. Tracking learner usage of mobile phones for language learning outside of the classroom. *CALICO Journal*, 30(1):118–136, 2013.

[235] Margaret Anne Storey, B Phillips, Mechthild Maczewski, and Mei Wang. Evaluating the usability of web-based learning tools. *Educational Technology & Society*, 5(3): 91–100, 2002.

[236] C-H Su and C-H Cheng. A mobile gamification learning system for improving the learning motivation and achievements. *Journal of Computer Assisted Learning*, 31(3): 268–286, 2015.

[237] Ángel Suárez, Marcus Specht, Fleur Prinsen, Marco Kalz, and Stefaan Ternier. A review of the types of mobile activities in mobile inquiry-based learning. *Computers & Education*, 118:38–55, 2018.

[238] Yao-Ting Sung, Kuo-En Chang, Huei-Tse Hou, and Pin-Fu Chen. Designing an electronic guidebook for learning engagement in a museum of history. *Computers in Human Behavior*, 26(1):74–83, 2010.

[239] Yao-Ting Sung, Kuo-En Chang, and Tzu-Chien Liu. The effects of integrating mobile devices with teaching and learning on students' learning performance: A meta-analysis and research synthesis. *Computers & Education*, 94:252–275, 2016.

[240] Lennart Svensson. Symposium: Learning processes and strategies iii – on qualitative differences in learning: Iii study skill and learning. *Br. J. Educ. Psychol.*, 47(3): 233–243, 1977.

[241] Bernardo Tabuenca, Marco Kalz, Dirk Börner, Stefaan Ternier, and Marcus Specht. Where is my time? identifying productive time of lifelong learners for effective feedback services. In *International Computer Assisted Assessment Conference*, pages 149–161. Springer, 2014.

[242] Bernardo Tabuenca, Marco Kalz, Hendrik Drachsler, and Marcus Specht. Time will tell: The role of mobile learning analytics in self-regulated learning. *Computers & Education*, 89:53–74, 2015.

[243] Kevin Thomas and Marco A Muñoz. Hold the phone! high school students' perceptions of mobile phone integration in the classroom. *American Secondary Education*, 44(3): 19–37, 2016.

[244] Patrick R Thomas and John D Bain. Consistency in learning strategies. *Higher Education*, 11(3):249–259, 1982.

[245] Mary Thorpe. Effective online interaction: Mapping course design to bridge from research to practice. *Australasian Journal of Educational Technology*, 24(1), 2008.

[246] Richard AW Tortorella and Sabine Graf. Personalized mobile learning via an adaptive engine. In *Advanced Learning Technologies (ICALT), 2012 IEEE 12th International Conference on*, pages 670–671. IEEE, 2012.

[247] Chad C Tossell, Philip Kortum, Clayton Shepard, Ahmad Rahmati, and Lin Zhong. You can lead a horse to water but you cannot make him learn: Smartphone use in higher education. *British Journal of Educational Technology*, 46(4):713–724, 2015.

[248] John Traxler and Agnes Kukulska-Hulme. The evaluation of next generation learning technologies: the case of mobile learning. 2006.

[249] Hastie Trevor, Tibshirani Robert, and Friedman JH. The elements of statistical learning: data mining, inference, and prediction, 2009.

[250] Katrien Verbert, Sten Govaerts, Erik Duval, Jose Luis Santos, Frans Van Assche, Gonzalo Parra, and Joris Klerkx. Learning dashboards: an overview and future research opportunities. *Personal and Ubiquitous Computing*, 18(6):1499–1514, 2014.

[251] Yvonne J Vermetten, Hans G Lodewijks, and Jan D Vermunt. Consistency and variability of learning strategies in different university courses. *Higher Education*, 37(1): 1–21, 1999.

[252] Yvonne J Vermetten, Jan D Vermunt, and Hans G Lodewijks. A longitudinal perspective on learning strategies in higher education-different view-points towards development. *Br. J. Educ. Psychol.*, 69(2):221–242, 1999.

[253] Jan D Vermunt. The regulation of constructive learning processes. *Br. J. Educ. Psychol.*, 68(2):149–171, 1998.

[254] Jan D Vermunt and Yvonne J Vermetten. Patterns in student learning: Relationships between learning strategies, conceptions of learning, and learning orientations. *Educ. Psychol. Rev*, 16(4):359–384, 2004.

[255] Iris Shuk Han Wai, Sara Sze Yan Ng, Dickson KW Chiu, Kevin KW Ho, and Patrick Lo. Exploring undergraduate students' usage pattern of mobile apps for education. *Journal of Librarianship and Information Science*, page 0961000616662699, 2016.

[256] Mirabelle Walker. An investigation into written comments on assignments: do students find them usable? *Assessment & Evaluation in Higher Education*, 34(1):67–78, 2009.

[257] Sean Wallace, Marcia Clark, and Jonathan White. 'it's on my iphone': attitudes to the use of mobile computing devices in medical education, a mixed-methods study. *BMJ open*, 2(4):e001099, 2012.

[258] Alvin Y Wang and Michael H Newlin. Predictors of performance in the virtual classroom: Identifying and helping at-risk cyber-students. *THE Journal (Technological Horizons In Education)*, 29(10):21, 2002.

[259] Alvin Y Wang, Michael H Newlin, and Travis L Tucker. A discourse analysis of online classroom chats: Predictors of cyber-student performance. *Teaching of Psychology*, 28 (3):222–226, 2001.

[260] Minjuan Wang, Ruimin Shen, Daniel Novak, and Xiaoyan Pan. The impact of mobile learning on students' learning behaviours and performance: Report from a large blended classroom. *British Journal of Educational Technology*, 40(4):673–695, 2009.

[261] Yuping Wang. Supporting synchronous distance language learning with desktop videoconferencing. *Language Learning & Technology*, 8(3):90–121, 2004.

[262] Pieter Warnich and Clare Gordon. The integration of cell phone technology and poll everywhere as teaching and learning tools into the school history classroom. *Yesterday and Today*, (13):40–66, 2015.

[263] Mark Warschauer, Douglas Grimes, Michele Rousseau, Kurt Suhr, and Julia Nyberg. First year evaluation report: Fullerton school district laptop program. *Retrieved February*, 21:2007, 2005.

[264] Audrey Watters. The invented history of 'the factory model of education', Apr 2015. URL `http://hackeducation.com/2015/04/25/factory-model`.

[265] Philip Winne. Leveraging big data to help each learner and accelerate learning science. 119, 01 2017.

[266] Philip H Winne. How software technologies can improve research on learning and bolster school reform. *Educational Psychologist*, 41(1):5–17, 2006.

[267] Philip H Winne and Dianne Jamieson-Noel. Exploring students' calibration of self reports about study tactics and achievement. *Contemporary Educational Psychology*, 27(4):551–572, 2002.

[268] Alyssa Friend Wise and Ying-Ting Hsiao. Self-regulation in online discussions: Aligning data streams to investigate relationships between speaking, listening, and task conditions. *Computers in Human Behavior*, 96:273–284, 2019.

[269] Alyssa Friend Wise, Yuting Zhao, and Simone Nicole Hausknecht. Learning analytics for online discussions: a pedagogical model for intervention with embedded and extracted analytics. In *Proceedings of the third international conference on learning analytics and knowledge*, pages 48–56. ACM, 2013.

[270] Steven Wolk. The benefits of exploratory time. *Educational Leadership*, 59(2):56–59, 2001.

[271] Christopher A Wolters, Sungjun Won, and Maryam Hussain. Examining the relations of time management and procrastination within a model of self-regulated learning. *Metacognition and learning*, 12(3):381–399, 2017.

[272] Gary KW Wong. A new wave of innovation using mobile learning analytics for flipped classroom. In *Mobile Learning Design*, pages 189–218. Springer, 2016.

[273] Xiang Xiao and Jingtao Wang. Towards attentive, bi-directional mooc learning on mobile devices. In *Proceedings of the 2015 ACM on International Conference on Multimodal Interaction*, pages 163–170. ACM, 2015.

[274] Kaijian Xu, Manli Zhu, Daqing Zhang, and Tao Gu. Context-aware content filtering & presentation for pervasive & mobile information systems. In *Proceedings of the 1st international conference on Ambient media and systems*, page 20. ICST (Institute for Computer Sciences, Social-Informatics and ..., 2008.

[275] Ji Won You. Identifying significant indicators using lms data to predict course achievement in online learning. *The Internet and Higher Education*, 29:23–30, 2016.

[276] Li Yuan, SJ Powell, and Bill Olivier. Beyond moocs: Sustainable online learning in institutions. 2014.

[277] Jerrold H Zar. Biostatistical analysis. *Biostatistical Analysis (5th Edition)*, 9:09685, 2010.

[278] Janosch Zbick, Isabella Nake, Marcelo Milrad, and Marc Jansen. A web-based framework to design and deploy mobile learning activities: Evaluating its usability, learnability and acceptance. In *Advanced Learning Technologies (ICALT), 2015 IEEE 15th International Conference on*, pages 88–92. IEEE, 2015.

[279] Petrus Zeegers. Approaches to learning in science: A longitudinal study. *Br. J. Educ. Psychol.*, 71(1):115–132, 2001.

[280] Mingming Zhou and Philip H Winne. Modeling academic achievement by self-reported versus traced goal orientation. *Learning and Instruction*, 22(6):413–419, 2012.

[281] Barry J Zimmerman. Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *Am. Educ. Res. J.*, 45 (1):166–183, 2008.

[282] Marjolein BM Zweekhorst and Jeroen Maas. Ict in higher education: students perceive increased engagement. *Journal of Applied Research in Higher Education*, 7(1):2–18, 2015.

Appendix A

Details of the Learning Tasks

A.1 Discussion Task Description

For the online discussion task, the students were given a set of open-ended questions related to the course content. The students were expected to engage in these discussions by exploring different aspects surrounding the topic, formulating ideas and justifying those ideas with clear rationale, facts and resources. The marking criteria (see Figure A.1 and guidelines for participation in the discussion task (see Figure A.2) were presented in each of the three individual discussion task pages in the LMS. The three discussion tasks investigated as part of Chapter 7 are as follows:

- Discussion 1: Importance of learning a particular programming language for the web

  Question: *"In a course like IAT 352, is it or is it not important that students learn how to program web applications in the programming/scripting language X?" Discuss and come up with pros and cons arguments for the question. Support with facts and sources. Discuss what the language X should be, and why.*

- Discussion 2: Challenges and opportunities of big data

  Question: *What are the NEW challenges and opportunities that the big data phenomenon brings when compared to database technology of yesterday?" Discuss all possible angles of the topic ranging from technical and management issues, through societal, policy making aspects to personal (and anything else you identify). Support with facts/sources.*

- Discussion 3: Personalization/Recommendation in Canvas

  Question: *As a group, develop a design brief for adding personalization and/or recommendation to Canvas. Outline main data, how the system would collect those, and main technical components of the proposed system and how these components would inter-operate. Highlight potential deployment and uptake issues and how you would address them.*

Expectations and Marking

You are expected to post a minimum of 4 posts as follows. To get the discussion going, we recommend that you post **minimum 1 post within first 2 days, minimum 2 posts on days 3-5.** For expected quality of messages see the marking rubric below. This discussion activity is worth 5% of the course mark. The 5% comprises of the following components:

Quantity – Reading and posting as specified for each message category. The rest of the marks will be scaled based on number of posts: 4+ posts (100%), 3 posts (75%), 2 posts (50%), etc.

Quality

- 40% **Content** – based on posts within each category (Identify, Explore, Integrate)
  - ***Below average:*** Message tends to address peripheral issues and/or ramble. Tendency to recite facts and provide opinions. Relevant concepts not discussed *****.
  - ***Average***: Messages tend to provide good general contributions, but may not always directly address discussion topics. Assertions are not always supported by evidence. Relevant concepts included into the discussion but not strongly connected to other logically related ideas***** .
  - ***Above average***: Messages are characterized by conciseness, clarity of argument, depth of insight into theoretical issues, originality of treatment, relevancy, and sometimes include unusual insights. Relevant concepts included into the discussion and connected well to other logically related ideas.
- 30% **Collaboration** – Engaging in the dialogue with others' ideas presented in the posts.
- 10% **Tone & Mechanics** – Conducting yourself appropriately in a professional relationship. The messages are carefully formulated with minimum of spelling and grammatical errors.

Final Response) -

- 20% **Quality of the brief** in the final response – shared by all group members.

Figure A.1: Marking criteria for the discussion tasks.

A.2 Assignment Task Description

The objective of the assignment tasks was to allow opportunities for students to learn object oriented programming (OOP) concepts. As part of each week's assignment, students wrote snippets of code using the Java programming language, showcasing the concept learnt in that week's lecture. The overarching aim of the code snippets in the eight assignments (four main assignments (A1, A2, A3, A4) composed of two phases each - P1 and P2) was to create a simulation of a natural world with animals (birds, fish, insects, mammals, etc) that move, eat, die and predators that hunt them. The assignments were incremental in nature, meaning they were built on top of one another by adding new functionalities and features to previous week's assignment. Thus, the complexity gradually increased with each assignment. A brief description of the objectives and concepts assessed in the assignments are as follows:

- Assignment A1 (P1+P2): Learn how to create different objects of the same class, and implement movement in the simulation model.
- Assignment A2 (P1+P2): Learn how to process mouse events, work with ArrayList, handle between-objects collisions, and improve the simulation model by incorporating forces.

Discussion Participation Guidance

You are expected to engage in the discussion that will explore different aspects of the task itself, propose different ideas to address these aspects, select some ideas and justify why these were included and other rejected, and finally decide on the answer with a clear rationale.

Everyone is expected to contribute meaningfully in teh task at hand. You are asked to post **at least** 4 times. Your contributions have to be at the appropriate level and depth. The following contributions are expected at each level:

- **Identify** aspects to explore (1-3 messages from each participant) – engage in an analysis of the question being asked, as a group come with set of aspects that should be explored to address the question.
- **Explore** ideas to address the aspects (2-4 messages each) – do individual research to explore the aspects, integrate material from the readings for the class, and post your finding to share with others. Read others' posts, build on their ideas or argue the points they brought up by bringing new evidence or interpreting existing evidence and points in the discussion so far.
- **Integrate** ideas (1-3 posts each) – participate in constructing a meaningful response from ideas raised in the previous posts. Select well-supported ideas to use in shaping group's position on the question, decide on the way to structure the response.
- **Final statement** – 1 message for the group posted by ***wrapper*** role. Each group selects a wrapper. The wrapper is responsible for creating a brief from teh contributions of others. It may be a good idea having a brief ready as a draft and let others comment on it and posting the final submission afterwards.

Figure A.2: Guidelines for participation in the discussion tasks.

- Assignment A3 (P1+P2): Learn how to design program with subclasses, add textual information into the display using fonts, and process events from the keyboard.
- Assignment A4 (P1+P2): Learn how to build user interface (UI) using Java Swing components, control functionality of the program via UI, expand on the functionality of the simulation in one of several possible ways, such as by creating complex UI, or storing the state of the simulation and restoring it later.

The detailed description of the eight assignments are as follows:

Assignment 1 – Phase 1 requirements

- Create a drawing space within JPanel.
- Draw your animal - bird, fish, insect ... - using graphics primitives.
- Your creature should move. Start in the center and move in the randomly determined direction with constant speed. Your animal can look the same regardless the direction it is moving in.
- Create new animal when your creature leaves the drawing space
- Animal must be represented as an object of a class.

Assignment 1 – Phase 2 requirements

- You will continue improving your project from Phase 1
- You must use PVectors where appropraite
- The visual appearance of your animal should look "natural" when moving in different directions. Choose the view of an animal that is the best for showing in your envisioned environment when later filled with many animals and some predators
- You should have at least three different visual characteristic which appearance will be determined randomly. For example, for a fish you can determine number of stripes, slimness of the body, and proportion of tail fin size to the body. At least one characteristic should be deterministic (e.g. number of stripes – none, 3, or 7), and at least one must be continuous (e.g. body width from 5 to 20).

BONUS (3 points): when animal is moving, there should be a low fidelity animation of the movement, such as running, flying, swimming, crawling, etc.

- The food randomly appears in the space. Render the food as realistically as possible. Food must be represented as an object of a class.
- When food appears, your animal will move towards it until it reaches the food location (or is close enough to reach it – justify your algorithm).
- When food is reached, it is consumed and new one appears at another random location.

BONUS (1 point): Your animal will gracefuly turn around towards the new food source, rather than abruptly changing the direction of the movement.

A2: Phase 1 Requirements

- Add food using mouse, at the mouse-click location. You can keep increasing size of the food by clicking on the created food. Your food object should hold the size information and food drawing should reflect the food size.

Bonus (1 point): The longer you keep the mouse button pressed on teh food, the larger the food portion. This bonus point will be marked with Phase 2 and will contribute to the overall bonus point sum.

- When you Ctrl-Click on food it is removed from the list.
- You must create MouseAdapter for processing MouseEvents.
- You should be able to create several food sources at the same time. Store food objects in an ArrayList. When food is created, you add it to the list, when food is eaten, remove it from the list.
- When you animal eats all food you created, it should continue moving in a straigt line, turning at the edges of the environment.
- In Phase 1, let your animal pursue the food source that is the closest, regardless of the food size.

A2: Phase 2 Requirements

- You will continue improving your project from Phase 1
- Create several animals and place them into the ArrayList. The animals should be of different sizes (randomly generated, within certain range), have a slight variation in appearance (as required in assignment 1).
- Set animal's maximum speed based on their size. By default, the larger the animal the slower it moves.

BONUS (2 points): Change the model to reflect a concept of an 'ideal weight'. Animal with an ideal weight will move the fastest. Underweight and overweight animals will move progressively slower.

- Incorporate a model for selecting food your animal will pursue (aka an attraction force). The attraction force should be proportional to food size and diminish with distance (AF=FOOD_SIZE/DISTANCE)
- Incorporate an energy model for your animals.
  - When animal moves, it loses energy at certain rate based on their size (you may need to experiment with different values).
  - When food is consumed, it adds animal an amount of energy proportional to food size.
  - When energy falls below certain level, draw animal as sick. Sick animal move at half of their speed. When animal walls below second threshold, they will die. Remove an animal and generate a new one.

BONUS (2 points): Change the energy model in the way that animal with energy above certain threshold will grow, which will consume some energy. As a larger animal it will start consuming more energy to move and it will move slower (or if you have implemented an 'ideal weight' model from above, then it will move accordingly)

- Detect conflict between animals. When two different sized animals collide, the smaller one has to change the direction in which it is moving. This way the bigger animals can "push aside" smaller ones when pursuing the same food source.

A3: Phase 1 requirements

- Add a predator to your simulation. For this you have to refactor (redesign) your code. You need to create a superclass with two subclasses. One subclass will be for your 'regular' animals as you have them right now. The second subclass will be for the predator. As a result you will have at least three instantiated kinds of object: 1) regular animals, 2) predators that eat regular animals, and as before 3) food that regular animals eat. For regular animals and predators, you have to keep all the shared functionality in the superclass. In the subclass either add functionality specific to the subclass, or extend or override the superclass functionality. You will be marked on the clarity of design and justification for decision made (provide justification in the comments).
- Make predators to pursue your other animals. When they catch them, the animal disappears. A new animal is generated with and it moves according to its size and energy model, as specified in A2. Predators do not pursue each other.

  Bonus (1 point): After an animal has been eaten, make the new animal appear with a delay of 3 seconds (or other value that makes sense in your simulation).

- You will reuse code from A2 for animal movement around the environment (except animation of animal micro-movement, such as wiggling of the tail), boundary detection, collision detection and avoidance, "food" detection, mechanics for choosing the food to pursue. For predators, you will modify their energy model, which animals they choose to pursue, and override how they are drawn.
- Make food appear automatically at random sizes and locations as it is consumed (As in A1P2). This way your animals always have something to feed on. You should still be able to add food by mouse, as in A2P2.)
- Submit a simulation with 5 animals and two predators. As before, all predators should be in an array list.

A3P1 submit requirement: Submit ONLY video showing the behaviours as above, plus eclipse showing the tab with the Animal superclass, tab showing the predator subclass file, and a tab showing the regular animal file. For the files, 5 sec is enough – no need to scroll. No need to submit code for A3P1, the code will be marked with A3P2.

A3: Phase 2 requirements

- You will continue improving your project from Phase 1.
- Incorporate an energy model for predators.
    - When predator moves, it loses energy at certain rate based on their size AND their speed (you may need to experiment with different values).
    - When predators catch the animal and eat it, predator gains energy proportional to the caught animal's size.
    - When energy falls below certain level, draw predator as sick. Sick predator moves slower. When predator falls below second threshold, they will die. Remove the predator and generate a new one.

  BONUS (3 points): Make your animals try to escape predators. If they see the predator (e.g. using Field of View), they should run away from predator until they are out of certain radius. When they are escaping, they should not pursue any food, and they can move at the twice of their speed limit (burning energy faster). To show that you implemented this functionality, submit a video that shows FOV of the animal drawn until they detect the predator. While they are in the escape mode, draw the radius around the animal until they escape predator. After they escaped, return to the regular feeding behavior.

- Add textual information to be displayed above the animal as a label and be moving with and animal or predator. The information should include energy level and speed magnitude. You should be able turn the display of information on by Shift-click the mouse on the animal (predator and animal) and turn it off with another Shift-click. All animals selected in this way should be displaying the information as they are moving around. You should be able to toggle the display of the information on and off with the keyboard Shift-D combination.

A4: Phase 1 requirements (4pt)

- Create a control panel for your simulation. The control panel should show the internal data for your selected animal or predator, such as location, energy level, speed. You should be able to select and deselect the animal/predator using mouse. Selected animals should be drawn highlighted (any way you choose). The data in the control panel should be continually updated.
- There should be the segment of the control panel that provides updates on the application as a whole and allows you to control some high-level parameters, such as max number of animals, number of predators, max food size, or similar.
- You should have at least three different kinds of action for your application that you can initiate using the control panel. At least one of those should modify the individual animal's behavior, and at least one should affect the application as a a whole.
- You need to refactor your application so you have one class that extends JFrame, you have another class that extends JPanel for your simulation (as before), and you have one class that extends JPanel and contains Control Panel. You will continue to have classes for your animals, predators and food.
- Control panel should be added into the same frame together with your simulation panel.

Bonus (1 point): you should be able to dynamically show/remove the control panel using some key combination.

A4: Phase 2 requirements (16pt)

- You will be adding to the code from Phase 1.
- There are three options for you that you can choose from. You will have to learn how to implement the new functionality from the provided resources on your own, as an independent project. You will be given a minimal guidance, and you have to come up with the design and implementation on your own. In the lecture, we will cover some basic Java capabilities that are key to each option, but you will have to design and implement your own project. The main goal here is to demonstrate your programming skills, i.e. that you can design an extension of the functionality on your own, work effectively with your existing code when adding new functionality (refactoring), and be able to add to your knowledge of programming by studying a (small) technique on your own.

Option 1: Add flocking behavior to the simulation

- Your starting point is an environment with all implemented mandatory functionality up to the A4P1. If you have not implemented some of the functionality, you have to complete it for this assignment.
- Some animals move in groups, such as flock of birds, school of fish, herd of wildebeests, etc. The movement of each animal depends on the movement of their neighbors. The movement of each animal is determined by three forces: attraction force to other animals (to keep them together), repulsion force from other animals (to keep them apart), and speed of movement (to keep them moving in same direction). The algorithms and formulas are described in Chapter 6, section 6.13 of Shiffman's book (http://natureofcode.com/book/chapter-6-autonomous-agents/) . Here is another paper that describes the forces: https://www.red3d.com/cwr/boids/
- Additionally, animals need to move with purpose, in our case seek food. For the flock/swarm of your animals you need to have a desired direction. Compute that direction as towards the segment of the environment that has the highest concentration of food. Divide your environment into 5x4 or AxB grid and compute the food amount in each grid. In nature, animals that swarm usually feed on things that are in abundance too, such as plankton or insect, or seeds. Reconsider the type of food and amount that is generated, e.g. many small food bites instead of few larger food sources. Also reconsider the energy model in a way that your animals do not burn energy too fast. What you should see is that as the swarm pushes the front animals forward, they will leave uneaten food behind for others.
- Remove the rule that smaller animal gets pushed away by bigger ones. You may want to consider having animals of the same size, just play with energy levels.
- Animals swarm to protect themselves from predators. Animals should be avoiding predators, i.e. there should be the force that pushes them away from predators. You need to implement this behavior. However, you also need to change the predators' behavior in a way that they cannot get closer to the animal that is "in flock" than a certain distance (i.e. "in-flock" means that an animal has a distance from at least 2 other animals less than some number). Only singled out animals can be caught. See here what I mean .
- You need to add some parameters to the control panel that would allow you to control the flocking behavior and predator hunting behavior easily.
- To be able to show the flocking you need to have enough space and animals on the screen. You need to make the screen a bit bigger and animals smaller, maybe removing moving animation if they are too small. It may be that the animals your application displays do not exhibit the flocking behavior in the nature. You can still implement it in your simulation though – it may be weird, but we can live with this, let's call it an artistic license.

Option 2: Complex GUI

- Your starting point is an environment with all implemented mandatory functionality up to the A4P1. If you haven not implemented some of the functionality, you have to complete it for this assignment.
- This goes beyond the Control Panel that you have done in Phase 1. It should include capabilities to control every aspect of the application, including controlling the number of animals, animal generation parameters, food generation, predators, setting/controlling the max values for speed and energy levels, and other parameters around how you compute forces etc. You need to design a series of dialogs and menus to create a GUI. You also need to include the menubar with menus that will allow you controlling each kind of object specifically, e.g. menu for Animal, menu for Predator, menu for Food. Items in menus should allow you to control aspects related to each class for existing objects. You should also have a "Properties…" menu item that will open a dialog box that will allow you to change the properties for the next new generated animal/predator/food, i.e. you need to have three dialog boxes.
- You will need to refactor your code so you eliminate the fixed values for parameters you used to generate animals. For example, you may have used minimum and maximum fixed values for the lover and upper limit for your random number generator for animal size. Instead, now you will have these two parameters that can be modified in via the dialog window.
- There is a tutorial for building GUI: https://docs.oracle.com/javase/tutorial/uiswing/components/index.html
- If you go to the very top of the tutorial, it tells you to use Netbeans IDE for building GUI. Creating graphical layout might be faster, but you have to modify a lot of code in generated code, which is confusing. I suggest that you build from scratch, you can find snippets of code how to do certain things (reference code you found), but you will still have to connect it to your reworked code of your simulation.

Option 3: Higher aesthetics and adding complexity

- In this option, you will perfect the simulation to be as appealing and natural looking as possible. You will increase the complexity of your environment and make all the techniques for movement, collision detection, and obstacle avoidance work as flawlessly as possible.
- Your starting point is the environment that has *all the optional bonus features implemented*. If you have not implemented those so far, you need to implement those first.
- Environment: you need to add at least one obstacle into your environment that has a concave shape (learn what it is). You also need to make at least two edges of the environment to be irregular in shape, i.e. not a straight line. Your animals and predators need to move around this new environment using a fluid motion without bumping to things and turning abruptly (i.e. no bouncing of things). You need to place a proper imagery into the background. Resize your environment to be large enough to accommodate all the features as specified further below.
- Animals: you need to have at least two different kinds of animals that are not predators. They need to look as different species and they need to have different behaviors with respect to food and predators.
- Graphical rendering: Your animals, predators and food should be rendered with the quality expected from the polished graphically rich applications, such as games. You should implement micro-movement that should be different in the regular search-for-food mode and escape-the-predator mode.
- You need to change the behavior for animals and predators when they are not hungry, based on their energy model. Instead of constantly following food, when they are not hungry, they should move around the environment in somewhat random fashion, changing their direction from time to time.