Intelligent Systems Reference Library 158

Maria Virvou
Efthimios Alepis
George A. Tsihrintzis
Lakhmi C. Jain *Editors*

Machine Learning Paradigms

Advances in Learning Analytics

Springer

Intelligent Systems Reference Library

Volume 158

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Editors
Maria Virvou
Department of Informatics
University of Piraeus
Piraeus, Greece

Efthimios Alepis
Department of Informatics
University of Piraeus
Piraeus, Greece

George A. Tsihrintzis
University of Piraeus
Piraeus, Greece

Lakhmi C. Jain
Faculty of Science, Technology
and Mathematics
University of Canberra
Canberra, SA, Australia

University of Technology
Sydney, NSW, Australia

Liverpool Hope University
Liverpool, UK

ISSN 1868-4394 ISSN 1868-4408 (electronic)
Intelligent Systems Reference Library
ISBN 978-3-030-13742-7 ISBN 978-3-030-13743-4 (eBook)
https://doi.org/10.1007/978-3-030-13743-4

Library of Congress Control Number: 2019931820

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

To our beloved daughters, Evina,
Konstantina and Andreani

Maria Virvou and George A. Tsihrintzis

To my beloved family

Efthimios Alepis

To my beloved family

Lakhmi C. Jain

Foreword

The recent availability of smaller, more powerful and affordable computing hardware, along with advanced technologies such as artificial intelligence and virtual and augmented reality, is transforming the education and training landscape and shifting it towards a student-centered, technology-enhanced approach that is data intensive. Educators now have access to a large amount of data related to trainees' background and performance. Although the analysis of educational data is not a new phenomenon, these advanced educational technologies are resulting in a large amount of data that may be difficult to interpret and make sense of, particularly in real time.

As a result, one of the sub-disciplines of *Machine Learning*, namely *Learning Analytics*, is emerging as a very active research discipline worldwide. The techniques of Learning Analytics come from a combination of methodologies from Artificial Intelligence, Software Engineering and Big Data, as well as Pedagogical and Psychological Sciences. Learning Analytics is also taking advantage of recent advances in technological infrastructure in Human–Computer Interaction, Communications, the Internet and Mobile Computing. Consequently, Learning Analytics appears as a promising research area with the potential to impact educational processes in the decades to come.

But what is Learning Analytics? As the field is still emerging, it is difficult to define it in a way that covers all of its aspects. However, we can describe Learning Analytics as the field concerned with the collection, advanced processing and useful information extraction from both educators and learners' data with the goal of continuously improving education and learning systems.

In this volume, the Editors have invited internationally respected researchers to examine and present aspects of the emerging field of Learning Analytics and some of its application areas, including

- *Learning Analytics with the purpose to measure Student Engagement, to quantify the Learning Experience and to facilitate Self-Regulation;*
- *Learning Analytics to predict Student Performance;*

- *Learning Analytics incorporated in Tools for Building Learning Materials and Educational Courses; and*
- *Learning Analytics as Tools to support Learners and Educators in Synchronous and Asynchronous e-Learning.*

The book audience includes professors, graduate students, practitioners and researchers in *Advances in Learning Analytics* and other related areas. As such, it is self-contained and its chapters are appropriately grouped into four parts, which correspond to the items in the previous paragraph. An extensive list of references at the end of each chapter guides readers to probe further into application areas of interest to them.

I believe that the Editors have done an outstanding job in addressing the pertinent topics and associated problems. I consider the book to be a great addition to the area of *Advances in Learning Analytics*. I am confident that it will help professors, graduate students, researchers and practitioners to understand and explore further Learning Analytics methods and apply them in real-world systems.

Oshawa, ON, Canada

Dr. Bill Kapralos
Associate Professor
Software Informatics Research Centre
University of Ontario
Institute of Technology

Preface

Over the recent years, a new research discipline has been emerging worldwide, which is concerned with the collection, advanced processing and useful information extraction from both educators' and learners' data with the goal of improving and, hopefully, optimizing education and learning systems. This discipline is termed *Learning Analytics* and, despite it being a sub-field of *Machine Learning*, it is evolving into a field of its own.

In this volume, we have invited world-class researchers to examine and present aspects of the emerging field of *Learning Analytics* and some of its application areas, including

(1) Learning Analytics with the purpose to measure Student Engagement, to quantify the Learning Experience and to facilitate Self-Regulation;
(2) Learning Analytics to predict Student Performance;
(3) Learning Analytics incorporated in Tools for Building Learning Materials and Educational Courses; and
(4) Learning Analytics as Tools to support Learners and Educators in Synchronous and Asynchronous e-Learning.

This research book is directed towards professors, researchers, scientists, engineers and students of all disciplines. Extensive bibliography at the end of each chapter guides readers to probe further into their application areas of interest. We hope that they all find it useful in their works and researches.

We are grateful to the authors and the reviewers for their excellent contributions and visionary ideas. We are also thankful to Springer for agreeing to publish this book. Last, but not least, we are grateful to the Springer staff for their excellent work in producing this book.

Piraeus, Greece — Maria Virvou
Piraeus, Greece — Efthimios Alepis
Piraeus, Greece — George A. Tsihrintzis
Canberra/Sydney, Australia — Lakhmi C. Jain

Contents

Chapter 1
Machine Learning Paradigms

Advances in Learning Analytics

Maria Virvou, Efthimios Alepis, George A. Tsihrintzis and Lakhmi C. Jain

Abstract Recent major advances in Information Technologies are leading to an entirely new era in the educational process, which is characterized by the development of more engaging and human-like computer-based learning, personalization and incorporation of artificial intelligence techniques. A new research discipline, termed *Learning Analytics*, is emerging and examines the collection and intelligent analysis of learner and instructor data with the goal to extract information that can render electronic and/or mobile educational systems more personalized, engaging, dynamically responsive and pedagogically efficient. In this volume, internationally established authors are contributing their research ideas and results towards aspects of Learning Analytics with the purpose to (1) measure Student Engagement, to quantify the Learning Experience and to facilitate Self-Regulation, (2) to predict Student Performance (3) to be incorporated in Tools for Building Learning Materials and Educational Courses, and (4) to be used as Tools to support Learners and Educators in Synchronous and Asynchronous e-Learning.

Recent major advances in Information Technologies including Artificial Intelligence, Sophisticated Software Engineering and Big Data as well as Communication Tech-

M. Virvou · E. Alepis · G. A. Tsihrintzis (✉)
University of Piraeus, Piraeus, Greece
e-mail: geoatsi@unipi.gr

M. Virvou
e-mail: mvirvou@unipi.gr

E. Alepis
e-mail: talepis@unipi.gr

L. C. Jain
University of Technology Sydney, Ultimo, Australia
e-mail: jainlakhmi@gmail.com

L. C. Jain
University of Canberra, Canberra, Australia

L. C. Jain
Liverpool Hope University, Liverpool, UK

M. Virvou et al. (eds.), *Machine Learning Paradigms*, Intelligent Systems Reference Library 158, https://doi.org/10.1007/978-3-030-13743-4_1

nologies, which have rapidly expanded the uses of the Internet and mobile software across all aspects of life, are leading to a whole new era in the educational process. Among recent important aims are, the development of more engaging and human-like computer-based learning [1] by combining personalisation and artificial intelligence techniques [2]. In order for the education systems to be able to cope with advances in human knowledge, civilization and technology, action needs to be continuously taken towards improving and, hopefully, optimizing the education and learning processes and making them more effective [3]. Of course, this endeavor has been pursued since early on in human civilization [4].

Nowadays, educational institutions worldwide expand the educational tools to include e-learning [5] and mobile learning [6] so that they may offer educational functionalities to students at any time and any place. As such, a lot of institutions have incorporated Course Management Systems such as Moodle and e-class to assist lectures and classes as well as examinations of students. In many cases, Massive Open Online Courses (MOOCs) have been developed and used. The data generated in educational contexts is often large, complex, and heterogeneous, making it difficult to understand—even with advanced data analysis capabilities [7]. As pointed out in [8], traditionally, log data analysis and visualization applied for the analysis of students' behavior and activities have been one of the main research topics in the research communities around venues such as AIED (Artificial Intelligence in Education) [9] and the area of ITS (Intelligent Tutoring Systems) and EDM (Educational Data Mining) [10].

The emerging research discipline interested in "the use of intelligent data, learner-produced data, and analysis models to discover information and social connections for predicting and advising people's learning", has been termed *Learning Analytics* [11]. Over the recent years, the area of Learning Analytics has been receiving a lot of research attention worldwide [1, 3, 7, 8, 11–14].

More specifically, some of the aspects of Learning Analytics include:

1. *Learning Analytics with the purpose to measure Student Engagement, to quantify the Learning Experience and to facilitate Self-Regulation*.
2. *Learning Analytics to predict Student Performance*.
3. *Learning Analytics incorporated in Tools for Building Learning Materials and Educational Courses.*
4. *Learning Analytics as Tools to support Learners and Educators in Synchronous and Asynchronous e-Learning*.

The book at hand aims at familiarizing its readers with the emerging field of Learning Analytics as a Machine Learning Paradigm. Special emphasis is placed on addressing the four Learning Analytics aspects itemized in the previous paragraph. This book comes as the *fourth volume under the general title MACHINE LEARNING PARADIGMS and follows two related monographs* [15, 16] *and one related edited volume* [17]. As such, it focuses on the collection and processing of both instructors' and learners' data, as well as other related data and making use of relevant paradigms in various applications. It covers Learning Analytics approaches that provide adaptivity in Learning Environments, on the processing of multi-modal information produced in the context of Learning Systems, on the optimization of e-Learning and Student testing, as well as on architectural software designs on Learning Analytics Designs.

More specifically, the book at hand consists of an editorial chapter (this chapter) and an additional ten (10) chapters. All chapters in the book were solicited from authors who work in the corresponding area of Learning Analytics and are recognized for their research contributions. In more detail, the chapters in the book are organized into four parts, as follows.

The first part of the book consists of three chapters devoted to *Learning Analytics with the purpose to measure Student Engagement, to quantify the Learning Experience and to facilitate Self-Regulation*.

Specifically, Chap. 2, by Troussas, Krouska and Virvou, is on "*A Multi-Module Model Using Learning Analytics to Predict Learners' Cognitive States and Provide Tailored Learning Pathways and Assessment Materials*." The authors employ learning analytics and present 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.

Chapter 3, by Vytasek, Patzak and Winne, is on "*Analytics for Student Engagement.*" The authors review works describing student engagement and its relations to learning and focus on engagement in online and distance learning in post-secondary education.

Chapter 4, by David Martín Santos Melgoza, is on "*Assessing Self-regulation, a New Topic in Learning Analytics: Process of Information Objectification*." The author presents an ontological perspective of the study of academic learning, considerations concerning the academic learning process are stated to establish his main assertions and an example of learning math is analyzed to illustrate the passage from subjective knowing to objectification.

The second part of the book consists of two chapters devoted to *Learning Analytics to predict Student Performance*.

Chapter 5, by Dirk Tempelaar, Quan Nguyen, Bart Rienties, is on "*Learning Feedback based on Dispositional Learning Analytics*." The authors present their Dispositional Learning Analytics analysis based on the learning processes of 1017 first-year students in a blended introductory quantitative course and draw conclusions on predicting learning performance and designing effective interventions.

Chapter 6, by Christos Pierrakeas, Giannis Koutsonikos, Anastasia-Dimitra Lipitakis, Sotiris Kotsiantis, Michalis Xenos, and George Gravvanis, is on "*The Variability of the Reasons for Student Dropout in Distance Learning and the Prediction of Dropout-Prone Students*." The authors identify the most appropriate comprehensive learning algorithm using the most informative attributes for the prediction of students' dropout and, additionally, explore the reasons of dropping out in order to examine on a large scale how they are affected over time.

The third part of the book consists of three chapters devoted to *Learning Analytics incorporated in Tools for Building Learning Materials and Educational Courses.*

Specifically, Chap. 7, by Arvind W. Kiwelekar, Manjushree D. Laddha, Laxman D. Netak, and Sanil Gandhi, is on "*An Architectural Perspective of Learning Ana-*

lytics." The authors present an architectural perspective of learning analytics tools and components with the primary objective to describe the functional elements and non-functional properties such as personalization, privacy, distribution, mobility, and security supported by such tools. Further, the chapter describes various techniques for realizing these functional and non-functional elements.

Chapter 8, by Man Ching Esther Chan, Xavier Ochoa and David Clarke, is on "*Multimodal Learning Analytics in a Laboratory Classroom.*" The authors describe the setting, hardware and software needed to implement/replicate multimodal analytical approaches to analyse the learning activities in a laboratory classroom and present results from such analyses.

Chapter 9, by Arita Li Liu and John C. Nesbit, is on "*Dashboards for Computer-Supported Collaborative Learning*." The authors examine research on student-facing and instructor-facing dashboards for problem-based learning, project-based learning, collaborative argumentation, and various team-based learning activities.

The fourth part of the book contains two chapters on *Learning Analytics developed for Specific Courses*.

Specifically, Chap. 10, authored by Kabassi and Alepis, is on "*Learning Analytics in Distance and Mobile Learning for Designing Personalised Software*." The authors focus on the collection and the combination of the learning analytics data offered by different modalities in personal computers and modern smartphones. For this combination, two different Multi-Criteria Decision making theories are used, namely the Analytical Hierarchy Process and the Simple Additive Weighting model.

Finally, Chap. 11, authored by Chrysafiadi, Virvou and Sakkopoulos, is on "*Optimizing Programming Language Learning through Student Modeling in an Adaptive Web-based Educational Environment.*" The authors present ELaCv2, which is a novel integrated adaptive educational environment that provides e-training in programming and the language 'C'.

In this book, we present some of the aspects of the emerging scientific and technological areas of Learning Analytics, which are expected to play a significant role in Human Education in the years to come.

Societal demand continues to pose an increasing number of challenging problems, which require ever more efficient and intelligent tools, advanced software methodologies, and systems to de devised to address them. Thus, the reader may expect that additional volumes on other related aspects of Machine Learning Paradigms and their application areas will appear in the future.

References

1. Virvou, M.: A new era towards more engaging and human-like computer-based learning by combining personalisation and artificial intelligence techniques. In: Keynote Address, 24th ACM Conference on Innovation and Technology in Computer Science Education, ITiCSE, pp. 2–3 (2018)

2. Tsihrintzis, G.A.: Classification with significant class imbalance and applications in software personalization. In: Keynote Address, 29th IEEE International Conference on Tools with Artificial Intelligence (ICTAI2017), Boston MA, USA, Nov 6–8 (2017)
3. Schumacher, C., Ifenthaler, D.: Features students really expect from learning analytics. Comput. Hum. Behav. **78**, 397–407 (2018)
4. Skinner, B.: The Technology of teaching. Appleton-Century-Crofts, New York (1968)
5. Chrysafiadi, K., Virvou, M.: Advances in Personalized Web-Based Education, volume 78 in Intelligent Systems Reference Library Book Series. Springer, Berlin (2015)
6. Alepis, E., Virvou, M.: Object-Oriented User Interfaces for Personalized Mobile Learning, volume 64 in Intelligent Systems Reference Library, pp. 1–129. Springer, Berlin (2014). ISBN 978-3-642-53850-6
7. Vieira, C., Parsons, P., Byrd, V.: Visual learning analytics of educational data: a systematic literature review and research agenda. Comput. Educ. **122**, 119–135 (2018)
8. Ali, L., Hatala, M., Gašević, D., Jovanović, J.: A qualitative evaluation of evolution of a learning analytics tool. Comput. Educ. **58**(1), 470–489 (2012)
9. http://iaied.org/
10. http://educationaldatamining.org/
11. Krumm, A., Means, B., Bienkowski, M.: Learning Analytics Goes to School: A Collaborative Approach to Improve Education. Taylor and Francis (2018)
12. Sclater, N.: Learning Analytics Explained. Taylor and Francis (2017)
13. Lockyer, L., Dawson, S.: Learning designs and learning analytics. In: Proceedings of the 1st International Conference on Learning Analytics and Knowledge (LAK '11), pp. 153–156. ACM, New York, NY, USA (2011)
14. Shum, S.B., Ferguson, Rebecca: Social learning analytics. J. Educ. Technol. Soc. **15**(3), 3–26 (2012)
15. Lampropoulos, A.S., Tsihrintzis, G.A.: Machine Learning Paradigms—Applications in Recommender Systems, volume 92 in Intelligent Systems Reference Library Book Series. Springer, Berlin (2015)
16. Sotiropoulos, D.N., Tsihrintzis, G.A.: Machine Learning Paradigms—Artificial Immune Systems and their Applications in Software Personalization, volume 118 in Intelligent Systems Reference Library Book Series. Springer, Berlin (2017)
17. Tsihrintzis, G.A., Sotiropoulos, D.N., Jain, L.C. (eds.): Machine Learning Paradigms—Advances in Data Analytics, volume 149 in Intelligent Systems Reference Library Book Series. Springer 2018

Part I
Learning Analytics with the Purpose to Measure Student Engagement, to Quantify the Learning Experience and to Facilitate Self-Regulation

Chapter 2
Using a Multi Module Model for Learning Analytics to Predict Learners' Cognitive States and Provide Tailored Learning Pathways and Assessment

Christos Troussas, Akrivi Krouska and Maria Virvou

Abstract Learning analytics brings considerable challenges in the field of e-learning. Researchers increasingly use the technological advancements emerging from learning analytics in order to support the digital education. The way learning analytics is used, can vary. It can be used to provide learners with information to reflect on their achievements and patterns of behavior in relation to others, or to identify students requiring extra support and attention, or to help teachers plan supporting interventions for functional groups such as course teams. In view of the above, this paper employs learning analytics and presents 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. Furthermore, it presents a multi module model consisting of the identification of target material, curriculum improvement, cognitive states and behavior prediction and personalization in order to support learners and further enhance their learning experience. The evaluation results are very promising and show that learning analytics can bring new insights that can benefit learners, educators and administrators.

Keywords E-learning · Learning analytics · Cognitive states prediction · Personalization · Target material · Evaluation

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C. Troussas (✉) · A. Krouska · M. Virvou
Software Engineering Laboratory, Department of Informatics, University of Piraeus, Piraeus, Greece
e-mail: ctrouss@unipi.gr

A. Krouska
e-mail: akrouska@unipi.gr

M. Virvou
e-mail: mvirvou@unipi.gr

M. Virvou et al. (eds.), *Machine Learning Paradigms*, Intelligent Systems Reference Library 158, https://doi.org/10.1007/978-3-030-13743-4_2

2.1 Introduction

During the last decade, a great deal of research interest has been put in the analysis of educational data which takes place by utilizing automatic ways so that the learners' experience is further increased. This interest led to the formation of a new research area, currently referred to as learning analytics (LA). Learning analytics can serve as a possible key future trend in learning and teaching [1]. It should be noted that learning analytics actually collect elements from different related fields, such as artificial intelligence or statistics, and compose several existing techniques. Spotting the dissimilarities of the fields of educational data mining, academic analytics and learning analytics has been a concern of several researchers [2, 3]. Educational data mining describes a research field focusing on the application of data mining, machine learning and statistics to information generated from educational settings (e.g., universities and intelligent tutoring systems). At a high level, the field seeks to develop and improve methods for exploring this data, which often has multiple levels of meaningful hierarchy, in order to discover new insights about how people learn in the context of such settings. Data mining is described as a process of discovering patterns in large data sets involving methods at the intersection of machine learning, statistics, and database systems with an overall goal to extract information (with intelligent methods) from a data set and transform the information into a comprehensible structure for further use [2]. On the other hand, educational data mining is defined as a field utilizing data mining techniques in order to provide solutions to digital learning issues [3]. On top of that, the goal of an academic analytics program is to help stakeholders being charged with strategic planning in a learning environment to measure, collect and handle data in an effective manner so that operational, program and student strengths and weaknesses can be identified [3]. In spite of several differentiations between the three areas, there are significant similarities between them concerning the aims and development way followed by the stakeholders.

Indeed, during the last years, there has been questioning on the process of big data mining that is followed by universities and colleges or by financial stakeholders of education [4]; however, education can benefit from LA and be enhanced according to related researches [4]. LA has the ability to expand the knowledge of learners and educators and can assist them on their decision making process so that they reap great benefits from their efforts [5]. Many applications of learning analytics are tracking and predicting learners' performance as well as diagnosing annoying issues affecting the students [6–8]. Learning analytics utilizes predictive modeling and serve as a source of valuable information. The aim of LA is to create a personalized and student friendly learning environment and provide recommendations to learners concerning the learning objects. Hence, LA focuses on the application of algorithmic approaches and techniques to treat issues affecting student learning and organization of learning material [9, 10].

LA, through multiple ways, has the opportunity to alter the environment of e-learning either offered by educational organizations (e.g. universities, schools etc.) or in corporate training. With the data collected through analytics, instructional designers and e-learning professionals can offer learners an incomparable learning experience which is what all students seek to receive. As such, LA has numerous benefits concerning learners, instructors and the learning process itself [9].

One of the most important benefits of analytics is that they can provide knowledge not only on how a learner is performing at a specific time, but also about his/her future performance during the duration of the e-learning course. For instance, LA can serve as a tool to predict if a particular learner is likely not to pass the e-learning course, or if the learner is likely to pass the e-learning course only if additional assistance is provided (such as learning material repetition or motivation). Therefore, analytics can help to determine if learners may benefit from supplementary e-learning materials and/or peer/educator assistance during the e-learning course. This can result in students' higher grades and an e-learning experience which will be thorough and full of importance. Another example is the case that LA shows that the majority of students is finding one particular unit of the e-learning course too demanding; then, the educators can change the difficulty level of that specific e-learning unit. This will lead to more effective e-learning environments in the future, because of the data that has been collected previously.

Through learning analytics, e-learning professionals and instructors have the capability to create a learning environment which will be tailored to the specific needs and preferences of each individual student [11]. If the data shows that a student requires a lot of time to complete a particular e-learning unit, then corrective actions can take place to offer students more customized educational tools and e-learning course resources. For instance, learners can be provided with links to external sites that may help them to efficiently understand the learning unit, or even multimedia allowing them to learn through a more auditory/visual way. Given that learners are not alike, and learning analytics gives e-learning professionals the possibility to ensure that e-learning experiences, as perceived by students, are not alike either.

More learners have the opportunity to ameliorate their performance because of learning analytics data and intervention; fewer learners will drop out or fail the e-learning course. If a learner does not have a good time while interacting with the e-learning system, then s/he is less likely to be motivated to remain enrolled. As a result, a learner will simply stop participating, which means that educational organizations may realize a steep decrease dropout rate and/or profits and learners simply won't benefit from the informative e-learning courses that are being provided.

As mentioned above, through LA, an in-depth understanding pertaining to the e-learning courses is gained and specifically on how their respective resources are being utilized and how learners are actually acquiring information; as such, a higher quality in e-learning can be achieved at a lower cost. For example, if LA reveals that a particular section of the e-learning course simply isn't helping learners to achieve their learning goals, then the specific resources can be either improved or removed in order to achieve a more worthwhile investment.

In view of the above, this paper presents a multi-module model which identifies learners' cognitive states and predicts their behavior in order to provide learning object recommendations, curriculum improvement supporting personalized instruction. Through this model, the digital learning environment becomes more supportive regarding each individual student's needs and the learning experience is enhanced. The cognitive states are recognized with the use of machine learning techniques that take as input important students' characteristics. Then, the learning environment is fully adapted to each student with the objective to enhance his/her knowledge acquisition.

2.2 Related Work

LA uses several different kind of data and employs multiple techniques to conduct analysis, including statistical tests, explanatory and predictive models and data visualization [12]. Several stakeholders, such as administrators, educators, and learners, can then act on the data-driven analysis. Without a standardized methodology, LA has been implemented using diverse approaches for various objectives. In [13], the authors summarized three major themes in LA implementation, namely the development of predicators and indicators for various factors (e.g. academic performance, student engagement, and self-regulated learning skills); the use of visualizations to explore and interpret data and to prompt remedial actions; and the derivation of interventions to shape the learning environment. The diversity in LA implementation presents difficulties for education institutions which plan to be involved in it, leading to questions concerning the adoption of institutional learning analytics [13].

LA has attracted the interest of many researchers worldwide who have conducted studies concerning the embodiment of LA in higher education. In [14], the authors reviewed the research methods of these studies. The findings showed that existing studies have focused on six types of research questions: qualitative evaluation; quantitative measures of use and attendance; differentiation between groups of students; differentiation between learning offerings; data consolidation; and effectiveness. The research methods used include online surveys, log files, observations, group interviews, students' class attendance, eye tracking, and the analysis of examination grades. Based on the results, suggestions were given on LA indicators for improving teaching.

In [15], the authors focused on the impacts of LA and the educational data mining on adaptive learning. They identified four distinct categories, namely pedagogy-oriented issues, contextualization of learning, networked learning, and the handling of educational resources, which are adjoining to LA.

Furthermore, in [16], the authors presented LA's methods, benefits, and challenges. The authors declared that the methods used included visual data analysis, social network analysis, semantic analysis, and educational data mining. The benefits of LA were seen to revolve around targeted course offerings; curriculum development; student learning outcomes; personalized learning; improvements in educators' performance; post-educational employment opportunities; and enhancement of educational research. The challenges included the tracking, collection, evaluation and analysis of data, as well as a lack of connection to learning science and the need for learning environment optimization.

With regard to computer science courses, in [17], the authors surveyed LA in terms of their goals, approaches, contexts, subjects, tasks, data and collection, and methods of analysis. The goals were related to learners programming and the learning environment. The authors' approach included case studies, constructive research, experimental studies, and survey research. They also found that most of the research work was undertaken in a course context. In most of the studies, learners were required to complete multiple programming tasks. The majority of studies used automated data collection that logged students' actions, and a variety of data analysis methods such as descriptive and inferential statistics.

However, after a thorough investigation in the related scientific literature, we came up with the result that there has never been presented a multi-module framework for learning analytics. As such, in this paper, we present and fully evaluate a multi-module model for learning analytics which consists of the identification of target material, curriculum improvement, cognitive states and behavior prediction and personalization. As for the cognitive states, they are recognized with the use of machine learning techniques taking as input important students' characteristics. As such, adaptive actions take place in order to deliver a learning environment tailored to the preferences and needs of each student.

2.3 Multi Module Model and Logical Architecture of the System

The use of big data can be proved as a potentially powerful tool for higher education and involves various aspects from learning analytics that closely examine the educational process to improve learning. In the field of digital education, big data includes learner's educational data and learning content data. Through careful analysis of big data, useful information can be determined; such information can benefit educational institutions, students, instructors, and researchers in various ways. These benefits include targeted material offerings, curriculum development, student learning outcomes and behavior, and personalized learning. Learning analytics concern the measurement, collection, analysis and reporting of the aforementioned data about learners and their contexts. To this direction, the architecture of our system includes the aforementioned modules, as shown in Fig. 2.1.

The purposes of understanding and optimizing our learning environment are achieved by the four modules, as follows

- Identifying target material module: With the use of big data coming from a big pool of students, our system can identify which learning material needs to be delivered to each student so that his/her learning experience is ameliorated. The students' needs and preferences along with other exploratory data are fully analyzed with the use of machine learning (as shown in the next chapter) and different learning objects are recommended to them in order to fit their personal way of instruction. Also, possible and different gaps that students may have in the given domain

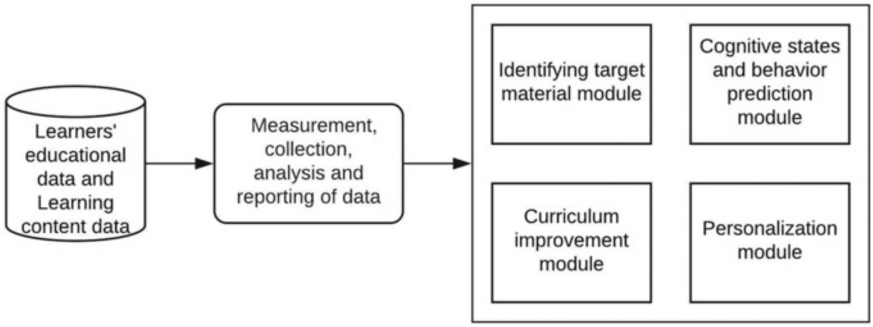


Fig. 2.1 Multi-module model of learning analytics

knowledge model, are healed by proposing specific learning objects to them. As such, student enrollment is further enhanced in the most needed areas of study.

- Curriculum improvement module: The use of big data gives the opportunity to educators to make changes and adjustments in order to improve curriculum development in the educational system, such as in the use of curricular mapping of data. A centralized curriculum mapping process runs in parallel as the curriculum is developed. As such, the content integration is appraised, gaps and redundancies can be identified, and the teaching schedules, instruction methods and assessment tools are organized. Through the analysis of big data, instructors can determine weaknesses in the educational process and students' learning and comprehension to determine whether or not improvements to the curriculum may be necessary. Instructors can engage in educational strategic planning to ensure that the learning curriculum targets student needs to maximize learning potential.
- Cognitive states and behavior prediction module: This module concerns the student learning outcome, behavior, and process. Another key benefit of big data and text mining focuses on the ability of instructors to determine student learning outcomes in the educational process as well as determine how to improve student performance. The use of educational data mining by our system contributed to positive results in the learning process. Moreover, the analysis of data can help educators understand the student learning experience through learner interactions with technology tools. The use of big data also reveals learning behavior, the impact on adaptive learning, and the level of persistence in the learning process. By understanding the effects on learner outcomes, use of this data also reveals how to make improvements in student learning and performance in academic coursework. Therefore, the learning analytics allows instructors to evaluate forms of knowledge and adjust educational content accordingly.
- Personalization module: The cornerstone of the benefits and power of learning analytics lie in the personalization of the system to the needs and preferences of students. The components of students' grades, demographic characteristics, academic background, and demonstrated effort are all addressed. The system employs

distinct ways to indicate progress or lack of progress shown by the students. Using learning analytics, the concept of personalized learning reveals student success. Course designers do not account for students who do not begin specific coursework at the same learning stage and who do not proceed, learn, and master course competencies at the same pace. Learning analytics allows educators to use data collected by the learning management system to observe the frequency of student login. Instructors can also see student interaction within the course, total engagement, pace, and grades. These components serve as predictors of students' potential success or failure. Learning analytics allows for real-time reception of the pertinent data, review as well as the incorporation of data, and real-time feedback for every student.

2.4 Learners Clustering, Using the K-Means Algorithm, Supporting System's Modules

The clustering techniques offer a structure discovery of data. They aim to find similar points of heterogeneous data resources that group items into a set of clusters, and provide the possibility to identify dense and sparse regions in item space and the correlations among data attributes [18]. It can be used as an effective tool to difference groups or classes of objects. Clustering is specifically useful in the case where the most common categories within the data set are not known in advance. Clustering can be applied in several communities, for example students in schools could be clustered together to investigate similarities and differences among them, also student actions could be clustered together to investigate patterns of behavior. Clustering algorithms typically split into two categories, either "bottom up" in the hierarchical agglomerative clustering by grouping small clusters into larger ones, or "top down" in the divisive clustering by splitting big clusters into small ones, as in the divisive clustering provided by several algorithms such as k-means and spectral clustering. Although the agglomerative clustering assumes that clusters themselves cluster together, the non-hierarchical approaches assume that clusters are separate from each other.

In our case, we provide an application of the hierarchical clustering with the purpose to divide the learners' data into distinct clusters to propose effective learning analytics for ameliorating their learning experience.

The k-means algorithm selects randomly k number of objects, each of them initially represents a cluster mean or center, an object is assigned to the cluster to which it is most similar, based on the distance between the object and cluster mean. Then it computes the new mean for each cluster. This process iterates until the criterion function converges and no change in the cluster centers is discovered. The k-means algorithm produces exactly k different clusters that have the greatest possible difference. The best number of clusters leading to greatest distinction must be computed from the data. The principle that we incorporated in the implementation of k-means algorithm sets the number to: k = 3, where k is the number of cluster. The number of the clusters is set a priori equal to three and arises from the cognitive hierarchy that is followed in our system, namely the Revised Bloom Taxonomy (RBT). RBT provides a valuable framework for instructors and instructional designers in order to focus in higher order thinking. There are six levels of cognitive learning according to the RBT. Each level is conceptually different. The six levels are described as follows:

- Remembering: Retrieve relevant knowledge from long-term memory.
- Understanding: Construct meaning from instructional messages, including oral, written and graphic communication.
- Applying: Carry out or use a procedure in a given situation..
- Analyzing: Break material into constituent parts and determine how parts relate to one another and to an overall structure or purpose.
- Evaluating: Make judgments based on criteria and standards.
- Creating: Put elements together to form a coherent whole; reorganize into a new pattern or structure.

The aforementioned levels are treated in groups of two, namely "Remembering and Understanding", "Applying and Analyzing" and "Evaluating and Creating" and thus the number of cluster is 3, as mentioned above.

For the incorporation of the k-means algorithm into the resulting system, the following steps are followed:

- For the initialization of the system, the algorithm takes as input several students' data, related to their personal profile and their interaction with the system and namely:
  - student's age;
  - student's previous knowledge;
  - student's grade;
  - types of errors that a student makes (e.g. syntax errors, careless mistakes, etc.);
  - student's learning style (Visual, Aural, Verbal, Physical, Logical, Social and Solitary);
  - Time that the student needed to complete an assessment;
  - the exact number of times that the student answered at the same assessment;
  - the exact number of times that the student has checked the same learning object.
- Following, the K-means clustering algorithm is utilized in order to detect students' behavioral patterns, needs and preferences.
- Based on the aforementioned characteristics, the system creates clusters of the already existing students. These clusters contain valuable information about their members, considering their behavior, their preferences and generally their interaction with the system.

Using the k-means clustering algorithm, the system figures out in which group of cognitive state each student belongs and specifically if s/he belong to the groups: "Remembering and Understanding", "Applying and Analyzing" and "Evaluating and

Creating”. After the student has been set to a cluster, the system adapts the learning environment to each student based on his/her cognitive state, as follows:

- if the student belongs to the “Remembering and Understanding” cluster, then the system delivers more learning objects and theoretical topics in a different way so that the student acquires all the learning material;
- if the student belongs to the “Applying and Analyzing” cluster, then the system delivers more examples on how the theoretical aspects can be applied in reality and comparative tables. Also, the students is checked concerning his/her analytical thinking, namely to separate different parts of a whole;
- if the student belongs to the “Evaluating and Creating” cluster, then the systems delivers solved problems that are based on the composition of knowledge; as for the domain knowledge, it delivers more critical issues.

2.5 Evaluation and Discussion of Experimental Results

Our prototype web-based application was used to evaluate how students perceive the use of learning analytics for the improvement of their learning environment. The population includes 32 postgraduate students from the Department of Informatics of the University of Piraeus. All the students used our prototype application as part of a postgraduate course pertaining to software technology.

Regarding the profile of the participants, all of them hold a bachelor degree in computer science, are between 23 and 35 years old and have 1–15 years work experience in the information technology industry. Their interest to participate in the experiment was primarily to learn advanced topics in the field of software technology and to experience an optimized learning environment.

The students used our prototype application for an academic semester under the guidance of the evaluators, namely a faculty member who is responsible for the postgraduate course and two research assistants. After the completion of the learning process at the end of the semester, all students were given questionnaires to complete.

The evaluation study was conducted with the use of self-supplemented scale questionnaires incorporating closed questions for the students. For our research, we have used 18 questions regarding students:

- two (2) exploratory questions
- five (5) questions regarding navigation in the platform
- four (4) questions regarding the user interface
- four (4) questions regarding learning analytics and their modules
- three (3) questions regarding evaluation of learning

Table 2.1 Sample of questionnaire

N	Questions
1	Rate the targeted material offerings (1–10)
2	Rate the prediction of your cognitive states and behavior (1–10)
3	Rate the curriculum development process (1–10)
4	Rate the personalization offered by the system (1–10)

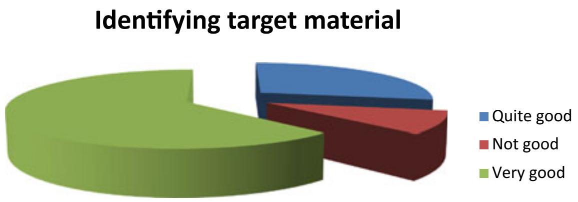


Fig. 2.2 Experimental results for the identification of the target material delivered to students

As expected, students became familiar easily and very quickly with the educational software, its modules and its functionalities. Their interest was undiminished during the whole period of their interaction with the educational application. Table 2.1 summarizes the set of questions pertaining to the learning analytics and the modules of the system. These questions follow a 1–10 ranking model (lower is negative, higher is positive).

Given that computer science students have an inherent tend towards new technological advancement, they were very familiar to the optimized learning environment, holding learning analytics developments. The findings of this study are very encouraging since the authors' attempts towards incorporating novel modules using learning analytics were successful in creating an optimized learning environment.

Analyzing the results of the evaluation study, there is considerable evidence that the novel modules incorporated in the prototype system provide tailored learning pathways to students. More specifically, 20 students declared that the identification of the target material was very successful, 9 of them declared that it is quite successful, while 3 of them declared that it is not successful (Fig. 2.2). Concerning the cognitive states and behavior prediction, 22 students declared that it is very accurate, 6 of them declared that it is quite accurate, while 4 students declared that it is not accurate (Fig. 2.3). Regarding the curriculum improvement, 20 students declared that is was achieved in a high percentage, 10 students declared that it was achieved in a quite good percentage, while 2 of them declared that it was not achieved (Fig. 2.4). Finally, the personalization to students' needs and preferences was in an excellent degree according to 21 students; 11 students declared that it was at a quite good degree, while there was not any student declaring that it was not achieved (Fig. 2.5).

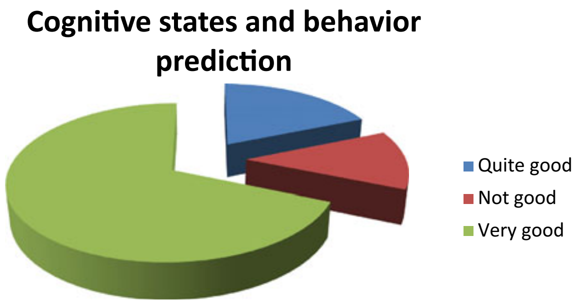


Fig. 2.3 Experimental results for the prediction of students' cognitive states and behavior

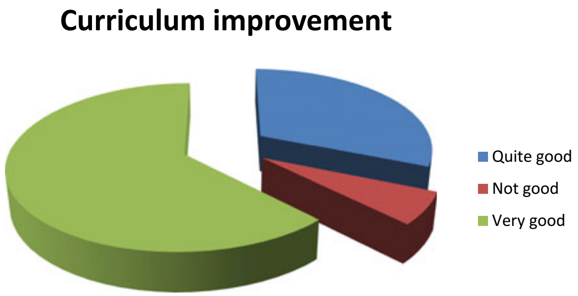


Fig. 2.4 Experimental results for curriculum improvement

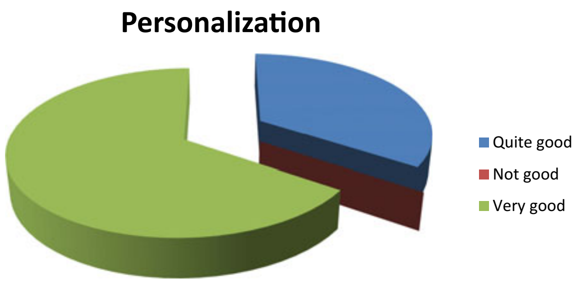


Fig. 2.5 Experimental results for the personalization of the learning environment to students

2.6 Ethics and Privacy for Learning Analytics

Learning analytics brings considerable challenges for data control, privacy, and data ownership. As institutions work to define privacy standards and policies for their students and faculty, understanding the implicit and explicit motivations of interested parties will be an important part of the discussion.

Reacting to the growth and speed with which data from online learning is emerging, in June 2014, the Asilomar Conference[1] released six principles for discussion to guide online learning data; here we extract key features of these principles:

[1]Convention Document. The Asilomar Convention for Learning Research in Higher Education. http://asilomar-highered.info/asilomar-convention-20140612.pdf (2014).

1. Respect for the rights and dignity of learners. Data collection, retention, use, and sharing practices must be made transparent to learners, and findings made publicly available, with essential protections for the privacy of individuals.
2. Beneficence. Individuals and organizations conducting learning research have an obligation to maximize possible benefits while minimizing possible harms.
3. Justice. Research practices and policies should enable the use of learning data in the service of providing benefit for all learners.
4. Openness. Whenever possible, individuals and organizations conducting learning research have an obligation to provide access to data, analytic techniques, and research results in the service of learning improvement and scientific progress.
5. The humanity of learning. Digital technologies can enhance, do not replace, and should never be allowed to erode the relationships that make learning a humane enterprise.
6. Continuous consideration. Ethically responsible learner research requires ongoing and broadly inclusive discussion of best practices and comparable standards among researchers, learners, and educational institutions.

Many concerns arise from the policies surrounding ownership of data. As data becomes more important for the learning environments, it demands connection to multiple sources that have been traditionally managed by separate entities. Certain high-level, cross-sector data communication is already common in a university. Event-driven data requires that a student's characteristic becomes part of the learning model, which entails synchronous access to detailed, individual student demographic and past performance; this raises a host of new challenges. Working with learning analytics may provide an additional level of protection at the cost of increased administrative complication.

2.7 Conclusions and Future Work

Learning analytics concerns the educational data coming from observations that stakeholders can make and thus they are used to support immediately every new student logging in the learning environment. While educators can make predictions and recognize patterns, learning analytics allows them to have a deeper insight in the data, making connections that would be impossible to be found using traditional ways. Learning analytics helps educators in the classroom immediately by helping the development of curriculum mapping and learning interventions, while predicting behavior and determining competencies and helping personalize learning.

The use of learning analytics can be proved useful in higher education performance evaluation at the university level. It can provide higher education organizations, instructors, and students with improved metrics by which to measure the effectiveness of teaching methods, the engagement of learners in the educational environment, and the efficiency of the learning process using technological approaches.

This paper employs learning analytics and presents 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. Furthermore, it presents a multi module model consisting of the identification of target material, curriculum improvement, cognitive states and behavior prediction and personalization in order to support learners and further enhance their learning experience.

Future work includes the employ of social learning analytics, which aims at exploring the role of social interaction in learning, and disposition analytics, which seeks to capture data regarding student's dispositions to their own learning, and the relationship of these to their learning. For example, "curious" learners may be more inclined to ask questions, and this data can be captured and analyzed for learning analytics.

References

1. Chatti, M.A., Dyckhoff, A.L., Schroeder, U., Thüs, H.: A reference model for learning analytics. Int. J. Technol. Enhanced Learn. **4**(5/6), 318–331 (2012)
2. Hung, J.L., Hsu, Y.C., Rice, K.: Integrating data mining in program evaluation of k-12 online education. Educ. Technol. Soc. **15**(3), 27–41 (2012)
3. Romero, C., Ventura, S.: Educational data mining: a review of the state of the art. IEEE Trans. Syst. Man Cybern. Part C Appl. Rev. **40**(6), 601–618 (2010)
4. Clow, D.: An overview of learning analytics. Teach. High. Educ. **18**(6), 683–695 (2013)
5. Scheffel, M., Drachsler, H., Stoyanov, S., Specht, M.: Quality indicators for learning analytics. Educ. Technol. Soc. **17**(4), 117–132 (2014)
6. Troussas, C., Krouska, A., Virvou, M.: Automatic predictions using LDA for learning through social networking services. In: 2017 IEEE 29th international conference on tools with artificial intelligence (ICTAI), Boston, MA, pp. 747–751 (2017)
7. Karthikeyan, K., Kavipriya, P.: On Improving student performance prediction in education systems using enhanced data mining techniques. Int. J. Adv. Res. Comput. Sci. Softw. Eng. **7**(5), 935–941 (2017)
8. Acharya, A., Sinha, D.: Early prediction of students performance using machine learning techniques. Int. J. Comput. Appl. **107**(1), 37–43 (2014)
9. Troussas, C., Virvou, M., Espinosa, K.J.: Using visualization algorithms for discovering patterns in groups of users for tutoring multiple languages through social networking. J. Netw. **10**(12), 668–674 (2015)
10. Kavitha, G., Raj, L.: Educational data mining and learning analytics—educational assistance for teaching and learning. Int. J. Comput. Organ. Trends **41**(1), 21–25 (2017)
11. Troussas, C., Espinosa, K.J., Virvou, M.: Intelligent advice generator for personalized language learning through social networking sites. In: 2015 6th International Conference on Information, Intelligence, Systems and Applications (IISA), Corfu, 2015, pp. 1–5 (2015)
12. Shorfuzzamana, M., Shamim Hossainbc, M., Nazir, A., Muhammadd, G., Alamri, A.: Harnessing the power of big data analytics in the cloud to support learning analytics in mobile learning environment. Comput. Hum. Behav. (2018) (in press)
13. Gašević, D., Kovanović, V., Joksimović, S.: Piecing the learning analytics puzzle: a consolidated model of a field of research and practice. Learn. Res. Pract. **3**(1), 63–78 (2017)
14. Dyckhoff, A.L., Zielke, D., Bültmann, M., Chatti, M.A., Schroeder, U.: Design and implementation of a learning analytics toolkit for teachers. J. Educ. Technol. Soc. **15**(3), 58–76 (2012)

15. Papamitsiou, Z., Economides, A.A.: Learning analytics and educational data mining in practice: a systematic literature review of empirical evidence. Educ. Technol. Soc. **17**(4), 49–64 (2014)
16. Nunn, S., Avella, J.T., Kanai, T., Kebritchi, M.: Learning analytics methods, benefits, and challenges in higher education: a systematic literature review. Online Learn. **20**(2), 13–29 (2016)
17. Ihantola, P., Vihavainen, A., Ahadi, A., Butler, M., Börstler, J., Edwards, S.H., Isohanni, E., Korhonen, A., Petersen, A., Rivers, K., Rubio, M.Á., Sheard, J., Skupas, B., Spacco, J., Szabo, C., Toll, D.: Educational data mining and learning analytics in programming: literature review and case studies. In: The 20th Annual Conference on Innovation and Technology in Computer Science Education—Working Group Reports, ACM, New York, NY, pp. 41–63 (2015)
18. Troussas, C., Virvou, M., Alepis, E.: Comulang: towards a collaborative e-learning system that supports student group modeling. SpringerPlus **2**(1), 1–9 (2013)

Chapter 3
Analytics for Student Engagement

J. M. Vytasek, A. Patzak and P. H. Winne

Abstract Volumes of detailed information are now unobtrusively collected as students use learning management systems and digital learning environments in their studies. This significantly elevates opportunities to better understand how students learn. The learning analytics community is exploring these data to describe learning processes [117] and ground recommendations for improved learning environments [8, 102, 139]. One challenge in this work is need for more and more detailed information about each student's learning processes to mine for developing useful and timely feedback for students and teachers [150]. Student engagement is a strong focus in this work. Research consistently shows positive relationships between engagement and academic success (e.g., [68, 111]). However, to construct learning analytics describing student engagement and recommending more productive forms of engagement, the field needs to better understand what student engagement means, how it can be observed online and quantified, and how it relates to learning processes and achievement. We review literatures describing student engagement and its relations to learning focusing on engagement in online and distance learning in postsecondary education. We catalog conceptualizations, measurement approaches and benefits of student engagement for learning and academic achievement. Through lenses of learning analytics and learning science, we map the evolution of analytics about student engagement and propose future research to bridge the learning analytics—learning science gap. We note challenges of tracking and supporting student engagement and recommend strategies that are predicted to facilitate positive long-term change.

3.1 Effects of Student Engagement

In classrooms and in online learning environment, there is strong evidence for positive relations between student engagement and valued outcomes for students, instructors, and educational institutions. Some researchers describe student engagement

J. M. Vytasek (✉) · A. Patzak · P. H. Winne
Faculty of Education, Simon Fraser University, 8888 University Drive,
Burnaby, BC V5A 1S6, Canada
e-mail: jovita_vytasek@sfu.ca

M. Virvou et al. (eds.), *Machine Learning Paradigms*, Intelligent Systems Reference Library 158, https://doi.org/10.1007/978-3-030-13743-4_3

as a prerequisite for learning because it operationalizes students' commitment to a course of study and course activities [26, 53, 115]. Others highlight benefits of student engagement as due to opportunities it offers to measure and monitor students' academic development as grounds for improving teaching and learning [73]. Overall, three themes relate student engagement and learning: (1) students' perceptions of engagement, (2) how engagement relates to learning processes, and (3) student engagement and academic performance.

A compelling majority of studies report positive associations between the frequency of student-instructor interactions and students' perceived learning outcomes, actual learning outcomes and satisfaction [9, 35, 49, 129]. Students' perceived more engagement in learning and more active participation in class activities when encouraged to collaborate with classmates [32]. Students were more satisfied and perceived greater learning gains if they cooperated and communicated with their classmates [9, 49, 129]. Interestingly, students given opportunities to interact online (e.g., through blogging) were more reflective about their learning [155]. Gray and DiLoreto [49] found student engagement mediated the relationship between frequency of student-instructor interactions and students' perceived learning. Roorda et al. [118] meta-analysis reported medium to large positive effect sizes for effects of interactions and communications between students and instructors and school engagement.

Lin and Tsai [83] analyzed how students engaged in an online searching activity. They identified two levels of cognitive engagement, deep and surface. Behaviorally active students who created bookmarks, annotations, and wrote comments reported deeper cognitive engagement. Carini et al. [17] study investigated how student engagement related to outcomes across 14 colleges and universities. Student engagement positively related to critical thinking and academic achievement. Lower-achieving students particularly benefitted from strategies designed to increase student engagement.

Student engagement correlates positively with students' grades (e.g., [77, 80, 86, 88, 125]) but the magnitude of association varies considerably across studies. For instance, Morris et al. [94] reported student engagement explained approximately 31% of variance in academic achievement whereas Carini et al. [17] reported small correlations between subscales of student engagement and GPA ($r = 0.07$–0.13) and overall scores on the GRE ($r = 0.08$–0.16). Notably, active and collaborative learning as well as student-instructor interactions had the strongest relationships to students' GPA.

Academic achievement is positively correlated with active participation in discussion forums (e.g., [25, 59, 96, 134, 143]), interpersonal interactions [61], course attendance [86]. Um et al. [135] highlighted the importance of considering emotional engagement in multimedia learning. They reported students perceived learning materials less difficult and demonstrated increased comprehension and transfer when learning materials were developed in accord with emotional design principles.

There is also evidence student engagement correlates positively with retention and graduation rates [4, 10, 43] while it correlates negatively with dropping out [1, 39, 43, 69, 76, 114]. Alexander et al. [2] conducted a longitudinal study of student engagement and dropout rates by following first graders through high-school. Behavioral aspects of disengagement predicted dropout in high school independently of sociodemographic variables.

3.2 Conceptualizing Student Engagement

In the 1980s, research on student engagement focused primarily on supporting disadvantaged students with an emphasis on reducing alienation and student dropout [42]. Later, this focus shifted toward describing student engagement—individually and in collaboration—as necessary for students' learning (e.g., [104]). Although studies predominantly show positive effects of student engagement, there is weak consensus about how engagement should be conceptualized (e.g., [19]). Definitions and models are almost as plentiful as researchers theorizing about student engagement (see Azevedo [7]).

Most definitions of student engagement describe students' investing resources such as time, effort, and energy in study activities to enhance learning, build understanding, and elevate academic performance [60, 73–76, 98, 132]. While this rather broad view describes students' behaviors, which may indicate commitment, it does not illuminate what constitutes high quality student engagement. This makes interpretations ambiguous. For instance, is a student who does not spend a lot of time or effort on a class less engaged or appropriately engaged due to high prior knowledge or effective time management?

Other researchers merge aspects of previous definitions to operationalize student engagement in terms of invested time and energy, individual attitudes, cognitions, and behaviors, and communication with others. For example, Dixson [29] include students' interactions with learning materials, classmates and instructors as elements of student engagement. Their definition may be particularly applicable to online learning environments. Some research in online learning contexts emphasizes the importance of facilitating a sense of belonging and feeling connected to others (i.e., social presence) for students' engagement [23]. For example, social presence is a large component in the oft cited model by Garrison et al. [45], an adaptation of the community of inquiry model (CoI) to online learning contexts. Garrison et al. [45] argue meaningful online learning occurs when three factors are fostered: social presence, cognitive presence (constructing knowledge through interaction and reflection) and teaching presence (coordinating instructional design, teaching style, and goals of the educational institution).

Czerkawski and Lyman [24] introduced the E-learning Engagement Design (ELED) framework based on principles of instructional design. ELED introduces a feedback loop linking instructional needs (e.g., assess students' needs), instructional objectives (e.g., define instructional goals), learning environment (e.g., select instructional resources) and summative assessments (e.g., evaluate instructional effectiveness). Teachers and educational institutions can refer to ELED to design and facilitate classes encouraging students' engagements with class materials, classmates, and instructors.

Other researchers also emphasized how educational institutions can support student engagement. Finn's [41] participation-identification model describes how engagements in school activities influence academic performance and students' identification with the educational institution. In turn, students' identification with their educational institution influences their participation. Finn's model also depicts how students' abilities interact with instructional design to affect participation and performance. Similarly, other researchers point to roles for educational institutions in facilitating student engagement to promote learning and social integration [66, 132].

Most definitions and models of student engagement center on students. For instance, Moore's [93] interaction framework characterizes a network of interactions between learner-to-learner, learner-to-instructor, and learner-to-content as a basis for designing strategies to enhance student engagement (e.g., [89]).

One of the most detailed and comprehensive of these models is Fredricks et al. [43] 3-component framework: behavioral engagement, cognitive engagement, and emotional engagement. Behavioral or physical engagement includes: following the rules, participating and/or completing study related activities such as attending classes, asking questions, or joining a club or sports team of the educational institution. Cognitive engagement refers to how students tackle tasks, e.g., learning strategies they apply or approaches they use to solve problems or process information. Cognitive engagement also concerns a student's investment to master a task. Emotional engagement describes students' affective responses to learning materials, classmates, instructors and the educational institution. An emotionally engaged student experiences a sense of belonging and enjoys the class. All three components are dynamic and interconnected. Each component embraces positive and negative aspects, including desirable and undesirable behaviors, productive and maladaptive learning strategies, and positive and negative emotions.

Researchers have widely applied Fredricks and colleagues' tricomponent model of student engagement. However, views vary about how much attention should be given to each component. Finn and Zimmer [42], for instance, focus primarily on observable learning processes such as students' participation in class activities or completion of study tasks. Pentaraki and Burkholder [108] emphasize emotional engagement as the key feature. According to them, emotions determine how students engage with their learning environment while behaviors and cognitions are antecedents of emotions.

Other researchers investigate student engagement through lenses ground according to other lines of research e.g., cognitivism or constructivism [83], for instance, acknowledge the involvement of all three components in Fredricks and colleagues' model but, based on Greene and Miller's [50] framework, distinguish meaningful cognitive engagement (e.g., using elaboration strategies to improve mental representation) from shallow cognitive engagement (e.g., using flash cards for rote processing of information). Fredricks et al. [43] themselves identify some shortcomings of their model. For instance, effort can be mapped into behavioral or cognitive engagement without considering the quality of engagement, e.g., merely fulfilling minimum requirements versus "going beyond" to understand concepts.

3.3 Measuring Student Engagement

Numerous self-report surveys or questionnaires have been developed to assess aspects of student engagement. We cite representative examples to highlight the variety and scope of options. For a more complete review, see Fredricks et al. [43].

Perhaps the most widely administered self-report measure of engagement is the college student report developed within the National Survey of Student Engagement project (NSSE). It is administered annually by many postsecondary institutions across North America [74]. Students are asked to specify how frequently they engage in activities considered a priori good educational practice (e.g., using available resources), how many hours they spend on activities related to school, and other variables relating to how students' spend time (e.g., extracurricular activities, employment, family matters). Student engagement is categorized into four major themes: academic challenge, learning with peers, experience with faculty, and campus environment. Each theme is characterized by engagement indicators. For instance, higher order thinking, reflective and integrative learning, learning strategies, and quantitative reasoning are indicators for academic challenges; collaborative learning and discussions with others indicate engagement with peers [100].

The Student Course Engagement Questionnaire (SCEQ) [54] is another frequently used self-report measure. It was developed to measure students' classroom engagement based on four factors: skill engagement, emotional engagement, participation/interaction engagement, and performance engagement. Items concern whether students keep up with class readings (skills engagement), apply course content to their own life (emotional engagement), enjoy collaborative learning (participation/interaction engagement) and academic achievements (performance engagement). The SCEQ somewhat aligns to Fredricks et al. [43] framework: skills engagement appears to correspond to cognitive engagement, and participation/interaction engagement parallels behavioral engagement, respectively. Handelsman et al. [54] add a construct of performance engagement. Dixson [29] adapted the SCEQ to assess students' engagement in online education. Their online student engagement (OSE) survey positively correlated with some online learning activities such as reading discussion posts and accessing online resources [29].

Other self-report measures of student engagement include Roblyer and Wiencke's [116] Rubric for Assessing Interactive Qualities of Distance Courses (RAIQDC) and Ouimet and Smallwood's [101] Classroom Survey of Student Engagement (CLASSE). The RAIQDC was developed specifically for online and distance education settings to assess and potentially improve the quality of online courses. In contrast, items in the CLASSE ask respondents about perceptions and behaviors in and outside the classroom. Administering CLASSE to students and to faculty can identify discrepancies between these two perspectives.

Correlations between self-reported engagement and student success spurred many to explore how to measure student engagement using data generated directly within digital learning environments. Trace data—records of events that strongly support inferences about students' cognition or motivation [144, 146]—arise from various sources such as clickstream data, learning artifacts (e.g., students' essays or highlighted text), or time stamps.

Time-related measures can be analyzed as intervals (time on a task) or nominally as accessing a resource, e.g., a video. Time has been used as a proxy for various kinds of students' engagement, such as using learning strategies, managing time, procrastinating, or general engagement (e.g., [65, 157]). Guo et al. [53] measured engagement as time students watched course videos and their attempts to answer questions about the videos. Kovanovic et al. [72] identified several measures used to estimate time on task—time spent on assignments, with resources, in discussion forums, posting to discussions and updating discussion posts—and explored how these various measures affected research findings. He found different measures of time on task differentially shape research findings. Thus, attention to how time is gauged when investigating students' engagement matters in reporting how engagement relates to outcome variables.

Other researchers tracked student engagement using artifacts created, e.g., assignments, notes, or learning materials accessed, such as online readings. Lin and Tsai [83] used logs from an online social bookmarking application that recorded students' actions such as bookmarks created, shared, annotated, and commented on. Treating these data as operational definitions of students' behavioral and cognitive engagement, Lin and Tsai [83] categorized students' based on patterns of behavioral and cognitive engagement, classifying them as hitchhikers, individualists, commentators, or active learners; or deep versus surface processers. Stewart et al. [127] measured engagement by counting resources students voluntarily accessed in an online learning environment, including learning resources, information about course administration, a wiki and assessment tools.

Discussion posts are learning artifacts representing interactions among students, between students and teaching assistants, and between students and instructors. Petty and Farinde [110] judge engagement is best observed through interactions with others. Discussion posts can be analyzed quantitatively (e.g., time spent in discussion forums or number of posts created) or qualitatively. Wong et al. [154], for example, used a keyword taxonomy to analyze online forum conversations according to types of learning interactions (e.g., levels of learning). Future research in student engagement can build on this approach to estimate cognitive engagement using students' posts. Settanni and Marengo [122], for instance, used automated text analysis to identify emotion-related indicators in post texts and combined these data with self-report measures of depression, anxiety, and stress. While their study was conducted in the context of social media, it illustrates how forum data can be used in estimating students' emotional engagement.

In online classes and massive open online courses (MOOCs), measuring how students' engage with the learning environment has sometimes been assessed by a proxy of students' learning outcomes and completion rates (e.g., [57]). In MOOCs that cover multiple topics within a domain, some students might be interested and engaged in only one or a subset of all the topics (e.g., [123]). Students in an undergraduate online course might achieve good grades for merely "doing time" rather than engaging in learning [159]. Students' achievement may imply engagement but it is a poor proxy for direct measures of students' patterns of engagement and it ignores other aspects relating to engagement such as students' emotional engagement.

Advances in learning technologies and wider adoptions of online learning systems offer educators and researchers exciting opportunities to gather large volumes of trace data to supplement self-report measures of engagement [150], Trace data have an advantage of representing students' actual learning activities, independent of method effects and biases that arise in self-report measures such as current mood of the respondent, social desirability or response biases (e.g., [34, 44, 58, 149]).

3.4 Analytics for Student Engagement

Building on research linking engagement to student outcomes and newly accessible trace data generated within learning management systems and online learning tools, analytics about engagement emerged [102]. Early analytics focused on relations between students' engagement and academic performance at the level of a course or institution. These analytics based mainly on admission data and trace data, plus limited use of self-report data, were designed to guide policies for improving student retention. Goldstein's [47] extensive survey of 380 post-secondary institutions and interviews with 27 leaders identified 70% of institutions were heavily focused on extracting and reporting student activity to inform administration.

In the U.S., only half of students who started college graduated in 6 years; the number of dropouts was alarming [67]. Amidst strong concerns about the quality of education and unsatisfying graduation rates in the post-secondary sector [16], research blending assessment scores with online engagement data led to a strong emphasis on predictive modeling and analytics about the probability of student academic success. The enriched data environment created by emerging technologies supported the development of analytics leveraging early- and mid-course student engagement data to predict academic success. This set a stage for instructors and students to be forewarned before students disengaged, shifting earlier interests to describe risk to interventions "based on predictions and probabilities" [16, p. 7]. Accompanying this new emphasis on intervention, new work in learning analytics rapidly emerged to provide feedback on learning engagement: (1) early alert systems and (2) dashboard visualizations.

3.4.1 Early Alert Analytics

Early alert analytics use engagement data and other data to build models predicting the probability of disengagement or academic failure [78]. While some early alert systems display analytics directly to students, most alert instructors or advisors who then decide whether to contact the student or to enact another intervention [6, 16, 87, 142].

The Course Signals project at Purdue University is a well-known example of early alert analytics systems [84]. It amalgamated data from the student information system, course management system, and course gradebook to characterize students' levels of engagement in the course. These data were input to a sophisticated algorithm that predicted the probability of a student's failure in a course. The system was so fined-tuned that alerts could be generated as early as the second week of classes. Once a student was identified, instructors were provided a status icon using the metaphor of a red, yellow and green traffic light to indicate a student's probability of success [5]. Instructors then decided whether to share the traffic alert with the student on their individual course homepage, send the student an email or text message, refer the student to academic advising/resources or set up a face-to-face meeting. Several studies demonstrated this system's utility to improve student engagement and retention. For example, an experimental group in a biology course with access to Course Signals showed a marked decrease of 14% in the number of D and F letter grades relative to a control group without access to Course Signals [6]. How and when faculty used and acted on these analytics varied at Purdue. This was considered a limitation as the system only provided an alert without guidelines for best practice [5]. While not directly measured, the project suggests potential to alert students about self-correcting their at-risk behavior.

Analytics based on predictive modeling like Purdue's Course Signals became the archetype of the time, shaping educators' views about roles for analytics in learning [84]. Data related to student engagement in these models were hidden from users, calculated in the background. Analytics were provided only after a risk state was predicted.

Predictive modeling and alert analytics faced several challenges. Insights provided by alerts were limited [103, 112]. The target recipient of the analytic, instructor or student, was made aware of the probability of a problem but no details were available to understand what aspects of engagement were problematic. Ambiguity in feedback to instructors was associated with superficial feedback to students about how they might adapt engagement to improve learning [6, 51]. To fill this gap, instructors and students needed more detailed information about how a student was engaging.

3.4.2 Dashboard Visualization Analytics

Newer engagement analytics and dashboards visualizations were designed to open the "black box" of predictive models by revealing features of student engagement that contributed to predictions [78]. In this work, focus shifted from predicting outcomes to displaying information about students' engagements in easily interpretable displays about predictors of success or at-risk status [139]. This opened up potential to represent multiple aspects of engagement to teachers and students so they could consider how to improve engagement. This was a new direction in learning analytics [20, 37].

3.5 Dashboard Visualizations of Student Engagement

A deeper dive into learning analytics visualizations uncovers a large variety of types of data and feedback visualized in student-facing dashboards [33, 63, 64, 139, 140, 156]. Types of data used representing learner engagements fall into five categories: artefacts produced by learners, social interactions, use of resources, time logs, and scores on tests and self-assessments [140].

Artifacts produced by students and social interactions were the most common data visualized in dashboards appearing in 66% of the dashboards surveyed [139, 140]. Half (16/24) of the dashboards visualized artifacts produced by learners, including: student created resources (9/24), annotations (2/24), responses to questions (4/24), products of communication such as help requests (1/24), posts on blogs, and participation in discussion forums (4/24) or social networks (2/24). The second most common class of data underlying dashboard analytics described forms of social interaction (10/24), including forum posts and comments in chats (3/24), tweets (2/24), and speech in fact-to-face group work (1/24). Types of communication also were quantified and measured. For example, Yu et al. [158] identified social signals representing politeness, stress, agreement and disagreement in posts.

Data representing logs of time, use of resources, and scores on assessments were found in approximately 50% of the surveyed dashboards. Resource use was visualized in 11 of 24 systems [140]. Resources students used to quantify engagement included the number of forum posts a student read [97] and instructor-provided online resources accessed. Most dashboards tracked resource use to inform teachers about students' judgments of the relevance of resources or to estimate students' engagement in studying behavior.

Time log metrics were present in nearly half of all dashboards. Time was most often used as an indicator of disengagement patterns predicting at-risk behavior. For example, SAM [48], Student Inspector [120], LOCO-Analyst [3], Moodle dashboard [113] and StepUp! [119] visualized time students spent in various activities to help teachers identify students potentially at risk. Engaged time was also visualized for students, often comparing an individual student's time log to a peer group [48, 82, 119]. Time on task was rarely a proxy for engagements relating to learning content or level of concept knowledge [120].

Finally, 12 of 24 dashboards visualized students' attainment of content knowledge in both blended and online learning settings based on tests and self-assessments. As we noted earlier [36, 126], both individual- and group/class-level analytics indirectly represent learner engagement.

3.6 Comparative Reference Frame

A third frame of reference for analytics about engagement varies the reference frame for metrics about a student's engagement: absolute, relative and social [153]. Absolute comparisons use a fixed standard (goal) as a reference point for analytics about an individual. An exam score or course criterion are examples. Relative comparisons track an individual's progress over time using the individual's historical data as a reference. The social reference frame uses a select peer group or the class as the basis for comparison.

Time is a key dimension in reference frames [63]. An absolute reference frame is future-directed; it compares a student's engagement activities now to future standards. The relative reference frame is grounded in historical accomplishments. The social reference frame requires identifying a particular time interval within which an individual's engagement is compared to peers'.

In a recent systematic review, Jivet et al. [63] found learning outcomes were the most commonly used reference frame, appearing in 15 of 26 studies they reviewed. These studies represented engagement conceptualized in terms of normative references. Learning goals were used in only one study. Several dashboards (10/26) included relative reference frame metrics of students' progress up to a current point in time. Social reference frames appeared varyingly and compared an individual student to: the class average (15/26), teammates (2/26), previous graduates (2/26), top peers (4/26) or peers with similar learning goals (1/26).

Overall, dashboard visualizations have been designed to address the challenge of providing feedback to teachers and learners by portraying activities that might be changed to improve student engagement and, as a consequence, learning. However challenges remain in translating analytics into actionable feedback that guides learning [38, 46, 102]. In the next section, we examine analytics from our perspective of the engagement literature which we judge does a better job of showing how to intervene and illuminates paths for future research.

3.7 Challenges and Potential Solutions for Analytics of Student Engagement:

3.7.1 Challenge 1: Connecting Engagement Analytics to Recommendations for Improvement

So far, work on data visualizations has used learning artifacts, social interaction, resources and assessments as foundations for empowering teachers and students to make informed decisions about how to improve engagements in learning [13]. While dashboard analytics inform students and instructors about some proximal and some distal features of course engagement [71] recommendations based on these displays have been lacking. Merely opening "black box" characteristic of closed prediction models does not link those data to specific learning processes that give rise to achievements. To span that gap, there needs to be a stronger conceptual connection between valued aspects of engagement represented by data and characteristics of engagement lead to quality learning [38, 46, 102, 152]. The need to build this bridge is evident: 79% of 111 learning analytics experts believe learners cannot interpret what learning analytics suggest about how to remediate deficient learning processes [31].

We conjecture this problem arises, in part, from a limited view of student engagement. This might be due to the complexity of engagement as a construct (e.g. [7, 19]), as we previously described. Behavioral engagement, most commonly taken as a proxy for effort and time on task [63], dominates current dashboards. Using Fredrick's model [43], behavioural engagement is operationalized in terms of positive actions such as working persistently and effort on appropriate tasks [40, 125]. But quantifying time spent captures only the behavioral component of engagement while ignoring other dimensions of engagement.

Identifying *effortful* engagement is still a challenging task. Boundaries between behavioral engagement and productive cognitive engagement are not sharp. This is found in several studies using in-person observational methods [81, 98, 128]. Specifically, Peterson et al. [109] found that observers' judgments of students being on-task were sometimes contradicted in subsequent interviews when students reported not being appropriately engaged because they were not thinking about content being presented in a lesson. And, surprisingly, many students who observers classified as disengaged (off task) actually were quite cognitively engaged, e.g., trying to relate new ideas to what they had already learned. In this light, we conjecture digitally tracked traces limited to behavioral engagements offer limited and ambiguous information about the presence and qualities of cognitive engagement.

Cognitive engagement has been predominantly represented in dashboards in terms of artifacts students created (e.g., entries in portfolios, annotations and communication) or scores on self- or other-administered assessments. These were present in 66% of dashboards reviewed. These analytics focus on the products of engaged time but, under closer inspection, we see some pitfalls and limitations.

Counting artifacts like annotations reflects the frequency of cognitive engagements but reveals nothing about their important qualities, such as how information was processed or how well it was understood. Assessments like essay scores reflect what a student has learned but describe nothing about how learning took place. Counting socially-related artifacts such as posts to discussions similarly overlook qualities of information shared and important procedural features related to how effective collaborations are [92, 115]. We encourage more careful interpretation of these kinds of data when using them to reflect on the multifaceted nature of student engagement.

Emotional engagement has been rarely addressed in dashboards because identifying it in trace data remains a challenge. As we reviewed, only one study analyzed students' communications to explore emotional engagement in a discussion forum [64]. Gathering data and developing analytics about emotional engagement throughout digital learning spaces needs attention.

Overall, analytics about engagement underrepresent and may bias its multidimensionality. In turn, mapping relationships between engagement and academic success is truncated. While we recognize limitations of trace data to fully represent engagement and inform analytics, it is important to innovate methods to capture more fully the nature of engagement in online contexts.

3.7.2 Potential Solutions: Using Diverse Metrics of Engagement to Improve Feedback Provided

Data describing the multifaceted structure of engagement can increase opportunities to construct analytics for guiding students' approaches to learning beyond merely reflecting on past behavior. This is because trace data set a stage for characterizing behavioral, cognitive and emotional facets of engagement by detailing learning artefacts a student engages *with* as well as *how* they engage with artefacts. Presenting new opportunities to capture data on the presence and quality of engagement.

For example, there is increasing interest in capturing students' cognitive engagement when researching online resources to help them successfully apply information problem solving skills as they navigate the wide variety of information available in the internet (e.g., [121, 145]). Learning analytics grounded in continuously gathered online trace data are ideal for providing just-in-time and just-in-case formative feedback to guide the process of researching a project or term paper. As a student searches for sources, analyzes and annotates them, and develops a product, digital traces can identify which information students select and disregard, how they organize information, and ways they process it. Analytics generated using this broader and deeper set of data can reveal patterns of learning activities, features of metacognitive monitoring, metacognitive control of study tactics, and how information available in sources is used in drafts of the learning product. This fuller picture of engagement allows discovering and analyzing data to form new analytics. For instance, data on terms a student used to search for information, indexes of semantic similarity between documents retrieved and the subset that a student bookmarks, and term co-occurrences and term frequency are examples of data for building analytics that can recommend more helpful approaches to searching information. Supplementing these with student-reports about goals for search and for drafting a paper can personalize analytics to fit a student's interests (see for example Winne et al. [145]). As students self-regulate, these continuously gathered data allow rapid updating about the student's profile of cognitive engagement. Because a teacher could not "stand over the shoulder" of a student to observe all this activity, analytics incorporating trace data can supply new information students can draw on to help them improve the skill of searching.

Another dimension of engagement that was identified as challenging to capture is emotional engagement. Finding ways of tracing and representing emotional engagement is important, particularly in online and distance learning where instructors can not rely on in-person indicators of students in distress. Emotional engagement should not be overlooked as it is intimately tied to other components of engagement [106]. For instance, Pekrun [105] and Pekrun et al. [107] demonstrated that certain aspects of cognitive engagement, such as perceived academic control and self-regulation, are antecedents to students' emotional engagement that influences online learning. Other studies position emotional engagement as the main determinant of how students engage cognitively and behaviorally [108]. For example, Vuorela and Nummenmaa [141] found that students who experienced negative emotions tended to participate less in collaborative activities than those with positive emotions; highlighting the important role of emotion in behavioral engagement.

To address the challenge of identifying trace data that can be used as metrics for emotional engagement, recent research has explored the use of the frequency and intermittence patterns of click-stream data as a proxy for emotional states of the user [30]. This has great potential to be developed into analytics as it can unobtrusively provide insights into students' emotional states as they unfold; queuing the analytic to interject with just-in-time support, before emotions like frustration result in the student disengaging from the activity completely. Customizing learning material to students emotional states has been shown to improve how much students' use e-learning materials in experimental settings [123]. This however, required more obtrusive emotion detection technologies from biophysical signals combined with activity data. Future research could map patterns and changes in trace data observed in controlled lab experiments to establish links between different emotional states and trace data observed. This could be used as a guide for understanding in-situ patterns of engagement in authentic learning situations (e.g., in academic courses) so that an instructor can become aware and intervene appropriately or a system can adapt and provide customized support when needed. Making use of different valued aspects of cognitive and emotional engagement represented by data provides opportunities to greatly improve the variety, specificity and quality of recommendations provided to learners as it captures a more holistic and detailed picture of their engagement.

3.7.3 Challenge 2: Quantifying Meaningful Engagement

Finding meaningful ways to represent quantities of engagement is another challenge faced in current work. Most feedback about engagement during learning uses metrics of frequency and timing of various activities, artifacts produced or resources accessed. Our view is a "more-is-better" approach may not be the most useful tack. Qualities of artifacts and methods learners use to create them are as or perhaps more important to developing analytics about engagement that can serve as grounds for interventions.

Process feedback concerns how products are created. This kind of feedback is rare in dashboards and early alert systems. Students are left on their own to self-identify problem areas in the realm of processes. This markedly contrasts to recommendations of research. Feedback is more effective when information is provided "at the process level" [15, 56].

Another common characteristic of dashboard visualizations is their focus on a current state. Such point-in-time messaging might be more informing if adjustable time windows could be made available that allows students and instructors to visualize engagement in terms of how activities change over time. The inherent variability of engagement in response to varying features of content studied or discussions is likely misrepresented when time windows are rigidly defined.

3.7.4 Potential Solutions: Analytics Reflecting Quantity and Quality of Student Engagement

Learning analytics are only as good as data used to generate them. To date, the engagement and learning analytics literatures have primarily sampled quantitative data such as number of discussion posts, number of completed assignments, or number of time resources or e-learning tools used, rather than more qualitative feedback and feature of the learning process (e.g., [62, 66, 110, 127, 133]).

One approach to addressing the challenge of analytics capturing qualities of artefacts and methods students use to create them is to contextualize the activity in the learning context. Using information about the learning context at different points in time can provide insight into the strategies for learning students are applying. Nguyen et al. [99] for instance, ventured beyond the widely used proxy for engagement, time on task, by examining how timing of engagement combined with course objectives and course design can better characterize students' engagement patterns. Combining these sources of data, they found evidence for different patterns of engagement among high achieving students compared to students who seem to struggle. High-achievers spent more time studying in advance of assignments and reviewed material regularly throughout the course. Low-achieving students were occupied with trying to catch up. Providing instructors with learning analytics about these different patterns of engagement might allow them to speak more specifically to the needs of the student and his or her learning process. Research indicates that students benefit most if learning analytics and recommended strategies are tailored to their needs [21, 66].

Taking this research further, pictures of students' engagements traced through annotations of text, highlights, tags applied to highlights, summaries, notes, posts and shared artifacts can describe how a student is constructing knowledge and sharing it. Analyses that explore patterns of engagement with artefacts using graph theoretic approaches could elaborate descriptions of engagements (see for example Winne et al. [147]) and can fuel theoretical explanations for patterns. Previously, grading the products of learning has been one of the only tools available to generate recommendations for how students can improve their learning process. Adding trace data about students' engagements patterns that lead to this outcome can illuminate how personal strategies can be applied or modified, greatly enhancing their utility.

3.7.5 Challenge 3: Purposeful Engagement Reflection

Most applications of dashboard visualizations appear designed to foster basic awareness and encourage reflection. Promoting reflection was the dominant theme in 20 of 26 papers in a recent review of dashboards [64]. We judge mere presence of an easy-to-read display does not guarantee awareness or reflection. The challenge to be met is determining whether users are aware of and reflect on analytics before digging into deeper conceptual questions about how awareness of and reflection on engagement benefit learning [91]. Evaluations of dashboards should include measures of reflection, self-evaluation and which tactics and strategies students apply because analytics are presented via dashboards.

As a case in point, in Jivet and colleagues' review [63] more than half of dashboard studies claimed to improve self-regulated learning (SRL) but addressed only the monitoring and self-evaluation stages of the cycle [146] in only the broadest terms. There has been little attention to goal setting and planning phases of SRL—only two dashboards included planning and self-set goals. The iterative cycle of SRL was greatly underrepresented. These shortcomings imply learning dashboards are not affording students' reflections about and changes to cognitive engagement throughout the SRL cycle (see Winne [150]).

Also, emotional competence was predominantly presented as efforts to increase motivation, generated by comparison with peers as a reference frame to motivate students to work harder and increase their engagement [138]. However, research suggests that these types of peer referential norms are problematic, described further in the next challenge.

3.7.6 Potential Solutions: Options for Purposeful Engagement Reflection

Traces of engagement create opportunities for teachers and students to collaboratively reflect on engagement. Traces can serve as a language for discussing *processes* used in learning. Dashboards reflecting prior engagement are attempting to prompt learners to plan and adjust future engagement, yet plans are not explicitly captured in data. Considering and gathering data about students' future plans provides opportunities for identifying whether students know what to do but struggle with implementing those plans, a gap between phases 2 and 3 in Winne and Hadwin's [148] model of SRL. Instructors can then be more strategic in support by targeting actual needs of the student. Van Leeuwen et al. [137] found that instructors who had analytics tools at both the individual and group showed greater specificity in their diagnosis of situations requiring intervention and the actions that they took.

Taking this a step further to connect trace data about engagement to data about learning design could improve insights into the timing of when analytics should be provided to best impact engagement. Staging opportunities for students to reflect on the analytics feedback, state plans for revisions and receive further analytics on the implementation of their plans in a cyclical fashion could better address the challenge of enacting reflection to support engagement [151]. Additionally, students viewing their engagement activity analytics in the context of goals they set or study strategies they are learning to implement can be motivational, an important aspect of emotional engagement [150].

3.7.7 Challenge 4: Finding an Appropriate Reference Norm

A common reference frame provided for learners to reflect on their engagement is peer comparison. Intended as a motivational trigger, this reference frame can foster competition among learners [28]. At best, it may emphasize "being better than others" as a defining feature to motivate learners. At worst it reminds struggling students they are not as good as peers, undervalues personal progress and ignores strategies they may be striving to improve. Social reference norms can also promote negative emotions such as frustration or hopelessness, likely further disengaging students who are struggling. Peer or class comparison encourages performance goal orientation over interests in learning [28]. Peer comparison may be particularly detrimental for low-achieving students as it highlights failure and may invite maladaptive learning strategies to avoid failure such as academic self-handicapping [27, 136].

Most dashboards compared a class or peer average for generating individual-to-group comparison (16 dashboards), three ranked each learner in their reference group; while, only six showed analytics about individual progress as the focus [63]. Among these, options were to compare learners to "top" students, or learners could choose their comparison group, such as past graduates of the same course. Only one allowed learners to choose a more specific reference, peers with similar goals. Peer comparison was also present in dashboards depicting collaborative work where analytics described individual members in a working group or compared an individual's self-assessment of group performance to group mates' assessments. Notably, no dashboards relayed comparative analytics about alternatives for processes to complete tasks.

Greller and Drachsler [51] emphasize analytics must not discourage students. They worry using class averages or statistical modeling may box in "individual teachers or learners against a statistical norm [and] strongly stifle innovation, individuality, creativity, and experimentation that are so important in driving learning and teaching developments..." (p. 47). Potential to discourage students should not be overlooked in developing analytics for dashboards.

Additional reference frames for analytics displayed in dashboards focus heavily on achievement [63], e.g., use of key vocabulary concepts in discussion forums [12, 55], quiz scores on specific content [22, 52, 85, 95], or the number of modules completed [18]. A challenge lies in building on these kinds of feedback to support learning processes. As literature on formative feedback shows, the most effective analytics about engagement should be non-evaluative, supportive, timely and specific [124] and accompanied by explanations for processes that guide and support improvement.

Finally, teacher defined goals were also used as reference frames under the belief these support students' planning by offering guidance about expectations for the course [130]. However, research on goal-setting recommends care in setting goals appropriate to students' capabilities. If the goal exceeds an individual's ability or is too easy to attain, performance declines [90]. This suggests that personalized goals may be more appropriate than course-level goals for engagement leading to achievement. Moreover, specific learning goals resulted in greater task performance than setting performance goals [79]. Among the dashboards reviewed, only one dashboard afforded learner-set goals, but it shows great promise as a future direction if meaningful goals can be established. The dashboard was designed to allow students to establish the level of knowledge they aimed to achieve, the time they would allocate to that tool and then track their progress toward it [71]. This can provide context for the engagement reflected to learners through the dashboard and support evaluating progress towards goals.

To support learning, analytics should motivate efforts to engage in ways that build knowledge and develop skills. For this purpose, reference frames chosen for dashboard analytics should be carefully constructed, grounded in research, and considerate of students' varying levels of knowledge and skills. Some students may need more scaffolding or direct instruction to change engagement in ways that improve learning and "compress, rather than exacerbate, the learning and achievement gap between thriving and struggling students" [131].

3.7.8 Potential Solutions: Alternative Reference Frames

Reference frames should be carefully selected because they function as mediators between analytics and students' motivation to follow recommendations about how to improve engagement. The most common reference frames in learning analytics are assessment metrics and peer-comparison [63]. Analytics using these reference frames, however, merely display learning outcomes without recommendations about how to improve learning processes and may undermine motivation to change patterns of engagement.

Providing alternative reference frames may lessen these problems. Using individual reference frames, such as emphasizing students' learning activities and processes, supports motivational and emotional aspects of engagement as it can highlight students' progress. For instance, the Student Activity Meter [48] is a learning dashboard that tracks time spent on learning activities (average and total) and frequency of access to resources as a way of comparing time use. Using assessment data, QuizMap [14] allows students to look at different aspects of the quiz data by comparing topics and their progress over time. Other analytics use student-set learning goals as a reference frame, so that progress can be measured in personal terms [119]. While these analytics aim to elicit motivation to support emotional engagement, we suggest additional approaches supplementing individual reference frames to best support emotional engagement.

Numerous dashboards combine multiple measures of engagement into one presentation, such as progress in completing reading materials, number of posts in discussion forums and quiz scores (e.g., [139]). While having multiple measures of engagement is important, considering how the presentation of this data is supporting student engagement should be the primary focus. Analytics are designed to support students who are struggling; however, if all measures are highlighting deficits to the student, this could be disengaging. To support engagement, it is important to emphasize *what* is presented but also *how* combining these metrics of engagement can support future engagement. Future analytics can address this issue by selecting and customizing what is presented in dashboards to individual students to balancing emphasizing areas that need improvement with recognition of desired engagement patterns. This is in line with research on the design of feedback for students. Kluger and DeNisi's [70] meta-analysis demonstrate that students are more likely to withdraw from a task after initial negative feedback, especially if they do not make rapid improvements afterwards. Repeated negative feedback is particularly detrimental to performance [11, 70].

In addition to balancing positive and negative feedback within the dashboard, emotional engagement can be enhanced by presenting data in a way that help make the connection between reflection and actionable steps the student can take to improve. As an example, we previously highlighted that many dashboards show students' individual score on an assessment and provide peer average as a reference frame to elicit reflection [63]. This might discourage low-achieving students as it highlights failures (e.g., poor quiz scores) without explaining how the student can make positive changes. Instead, analytics could be expanded to include other forms of trace that point to terms and definitions tested in quizzes and prompt students to plan to review terms or engage in self-explanation before the next quiz. Data about the analytics provided and how the feedback was implemented can generate new analytics about students' progress and use of new study strategies, f-acilitating emotional and cognitive engagement. This can set the stage for scaffolding learners to apply positive study strategies through tailored reflection and actionable feedback.

3.8 Conclusion

Based on literature we reviewed, challenges outlined, and potential solutions, we propose exploring engagement analytics as an opportunity to identify aspects of learning overlooked by analytics so far proposed and as tools for describing to students how engagement might change for the better. Engagement analytics add to kinds of data now commonly gathered by introducing trace data that fuse fine-grained descriptions of actions students take in an interface to types of information they process. This stereoscopic view of engagement sets a stage for feedback about how students might engage differently and with what they might engage differently.

We recommend measuring solutions to the challenges in engagement-based analytics in relation to how fully they address all the dimensions of engagement—cognitive, emotional and motivational—and how helpful they are in providing students and teachers with shared language for discussing students' engagements in setting goals, tracking progress and adapting learning. We recommend more work on designing and analyzing trace data to more fully represent the multifaceted nature of engagement.

Acknowledgements This work was supported by a grants from the Social Sciences and Humanities Research Council of Canada (#435-2016-0379) and Simon Fraser University.

References

1. Alario-Hoyos, C., Pérez-Sanagustín, M., Delgado-Kloos, C., Munoz-Organero, M., et al.: Delving into participants' profiles and use of social tools in moocs. IEEE Trans. Learn. Technol. **7**(3), 260–266 (2014)
2. Alexander, K.L., Entwisle, D.R., Horsey, C.S.: From first grade forward: early foundations of high school dropout. Sociol. Educ. **87–107** (1997)
3. Ali, L., Hatala, M., Gasevic, D., Jovanovic, J.: A qualitative evaluation of evolution of a learning analytics tool. Comput. Educ. **58**(1), 470–489 (2012)
4. Appleton, J.J., Christenson, S.L., Furlong, M.J.: Student engagement with school: critical conceptual and methodological issues of the construct. Psychol. Sch. **45**(5), 369–386 (2008)
5. Arnold, K.E.: Signals: applying academic analytics. Educ. Q. **33**(1), n1 (2010)
6. Arnold, K.E., Pistilli, M.D.: Course signals at purdue: using learning analytics to increase student success. In: Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, pp. 267–270. ACM
7. Azevedo, R.: Defining and measuring engagement and learning in science: conceptual, theoretical, methodological, and analytical issues. Educ. Psychol. **50**(1), 84–94 (2015)
8. Baker, R.S., Inventado, P.S.: Educational data mining and learning analytics. In: Learning Analytics, pp. 61–75. Springer, Berlin (2014)
9. Bangert, A.W.: Identifying factors underlying the quality of online teaching effectiveness: an exploratory study. J. Comput. High. Educ. **17**(2), 79–99 (2006)
10. Banna, J., Lin, M.-F.G., Stewart, M., Fialkowski, M.K.: Interaction matters: strategies to promote engaged learning in an online introductory nutrition course. J. Online Learn. Teach. MERLOT **11**(2), 249 (2015)
11. Baumeister, R.F., Hutton, D.G., Cairns, K.J.: Negative effects of praise on skilled performance. Basic Appl. Soc. Psychol. **11**(2), 131–148 (1990)
12. Beheshitha, S.S., Hatala, M., Gasevic, D., Joksimovic, S.: The role of achievement goal orientations when studying effect of learning analytics visualizations. In: Proceedings of the Sixth International Conference on Learning Analytics & Knowledge, pp. 54–63. ACM (2016)
13. Bodily, R., Verbert, K.: Trends and issues in student-facing learning analytics reporting systems research. In: Proceedings of the Seventh International Learning Analytics & Knowledge Conference, pp. 309–318. ACM (2017)
14. Brusilovsky, P., Hsiao, H., Folajim, Y.: Quizmap: open social student modeling and adaptive navigation support with treemaps. Towards ubiquitous learning. In: European Conference on Enhanced Learning (2011)
15. Butler, D.L., Winne, P.H.: Feedback and self-regulated learning: a theoretical synthesis. Rev. Educ. Res. **65**(3), 245–281 (1995)
16. Campbell, J.P., DeBlois, P.B., Oblinger, D.G.: Academic analytics: a new tool for a new era. EDUCAUSE Rev. **42**(4), 40 (2007)
17. Carini, R.M., Kuh, G.D., Klein, S.P.: Student engagement and student learning: testing the linkages. Res. High. Educ. **47**(1), 1–32 (2006)
18. Chou, C.-Y., Tseng, S.-F., Chih, W.-C., Chen, Z.-H., Chao, P.-Y., Lai, K.R., Lin, Y.-L.: Open student models of core competencies at the curriculum level: using learning analytics for student reflection. IEEE Trans. Emerg. Top. Comput. **5**(1), 32–44 (2017)
19. Christenson, S.L., Reschly, A.L., Wylie, C.: Handbook of Research on Student Engagement. Springer Science & Business Media (2012)
20. Clow, D.: The learning analytics cycle: closing the loop effectively. In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, pp. 134–138. ACM (2012)

21. Coates, H.: Attracting, engaging and retaining: new conversations about learning (2008)
22. Corrin, L., de Barba, P.: Exploring students' interpretation of feedback delivered through learning analytics dashboards. In: Proceedings of the ASCILITE 2014 conference, pp. 629–633 (2014)
23. Cui, G., Lockee, B., Meng, C.: Building modern online social presence: a review of social presence theory and its instructional design implications for future trends. Educ. Inf. Technol. **18**(4), 661–685 (2013)
24. Czerkawski, B.C., Lyman, E.W.: An instructional design framework for fostering student engagement in online learning environments. TechTrends **60**(6), 532–539 (2016)
25. DeBoer, J., Ho, A.D., Stump, G.S., Breslow, L.: Changing "course" reconceptualizing educational variables for massive open online courses. Educ. Res. **43**(2), 74–84 (2014)
26. Dennen, V.P., Aubteen Darabi, A., Smith, L.J.: Instructor-learner interaction in online courses: the relative perceived importance of particular instructor actions on performance and satisfaction. Distance Educ. **28**(1), 65–79 (2007)
27. Deppe, R.K.: Self-handicapping and intrinsic motivation: self-handicaps as protection from the negative effects of failure feedback. J. Pers. Soc. Psychol. **70**(4) (1995)
28. Dickhäuser, O., Janke, S., Praetorius, A.K., Dresel, M.: The effects of teachers' reference norm orientations on students' implicit theories and academic self-concepts. Zeitschrift für Pädagogische Psychologie (2017)
29. Dixson, M.D.: Measuring student engagement in the online course: the online student engagement scale (OSE). Online Learn. **19**(4) (2015)
30. D'Mello, S.: Emotional learning analytics. Handbook of Learning Analytics, p. 115 (2017)
31. Drachsler, H., Greller, W.: The pulse of learning analytics understandings and expectations from the stakeholders. In: Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, pp. 120–129. ACM (2012)
32. Duderstadt, J.J., Atkins, D.E., Van Houweling, D.E.: Higher Education in the Digital Age: Technology Issues and Strategies for American Colleges and Universities. Greenwood Publishing Group (2002)
33. Duval, E.: Attention please!: learning analytics for visualization and recommendation. In: Proceedings of the 1st International Conference on Learning Analytics and Knowledge, pp. 9–17. ACM (2011)
34. Edwards, A.L.: The social desirability variable in personality assessment and research (1957)
35. Eom, S.B., Wen, H.J., Ashill, N.: The determinants of students' perceived learning outcomes and satisfaction in university online education: an empirical investigation. Decis. Sci. J. Innov. Educ. **4**(2), 215–235 (2006)
36. Fagen, W., Kamin, S.: Developing device-independent applications for active and collaborative learning with the SLICE framework. In: EdMedia: World Conference on Educational Media and Technology, pp. 1565–1572. Association for the Advancement of Computing in Education (AACE) (2012)
37. Ferguson, R.: Learning analytics: drivers, developments and challenges. Int. J. Technol. Enhanc. Learn. **4**, 304–317 (2012a)
38. Ferguson, R.: The state of learning analytics in 2012: a review and future challenges. Technical Report KMI-12-01, 4(18) (2012b)
39. Ferguson, R., Clow, D.: Examining engagement: analysing learner subpopulations in massive open online courses (MOOCS). In: Proceedings of the Fifth International Conference on Learning Analytics and Knowledge, pp. 51–58. ACM (2015)
40. Finn, J.G.P., Voelkl, K.: Disruptive and inattentive withdrawn behavior and achievement among fourth graders. Elementary Sch. J. **95**, 421–434 (1995)
41. Finn, J.D.: Withdrawing from school. Rev. Educ. Res. **59**(2), 117–142 (1989)
42. Finn, J.D., Zimmer, K.S.: Student engagement: what is it? why does it matter? (2012) https://doi.org/10.1007/978-1-4614-2018-7_5
43. Fredricks, J.A., Blumenfeld, P.C., Paris, A.H.: School engagement: potential of the concept, state of the evidence. Rev. Educ. Res. **74**(1), 59–109 (2004)

44. Furnham, A.: Response bias, social desirability and dissimulation. Pers. Individ. Differ. **7**(3), 385–400 (1986)
45. Garrison, D.R., Anderson, T., Archer, W.: The first decade of the community of inquiry framework: a retrospective. Internet High. Educ. **13**(1–2), 5–9 (2010)
46. Gašević, D., Dawson, S., Siemens, G.: Let not forget: learning analytics are about learning. TechTrends **59**(1), 64–71 (2015)
47. Goldstein, P.J., Katz, R.N.: Academic analytics: the uses of management information and technology in higher education. Educause (2005)
48. Govaerts, S., Verbert, K., Duval, E., Pardo, A.: The student activity meter for awareness and self-reflection. In: CHI'12 Extended Abstracts on Human Factors in Computing Systems, pp. 869–884. ACM (2012)
49. Gray, J.A., DiLoreto, M.: The effects of student engagement, student satisfaction, and perceived learning in online learning environments. Int. J. Educ. Leadership Prep. **11**(1) (2016)
50. Greene, B.A., Miller, R.B.: Influences on achievement: goals, perceived ability, and cognitive engagement. Contemp. Educ. Psychol. **21**(2), 181–192 (1996)
51. Greller, W., Drachsler, H.: Translating learning into numbers: a generic framework for learning analytics. J. Educ. Technol. Soc. **15**(3), 42 (2012)
52. Guerra, J., Hosseini, R., Somyurek, S., Brusilovsky, P.: An intelligent interface for learning content: combining an open learner model and social comparison to support self-regulated learning and engagement. In: Proceedings of the 21st International Conference on Intelligent User Interfaces, pp. 152–163. ACM (2016)
53. Guo, P.J., Kim, J., Rubin, R.: How video production affects student engagement: an empirical study of MOOC videos. In: Proceedings of the First ACM Conference on Learning@ Scale Conference, pp. 41–50. ACM (2014)
54. Handelsman, M.M., Briggs, W.L., Sullivan, N., Towler, A.: A measure of college student course engagement. J. Educ. Res. **98**(3), 184–192 (2005)
55. Hatala, M., Beheshitha, S.S., Gasevic, D.: Associations between students' approaches to learning and learning analytics visualizations. In: LAL@ LAK, pp. 3–10 (2016)
56. Hattie, J., Timperley, H.: The power of feedback. Rev. Educ. Res. **77**(1), 81–112 (2007)
57. Hew, K.F.: Promoting engagement in online courses: what strategies can we learn from three highly rated MOOCS. Br. J. Educ. Technol. **47**(2), 320–341 (2016)
58. Howard, G.S., Dailey, P.R.: Response-shift bias: a source of contamination of self-report measures. J. Appl. Psychol. **64**(2), 144 (1979)
59. Hung, J.-L., Zhang, K.: Revealing online learning behaviors and activity patterns and making predictions with data mining techniques in online teaching. MERLOT J. Online Learn. Teach. (2008)
60. Jacobi, M., Astin, A., Frank Jr., A.: College student outcomer assessment: a talent development perspective. ASHE-ERIC Higher Education Report, no. 7 (1987)
61. Jaggars, S.S., Edgecombe, N., Stacey, G.W.: Creating an Effective Online Instructor Presence. Columbia University, Community College Research Center (2013)
62. Jason, B., Niamh, S.: Do weekly online assignments promote student engagement and enhance learning in first-year psychology students? Psychol. Educ. Rev. **38**(2) (2014)
63. Jivet, I., Scheffel, M., Drachsler, H., Specht, M.: Awareness is not enough: pitfalls of learning analytics dashboards in the educational practice. In: European Conference on Technology Enhanced Learning, pp. 82–96. Springer (2017)
64. Jivet, I., Scheffel, M., Specht, M., Drachsler, H.: License to evaluate: preparing learning analytics dashboards for educational practice (2018)
65. Jo, I., Kim, D., Yoon, M.: Constructing proxy variable to analyze adult learners' time management strategy in LMS using learning analytics. In: Conference of Learning Analytics and Knowledge, Indianapolis, IN (2014)
66. Karaksha, A., Grant, G., Anoopkumar-Dukie, S., Nirthanan, S.N., Davey, A.K.: Student engagement in pharmacology courses using online learning tools. Am. J. Pharm. Educ. **77**(6), 125 (2013)

67. Kena, G., Hussar, W., McFarland, J., de Brey, C., Musu-Gillette, L., Wang, X., et al.: The Condition of Education 2016. NCES 2016-144. National Center for Education Statistics (2016)
68. Ketonen, E.E., Haarala-Muhonen, A., Hirsto, L., Hänninen, J.J., Wähälä, K., Lonka, K.: Am I in the right place? Academic engagement and study success during the first years at university. Learn. Individ. Differ. **51**, 141–148 (2016)
69. Kizilcec, R.F., Piech, C., Schneider, E.: Deconstructing disengagement: analyzing learner subpopulations in massive open online courses. In: Proceedings of the Third International Conference on Learning Analytics and Knowledge, pp. 170–179. ACM (2013)
70. Kluger, A.N., DeNisi, A.: The effects of feedback interventions on performance: a historical review, a meta-analysis, and a preliminary feedback intervention theory. Psychol. Bull. **119**(2), 254 (1996)
71. Konert, J., Bohr, C., Bellhäuser, H., Rensing, C.: Peer LA-assistant for individual learning goals and self-regulation competency improvement in online learning scenarios. In: 2016 IEEE 16th International Conference on Advanced Learning Technologies (ICALT), pp. 52–56. IEEE (2016)
72. Kovanovic, V., Gasevic, D., Dawson, S., Joksimovic, S., Baker, R.S., Hatala, M.: Penetrating the black box of time-on-task estimation. In: Proceedings of the Fifth International Conference on Learning Analytics And Knowledge, pp. 184–193. ACM (2015)
73. Krause, K.-L., Coates, H.: Students' engagement in first-year university. Assess. Eval. High. Educ. **33**(5), 493–505 (2008)
74. Kuh, G.D.: The national survey of student engagement: conceptual framework and overview of psychometric properties. Indiana University Center for Postsecondary Research & Planning. Retrieved 20 May 2007 (2003)
75. Kuh, G.D.: The national survey of student engagement: conceptual and empirical foundations. New Dir. Inst. Res. **2009**(141), 5–20 (2009)
76. Kuh, G.D., Cruce, T.M., Shoup, R., Kinzie, J., Gonyea, R.M.: Unmasking the effects of student engagement on first-year college grades and persistence. J. High. Educ. **79**(5), 540–563 (2008)
77. Lam, S., Wong, B.P., Yang, H., Liu, Y.: Understanding student engagement with a contextual model. In: Handbook of Research on Student Engagement, pp. 403–419. Springer (2012)
78. Larusson, J.A., White, B.: Learning Analytics: From Research to Practice. Springer (2014)
79. Latham, G.P., Seijts, G.H.: Distinguished scholar invited essay: similarities and differences among performance, behavioral, and learning goals. J. Leadership Organ. Stud. **23**(3), 225–233 (2016)
80. Lear, J.L., Ansorge, C., Steckelberg, A.: Interactivity/community process model for the online education environment. J. Online Learn. Teach. **6**(1), 71 (2010)
81. Lee, O., Anderson, C.W.: Task engagement and conceptual change in middle school science classrooms. Am. Educ. Res. J. **30**, 585–610 (1993)
82. Leony, D., Pardo, A., de la Fuente Valentín, L., de Castro, D.S., Kloos, C.D.: GLASS: a learning analytics visualization tool. In: Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, pp. 162–163. ACM (2012)
83. Lin, C.-C., Tsai, C.-C.: Participatory learning through behavioral and cognitive engagements in an online collective information searching activity. Int. J. Comput. Support. Collab. Learn. **7**(4), 543–566 (2012)
84. Liu, D.Y.-T., Rogers, T., Pardo, A.: Learning analytics—are we at risk of missing the point? In: Australasian Society for Computers in Learning and Tertiary Education (ASCILITE2015). Perth, Australia (2015)
85. Loboda, T.D., Guerra, J., Hosseini, R., Brusilovsky, P.: Mastery grids: an open source social educational progress visualization. In: European Conference on Technology Enhanced Learning, pp. 235–248. Springer (2014)
86. Lowes, S., Lin, P., Kinghorn, B.: Exploring the link between online behaviours and course performance in asynchronous online high school courses. J. Learn. Anal. **2**(2), 169–194 (2015)
87. Macfadyen, L.P., Dawson, S.: Mining LMS data to develop an "early warning system" for educators: a proof of concept. Comput. Educ. **54**(2), 588–599 (2010)

88. Marks, H.M.: Student engagement in instructional activity: patterns in the elementary, middle, and high school years. Am. Educ. Res. J. **37**(1), 153–184 (2000)
89. Martin, F., Bolliger, D.U.: Engagement matters: student perceptions on the importance of engagement strategies in the online learning environment. Online Learn. **22**(1) (2018)
90. Masuda, A.D., Locke, E.A., Williams, K.J.: The effects of simultaneous learning and performance goals on performance: an inductive exploration. J. Cogn. Psychol. **27**(1) (2015)
91. McAlpine, L., Weston, C.: Reflection: issues related to improving professors' teaching and students' learning. Instr. Sci. **28**(5), 363–385 (2000)
92. McLoughlin, D., Mynard, J.: An analysis of higher order thinking in online discussions. Innov. Educ. Teach. Int. **46**(2), 147–160 (2009)
93. Moore, M.: Distance education: new perspectives. In: Harry, D.K.K., John, M. (ed.) Three Types of Interaction, pp. 19–24. Routledge (1993)
94. Morris, L.V., Finnegan, C., Wu, S.-S.: Tracking student behavior, persistence, and achievement in online courses. Internet High. Educ. **8**(3), 221–231 (2005)
95. Muldner, K., Wixon, M., Rai, D., Burleson, W., Woolf, B., Arroyo, I.: Exploring the impact of a learning dashboard on student affect. In: International Conference on Artificial Intelligence in Education, pp. 307–317. Springer (2015)
96. Murphy, R., Gallagher, L., Krumm, A.E., Mislevy, J., Hafter, A.: Research on the use of Khan academy in schools: research brief (2014)
97. Nakahara, J., Hisamatsu, S., Yaegashi, K., Yamauchi, Y.: Itree: does the mobile phone encourage learners to be more involved in collaborative learning? In: International Society of the Learning Sciences (ed.) Proceedings of the 2005 Conference on Computer Support for Collaborative Learning: Learning 2005: the Next 10 Years! (CSCL '05), pp. 470–478 (2005)
98. Newman, F.M., Wehlage, G.G., Lamborn, S.D.: Student engagement and achievement in American secondary schools. In: The Significance and Source of Student Engagement, pp. 11–30. Teachers College Press (1992)
99. Nguyen, Q., Huptych, M., Rienties, B.: Linking students' timing of engagement to learning design and academic performance. In: Proceedings of the 8th International Conference on Learning Analytics and Knowledge, pp. 141–150. ACM (2018)
100. National Survey of Student Engagement: Bringing the institution into focus—annual results 2014. Indiana University Center for Postsecondary Research Bloomington, IN (2014)
101. Ouimet, J., Smallwood, R.: CLASSE the class-level survey of student engagement. Assess. Updat. **17**(6) (2005)
102. Papamitsiou, Z., Economides, A.A.: Learning analytics and educational data mining in practice: a systematic literature review of empirical evidence. J. Educ. Technol. Soc. **17**(4), 49 (2014)
103. Pardo, A., Han, F., Ellis, R.A.: Exploring the relation between selfregulation, online activities, and academic performance: a case study. In: Proceedings of the Sixth International Conference on Learning Analytics & Knowledge (2016)
104. Parsons, J., Taylor, L.: Student Engagement: What do we Know and What Should we do? University of Alberta (2012)
105. Pekrun, R.: A social-cognitive, control-value theory of achievement. In: Heckhausen, J. (ed.) Motivational Psychology of Human Development. Advances in Psychology, Elsevier Science B.V (2000)
106. Pekrun, R., Goetz, T., Daniels, L.M., Stupnisky, R.H., Perry, R.P.: Boredom in achievement settings: exploring control-value antecedents and performance outcomes of a neglected emotion. J. Educ. Psychol. **102**(3), 531–549 (2010)
107. Pekrun, R., Goetz, T., Frenzel, A.C., Barchfeld, P., Perry, R.P.: Measuring emotions in students' learning and performance: the achievement emotions questionnaire (AEQ). Contemp. Educ. Psychol. **36**(1), 36–48 (2011)
108. Pentaraki, A., Burkholder, G.J.: Emerging Evidence Regarding the Roles of Emotional, behavioural, and cognitive aspects of student engagement in the online classroom. Eur. J. Open Distance E-learn. **20**(1) (2017)

109. Peterson, P.L., Swing, S.R., Stark, K.D., Waas, G.A.: Students' cognitions and time on task during mathematics instruction. Am. Educ. Res. J. **21**(3), 487–515 (1984)
110. Petty, T., Farinde, A.: Investigating student engagement in an online mathematics course through windows into teaching and learning. J. Online Learn. Teach. **9**(2), 261 (2013)
111. Phan, T., McNeil, S.G., Robin, B.R.: Students' patterns of engagement and course performance in a Massive Open Online Course. Comput. Educ. **95**, 36–44 (2016)
112. Pistilli, M.D., Willis, J.E., Campbell, J.P.: Analytics through an institutional lens: definition, theory, design, and impact. In: Learning Analytics, pp. 79–102. Springer (2014)
113. Podgorelec, V., Kuhar, S.: Taking advantage of education data: advanced data analysis and reporting in virtual learning environments. Elektron. ir Elektrotechnika **114**(8), 111–116 (2011)
114. Ramesh, A., Goldwasser, D., Huang, B., Daume III, H., Getoor, L.: Uncovering hidden engagement patterns for predicting learner performance in MOOCS. In: Proceedings of the First ACM Conference on Learning@ Scale Conference, pp. 157–158. ACM (2014)
115. Robinson, C.C., Hullinger, H.: New benchmarks in higher education: student engagement in online learning. **84**, 101–109 (2008). https://doi.org/10.3200/joeb.84.2.101-109
116. Roblyer, M., Wiencke, W.: Exploring the interaction equation: validating a rubric to assess and encourage interaction in distance courses. J. Asynchronous Learn. Netw. **8**(4), 24–37 (2004)
117. Roll, I., Winne, P.H.: Understanding, evaluating, and supporting self-regulated learning using learning analytics. J. Learn. Anal. **2**(1), 7–12 (2015)
118. Roorda, D.L., Koomen, H.M., Spilt, J.L., Oort, F.J.: The influence of affective teacher-student relationships on students' school engagement and achievement: a meta-analytic approach. Rev. Educ. Res. **81**(4), 493–529 (2011)
119. Santos, J.L., Govaerts, S., Verbert, K., Duval, E.: Goal-oriented visualizations of activity tracking: a case study with engineering students. In: Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, pp. 143–152. ACM (2012)
120. Scheuer, O., Zinn, C.: How did the e-learning session go? The student inspector. Front. Artif. Intell. Appl. **158**, 487 (2007)
121. Schwarz, N.: Emotion, cognition, and decision making. Cogn. Emot. **4**, 433–440 (2002)
122. Settanni, M., Marengo, D.: Sharing feelings online: studying emotional well-being via automated text analysis of facebook posts. Front. Psychol. **6**, 1045 (2015)
123. Shen, L., Wang, M., Shen, R.: Affective e-learning: using "emotional" data to improve learning in pervasive learning environment. J. Educ. Technol. Soc. **12**(2), 176 (2009)
124. Shute, V.J.: Focus on formative feedback. Rev. Educ. Res. **78**(1), 153–189 (2008)
125. Skinner, E.A., Belmont, M.J.: Motivation in the classroom: reciprocal effects of teacher behavior and student engagement across the school year. J. Educ. Psychol. **85**(4), 571 (1993)
126. Son, L.H.: Supporting reflection and classroom orchestration with tangible tabletops. PhD thesis (2012)
127. Stewart, M., Stott, T., Nuttall, A.-M.: Student engagement patterns over the duration of level 1 and level 3 geography modules: influences on student attendance, performance and use of online resources. **35**, 47–65 (2011). https://doi.org/10.1080/03098265.2010.498880
128. Stipek, D.: Good instruction is motivating. In: Wigfield, A., Eccles, J. (eds.) Development of Achievement Motivation. Academic Press, San Diego (2002)
129. Swan, K.: Virtual interaction: design factors affecting student satisfaction and perceived learning in asynchronous online courses. Distance Educ. **22**(2), 306–331 (2001)
130. Tabuenca, B., Kalz, M., Drachsler, H., Specht, M.: Time will tell: the role of mobile learning analytics in self-regulated learning. Comput. Educ. **89**, 53–74 (2015)
131. Tan, J.P.-L., Yang, S., Koh, E., Jonathan, C.: Fostering 21st century literacies through a collaborative critical reading and learning analytics environment: user-perceived benefits and problematics. In :Proceedings of the Sixth International Conference on Learning Analytics & Knowledge, pp. 430–434. ACM (2016)
132. Trowler, V.: Student engagement literature review. The Higher Education Academy. In: Trowler, V., Trowler, P. (eds.) Student Engagement Evidence Summary (2010)

133. Trumbore, A.: Rules of engagement: strategies to increase online engagement at scale. **46**, 38–45 (2014). https://doi.org/10.1080/00091383.2014.925763
134. Tseng, S.-F., Tsao, Y.-W., Yu, L.-C., Chan, C.-L., Lai, K.R.: Who will pass? analyzing learner behaviors in MOOCS. Res. Pract. Technol. Enhanc. Learn. **11**(1), 8 (2016)
135. Um, E., Plass, J.L., Hayward, E.O., Homer, B.D., et al.: Emotional design in multimedia learning. J. Educ. Psychol. **104**(2), 485 (2012)
136. Urdan, T., Midgley, C.: Academic self-handicapping: what we know, what more there is to learn. Educ. Psychol. Rev. **13**(2), 115–138 (2001)
137. Van Leeuwen, A., Janssen, J., Erkens, G., Brekelmans, M.: Supporting teachers in guiding collaborating students: effects of learning analytics in CSCL. Comput. Educ. **79**, 28–39 (2014)
138. Venant, R., Vidal, P., Broisin, J.: Evaluation of learner performance during practical activities: an experimentation in computer education. In: 2016 IEEE 16th International Conference on Advanced Learning Technologies (ICALT), pp. 237–241 (2016)
139. Verbert, K., Duval, E., Klerkx, J., Govaerts, S., Santos, J.L.: Learning analytics dashboard applications. Am. Behav. Sci. **57**(10), 1500–1509 (2013)
140. Verbert, K., Govaerts, S., Duval, E., Santos, J.L., Van Assche, F., Parra, G., Klerkx, J.: Learning dashboards: an overview and future research opportunities. Pers. Ubiquitous Comput. **18**(6), 1499–1514 (2014)
141. Vuorela, M., Nummenmaa, L.: Experienced emotions, emotion regulation and student activity in a web-based learning environment. Eur. J. Psychol. Educ. **19**(4) (2004)
142. Whitmer, J.C.: Logging on to Improve Achievement: Evaluating the Relationship Between use of the Learning Management System, Student Characteristics, and Academic Achievement in a Hybrid Large Enrollment Undergraduate Course. University of California, Davis (2013)
143. Wilkowski, J., Deutsch, A., Russell, D.M.: Student skill and goal achievement in the mapping with Google MOOC. In: Proceedings of the first ACM conference on Learning@ Scale Conference, pp. 3–10. ACM (2014)
144. Winne, P.H.: Minimizing the black box problem to enhance the validity of theories about instructional effects. Instr. Sci. **11**(1), 13–28 (1982)
145. Winne, P.H.: Handbook of learning analytics. In: Learning Analytics for Self-regulated Learning. Society for Learning Analytics Research, Beaumont, AB (2017)
146. Winne, P.H.: Handbook of self-regulation of learning and performance. In: Schunk, D.H., Greene, J.A. (eds.) Cognition and Metacognition in Self-regulated Learning, pp. 36-48. Routledge, New York (2018)
147. Winne, P.H., Gupta, L., Nesbit, J.C.: Exploring individual differences in studying strategies using graph theoretic statistics. Alta. J. Educ. Res. **40**(2) (1995)
148. Winne, P.H., Hadwin, A.F.: Studying as self-regulated learning. Metacogn. Educ. Theory Pract. **93**, 27–30 (1998)
149. Winne, P.H., Perry, N.E.: Handbook of self-regulation. In: Boekaerts, M., Pintrich, P., Zeidner, M. (eds.) Measuring Self-Regulated Learning, pp. 531–566. Academic Press, Orlando (2000)
150. Winne, P.H., Vytasek, J.M., Patzak, A., Rakovic, M., Marzouk, Z., Pakdaman-Savoji, A., et al.: Designs For Learning Analytics to Support Information Problem Solving (2017). https://doi.org/10.1007/978-3-319-64274-1_11
151. Wise, A.F., Vytasek, J.M.: Learning analytics implementation design. In: Lang, C., Simens, G., Wise, A.F., Gasevic, D. (eds.) Handbook of Learning Analytics. Society for Learning Analytics Research, Solar (2017)
152. Wise, A.F.:. Designing pedagogical interventions to support student use of learning analytics. In: Proceedings of the Fourth International Conference on Learning Analytics and Knowledge, pp. 203–211. ACM (2014)
153. Wise, A.F., Vytasek, J.M., Hausknecht, S., Zhao, Y.: Developing learning analytics design knowledge in the "middle space": the student tuning model and align design framework for learning analytics use. Online Learn. **20**(2) (2016). https://doi.org/10.24059/olj.v20i2.783
154. Wong, J.-S., Pursel, B., Divinsky, A., Jansen, B.J.: Analyzing MOOC discussion forum messages to identify cognitive learning information exchanges. Proc. Assoc. Inf. Sci. Technol. **52**(1), 1–10 (2015)

155. Xie, Y., Ke, F., Sharma, P.: The effect of peer feedback for blogging on college students' reflective learning processes. Internet High. Educ. **11**(1), 18–25 (2008)
156. Yoo, Y., Lee, H., Jo, I.-H., Park, Y.: Educational dashboards for smart learning: review of case studies. In: Emerging Issues in Smart Learning, pp. 145–155. Springer (2015)
157. You, J.W.: Examining the effect of academic procrastination on achievement using LMS data in e-learning. J. Educ. Technol. Soc. **18**(3), 64 (2015)
158. Yu, Y.C., You, S.C., Tsai, D.R.: Social interaction feedback system for the smart classroom. In: IEEE (Ed.), Proceedings of the 2012 IEEE International Conference on Consumer Electronics (ICCE), pp. 500–501 (2012)
159. Zyngier, D.: (re) conceptualising student engagement: doing education not doing time. Teach. Teach. Educ. **24**(7), 1765–1776 (2008)

Chapter 4
Assessing Self-regulation, a New Topic in Learning Analytics: Process of Information Objectification

David Martín Santos Melgoza

Abstract This chapter concerns the theoretical viewpoint regarding the metacognitive process of academic knowledge object-building. An ontological perspective of the study of academic learning will be presented. First, considerations concerning the academic learning process will be stated to establish the main assertions regarding what has been found to be important in academic self-regulated learning. An example of learning math will then be analyzed to illustrate the passage from subjective knowing to objectivization.

4.1 Introduction

When school learning is discussed, some problematic aspects related to what is thought to be knowledge and how to assess the quality of learning results still remain unclear. For the school institution, knowledge and its objectivity seem to be the main concerns when evaluation is in turn. Students must learn the "right way" or at least a "better way". The idea that knowledge is the "right thinking" is still part of the beliefs that guide behavior when teacher and students approach teaching and learning academic issues. Researchers have focused some attention on understanding the way students acquire what are considered objective knowledge schemata and have developed theoretical explanations of the interaction between student subjectivity and knowledge objectivity [1, 2].

It can observe that individuals differ in terms of the degree of awareness they have regarding the nature of knowledge, as has been demonstrated by research into epistemological beliefs [1, 3]. It is assumed that knowledge is systematized information ordered by a function of logical criteria of validity [4, 5]. It is sustained in formal or empirical evidence and is maintained as valid as long as no contradictory evidence is presented [6]. If the organization, coherence and unity of the scientific knowledge taught is different from that existing in the subject's mind, what should take place for the subjective information schema to become objective knowledge?

D. M. Santos Melgoza (✉)
Chapingo Autonomous University, Texcoco, Mexico
e-mail: dmsm35@hotmail.com

M. Virvou et al. (eds.), *Machine Learning Paradigms*, Intelligent Systems Reference Library 158, https://doi.org/10.1007/978-3-030-13743-4_4

In this process a specific kind of knowledge has become the articulating element between subjectivity and objectivity: the knowledge a student develops of herself, that is her self-awareness. Knowledge is built through goals, intentions, and interests, all of which are subjective and constitute her attitude when facing objective information. Active intentional interaction must occur for the objective experience to be appropriated. The student's behavior toward herself must be articulated by intentions and personal goals to result in giving the epistemological character to the information schemata. Thus, it is not just self-awareness that is required but also awareness of the things that are to be learned as well as of the inter-subjectivity of learning.

In this sense, knowledge about knowing has become an essential part in developing understanding of the interaction between the target information and the student's personal epistemology. It is in the center of how students transform subjectivity into objectivity, what has been called the objectification process, which consists of "objectivizing" (assigning epistemic status to the information within their knowledge schema) and "objectifying", that is, making an object of the experiential process when understanding of the explanation schema is arrived at. The main issue of this chapter, then, is to describe how the learner's explanatory ability changes as the target information is transformed from subjective to objective. Some considerations will be offered of what it means to make an experience an object and a description of a learning task where the self-regulated way students construct their own experience to lead them to the object they are looking for could be observed.

Focus will be set on two elements of self-regulated behavior related to the process of academic learning. The first element is associated with Richter and Schmid's [7] epistemic strategies, which is included in self-regulated behavior as the action of assigning epistemological status to information. The second refers to the process of knowledge-building, seen as a process of becoming aware of the objective quality of academic information.

Objectivization of knowledge is a process of becoming aware also of the ontological difference between knowledge as an entity, that is a finished object, and knowledge as a process of knowing. It is assumed that knowledge then is a metacognitive process focused on understanding through personal experience with the explanatory schema. The central point is this link, the existence of which in the learner's mind depends on her awareness that academic learning is not spontaneous but rather is acquired through self-regulation.

Characterization of self-regulated academic learners would be as follows:

1. Self-regulated subjects are conscious, to some degree, that the learning process is not the same thing as the problem-solving process.
2. In the problem-solving process, self-regulated subjects make self-observations aimed at recognizing the status of their ideas.
3. For the self-regulated student, awareness, or immediate knowledge [8], the student has of her position in the context of learning is a function of the different skills necessary for the construction of academic knowledge, among which are found skills of objectivization, argumentation, identification of evidence, and

self-monitoring (or self-observation) that, together, emerge from the student's act of reflection during the learning process [9].

4. The self-regulated student's academic learning emerges when she objectivizes the learning situation and transforms it into an object of analysis.

In a school learning situation, the student may not know (or be aware of) what, how, why or for what to learn or act. For a student to be able to direct her behavior toward learning, it is necessary for her to make her skills an object of her knowledge, to both identify available information and understand it as an analyzable object, thus gradually becoming aware of what is required to be successful in dealing with information. Knowledge of her own skills can direct her more precisely and clearly in constructing her own informational schemata to acquire the category of knowledge she needs [10, 11]. Even when the student is committed cognitively to a task, the solution to a mathematical problem, for example, can represent, in adaptive terms, a means of reaching multiple ends [12–15].

To illustrate, let me describe an experience I had with a young man, Robin, who had symptoms of autism. He was given tasks to prepare him for "normal life". Because of his echolalia, we were never sure of what he had taken from what we were trying to teach him. In the task, Robin had to choose the right nut for a specific bolt. To motivate him, every time he chose the correct nut I shouted and jumped up, so he tried to do it well to make me happy. After several tries at this task, he always chose the right one. I called a colleague to show him what we had accomplished, but Robin could no longer choose the correct nut. After repeating the training, I realized that what Robin had learned was to see the correct answer in my face; every time he chose a nut he looked at me and saw my expression. He associated giving the expected answer with different elements of the context. Robin had learned what was necessary to be successful for that particular context.

In self-regulating the process of solving mathematical problems, ideas come into play impacting both motivation and the type of cognitive commitment the student assumes when facing a task. Research has demonstrated how goals take control over processes of attention, memory, and motivation, and thus the results of learning can be quite diverse [16, 17]. Each individual assumes a different position relative to the information she must deal with. Depending on this assumed position and on the particular situation, individuals will understand to different degrees what function a knowledge schema has in explaining reality. It is evident that acquisition of informational schemata in a school situation does not mean acquiring knowledge that can be generalized to other contexts.

During the learning episode (as conceived by Boekarts [18]), epistemological beliefs concerning what the student knows about her goals and the possibilities of reaching them come into play. Attention is focused on knowledge structures and on the "process of objectivization" by which the structures are constructed. Quite interesting is the subject's process of elaborating explanations of her current condition as a student in terms of how she attacks the academic task and of how she justifies her explanations. It is during this process when the subject assigns an epistemological status to the incoming information during the learning episode. A basic strategy is to develop and evaluate structural models that explain how personal variables relative to the epistemological status of the information (beliefs, values, expectancies, knowledge and know-how) influence, or even determine, motivation, decision-making and knowledge constructions.

4.2 Math Learning Process

As stated, although learning is a natural process that occurs even when an individual does not propose to do so, school learning does not occur spontaneously. Not everyone is motivated to learn abstractions that go beyond their natural understanding. School learning is aimed toward acquiring sufficient valid information (knowledge) to explain the different phenomena that make up reality. This means that when learning mathematics, the student's construction of knowledge does not necessarily occur together with the cognitive process that underlies the solution to the problem. It is expected the student to learn the reason that algorithms can be applied to a class of situations. The fact that the student constructs a solution to the problem does not necessarily imply that she has learned what she was supposed to. Her attention might have been on different aspects of her person or context [19].

In general, individuals assign value to and classify the information they deal with based on personal criteria. When students are learning, the criteria they use to validate inferences can be divided into two types: objective and subjective. A declaration of facts taught in the classroom, regardless of whether it is part of an objective theoretical schema called knowledge, is not precisely knowledge in the possession of a student who is capable of only repeating it. That is, a student who can state that $(a + b)^2 = a^2 + 2ab + b^2$ does not necessarily understand the underlying abstraction.

Leading academic learning more efficiently requires that both teacher and students consciously recognize the criteria with which an informational schema emerges as knowledge. Knowledge, from an epistemological perspective, has historical evolution and a clearly defined theory. However, from a subjective perspective, knowledge is a category that is used to designate a type of information considered to be "true", even when there are no grounds to sustain it. In most cases, a student will begin the task of acquiring knowledge without reflection or formal instruction of what, epistemologically speaking, knowledge is, a topic not found in the curriculum of elementary education, while in high school, when not absent, it is found dissociated from the learning process.

How a student assigns the status of knowledge (or of belief) to information she processes is determined by diverse contextual and personal elements. This process, in which this work is called "designation of epistemological status", has not been sufficiently studied. Research in this direction can contribute to better understanding of self-regulated learning and, more specifically, of personal epistemological processes.

For this inquiry, it is necessary to highlight three aspects of the process of self-regulating behavior during academic learning. First, knowledge[1] must be defined. Second, it must be established that generating a knowledge schema depends on the relationship between the logical structure of knowledge and the individual's recognition that this structure is independent of belief systems or other types of explanations. Third, to interiorize the knowledge schema, the individual must be conscious of the characteristics an informational schema must have to become knowledge and thus be distinguishable from beliefs, values, expectancies or any other subjective informational schema. These three aspects lead to the consideration that appropriating knowledge implicates a process, which we denominate objectivization of the target ideas put forth in a formal academic context.

If it is understood that subjective and objective information emerges parallel to knowledge appropriation, it is the position the student assumes toward her school experience that determines the level of appropriation of the knowledge schemata. This level varies depending on the epistemological status assigned and the degree of awareness the student has of the nature of the object of learning.

When confronted by a learning situation, the student may be able to give an account of some of the aspects described briefly above. The level of awareness with which she begins a task, however, may vary in accord with different personal and contextual factors that have an important influence on her commitment with the task and thus on her performance. Therefore, to analyze her own knowledge in a learning situation, the student must distinguish the epistemological status of the information she receives since not all the information is subjective, and some knowledge considered objective could be dogmatically accepted as true. For this reason, making the epistemological status of the ideas involved in a learning episode conscious is a focus of interest for research into self-regulated learning that requires greater attention.

It could be said that knowledge is not a concrete object since the term could be used in several different ways [20]. Even though it is a central concept for Educational Science, we are far from offering a finished definition. For our purpose, it is sufficient to be aware that most theoretical stances would not have difficulty understanding knowledge as a result of experience. But this brings us to the problem of distinguishing knowledge experience from beliefs, misunderstandings, and so on. From an enactivist point of view [21], knowledge arises from an interaction between the subject and her environment; the concept knowing would better define this idea. But then, does any knowledge exist as an object independent of a subject? Does knowledge exist as an informational scheme?

On one hand, the theoretical position that knowledge is an object, loosely defined as carrying truthfulness or correct representations of the world is posed. On the other, a conception of knowledge as immanent from the subject-environment interaction is assumed. This chapter attempts to offer a communicational approach to explain the objectivity feature of knowledge through symbols, signs, words and their abstractionist properties.

[1]Only knowledge, and not objective knowledge, since for some philosophers, knowledge is by nature objective.

There has been a growing body of articles tackling the problem of epistemic beliefs [22–25]. Their explicit aim is to solve the problem of the subjective-objective interaction in academic learning. A strand of this research into personal epistemology has focused on the interaction between what subjects say knowledge is and the outcomes in academic learning episodes [26]. There is no agreement on what kind of interaction exists between epistemic beliefs and academic learning. What is evident is the attitudinal component embedded in every learning episode, where assignation of epistemic status denotes the student's assumption of having or not having learned [19].

4.3 Analyzing Empirical Evidence

4.3.1 Observations on a Learning Episode

A math-related task requires understanding specific concepts related to regularities to consider that a student has learned in this discipline. Thus, 'academic features of math information' are taken as the rigor involved in math as a discipline; it is thought in the way that H. Freudental does [27]. He says that '…on no other science can be imposed so strong a deductive structure as on mathematics.' In mathematics it can be said, without doubt, that something is right or wrong, and being the discipline it is, the means are as important as the results. So, for the math student the learning process is not just about getting the right answer it also involves the deductive system that underlies it. Nevertheless, as Freudental says, 'rigor can be acted out without knowing what it is'. And so, manipulation of a geometric representation itself during the task is the means to enacting cognitive academic outcomes in a learning episode, it is assumed that the academic features of math information arise from the social context regarding the validity of their responses during the task and not only from the manipulation that takes place during the perceptually guided action they experience during the task [28].

The study of knowledge construction and development of self-regulating strategies in function of argumentative execution during a learning episode requires distinguishing at least two levels of self-regulated learning:

- The first refers to the students' immediate awareness of the valuations, expectations and beliefs concerning the attempted solution and the epistemological status of the ideas used during a learning episode. This awareness is evaluated through responses to demands for solution by a series of questions the student must answer regarding the graphic representation of type $f(x) = \mathbf{a}(x - \mathbf{b})^{\mathbf{n}} + \mathbf{c}$ algebraic functions.
- The second refers to mediating awareness by argumentation relative to self-regulated learning. This awareness is verified in the argumentation the student develops concerning the validity and pertinence of what she is learning and in the strategies she uses during the learning process.

Conceptualization of a self-regulatory process at two levels mutually informative and recursive led us to expect three main outcomes. First, the process of learning algebraic contents occurs after verifying a process of objectivization of information relative to the content in question. Second, gradual integration of new self-knowledge structures and new strategies leads the student to direct her own behavior. Third, a causal relationship exists that implicates the influence of variables that are conceptualized at a regulatory level in the context of problem-solving and have the goal of promoting learning. The regulatory level variables affect, in the end, the variables conceptualized from the process of objectivization of the information derived from the overall learning episode.

The episode described below illustrates how motivational, decision-making and knowledge-building processes is a function of awareness of the need to look for ideas as part of the metacognitive process of information objectivation during self-regulation of learning algebraic concepts. Through a computer interactive task, it will be shown how subjective factors interact with formal schemes of information during academic learning.

4.3.2 Setting the Task

To make sense of the learning episode, it is important to note that the main aim of the task was that the students fully understand the functional relationship between the algebraic expression and its corresponding graph. The interactive task consisted of using a computer interface that yields a geometric representation of the parameters a, b and c of $\mathrm{f(x)} = \mathbf{a}(\mathrm{x} - \mathbf{b})^{\mathbf{n}} + \mathbf{c}$ functions. Two tenth-year English students interact within a so called micro-world (see Fig. 4.1) that includes a compendium of functions such as $\mathbf{f(x) = a\varphi(x - b)^{n} + c}$. It is designed to present graphical representations of specific randomized functions [29]. The task was to match two graphs and there were no instructions other than to "play the game" (see Fig. 4.2). Basic instructions of how to play were displayed on the screen once they pressed start. One of the graphs (colored in green) was taken as the target; the second (colored in blue) was a graph that could be manipulated by students' direct actions in three different ways: (1) dragging points, (2) slider manipulation, and (3) directly typing parameter values (see Fig. 4.3). From the start, they were familiarized with the first two ways they could manipulate the blue graph. They then had to match the blue graph with the green one. The label 'got it' appeared when the blue and green graphs matched. The main activity during this episode was the students' direct manipulation of variation in the corresponding graphic representation of every parameter of the algebraic expression. At the end, the students were asked to identify and write down the algebraic expression of the graph.

The microworld–microidentity interaction [30] aimed to offer students an interactive environment in which to experience the topologic and topographic features of function parameters. The interactions between the two students will be described as a general learning episode taking into account the academic features of math

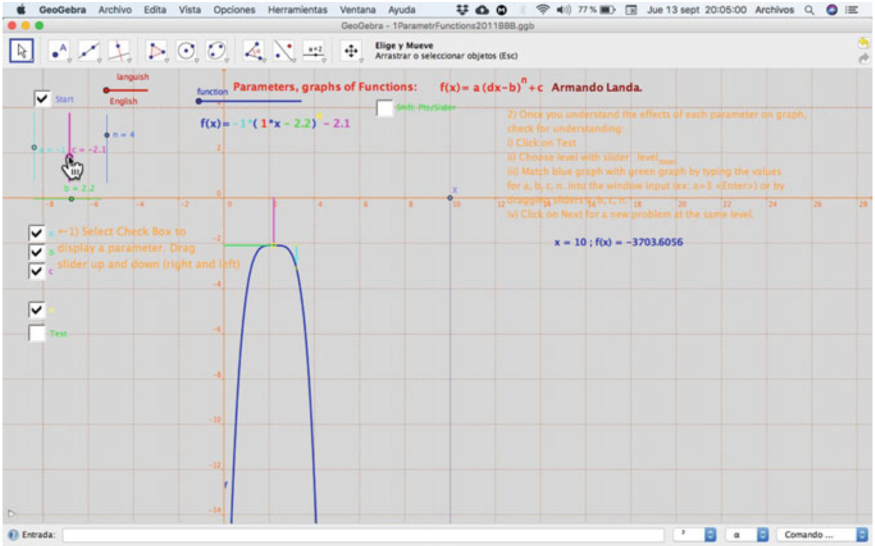


Fig. 4.1 Microworld designed to present graphical representations of specific randomized functions. Here in slider manipulation mode, without the target graph (no test mode)

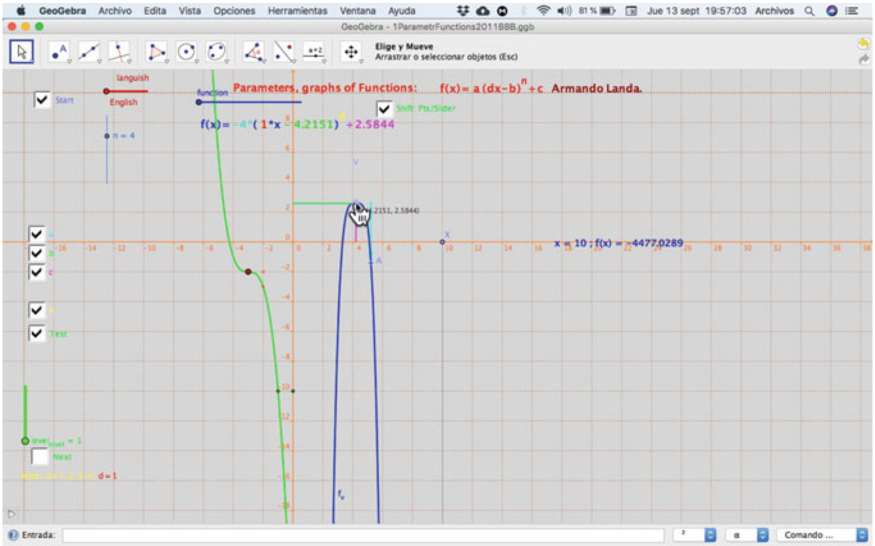


Fig. 4.2 Microworld in dragging points mode. Here in test mode (showing target graph in green)

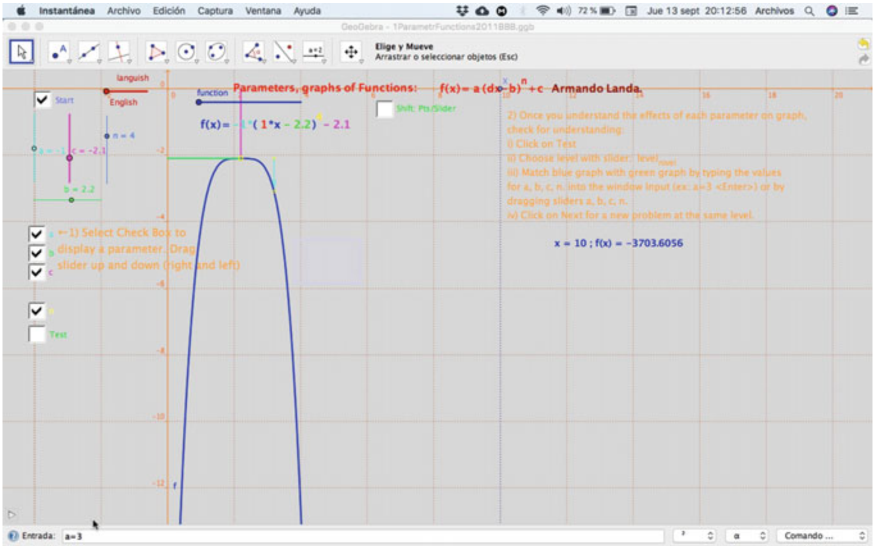


Fig. 4.3 Microworld in slider manipulation mode, show the place where "a" parameter is in the graph so students can write down the value in the algebraic expression

information to show the meaningfulness of specific elements that come up and are associated with math terms within a set of interrelated terms of specific process interpretations and give way to an "academic mode of knowing". Objectivity can be taken as an interpersonal way of coordinating action by conforming a specific formal code to activate ways of knowing. Attention is focused on the meaningfulness-building process concerning the 'a' parameter.

Of the different parameters, the functional properties of the 'a' parameter are the most difficult to perceive. For this reason, the focus will be set on the learning outcomes associated with the graphic elements of the 'a' parameter. It will be discussed how math terms in conjunction with the students' 'intention of finding out' may function as guiding cues to make sense of what it will be term 'experience of abstract objects' in an interactive task that involves mathematical thinking. It will be claimed that these terms can be understood as the concrete experience that helps students recreate similar knowledge-building experiences.

The learning evidence that resulted from the student's interaction with the microworld was the screen and students' voices recorded during the learning episode. Every comment and its correspondence with specific actions during the matching task were reviewed. Every action (effective or not) that led students to accomplish their main goal (matching the graphs together) and was related to the 'a' parameter was evaluated relative to conceptions about math they expressed during their activity.

4.3.3 Students and Knowing Math

It is proposed that meaningfulness comes up gradually as students attribute properties to events to which they relate the term, which arises as a new object. They refer to this 'object' as abstract because it arises from the subject knowing process but is attached to a specific contextual process, which enacts or recreates a specific experience associated to a (past, actual, future or hypothetical) communicational event. That is, this knowing process is a subjective matter bounded by social rules that are directly linked to facts in a way that allows experience of an idea that has been built and re-built by social doing. In this sense, one idea represents a specific way of perceiving sorts of facts. The social rules are patterns of coordinated actions, so every time a task takes place, words (or academic terms) "recreate these patterns" in both coordinated actions and subject meaningfulness interpretation.

The learning outcomes in this episode shows how the academic features of math information were brought about from students' previous experience and the constraining and promoting capabilities of the task (which represent the math deductive system) they were committing to. This pair of students started working with the micro-world with no formal academic explanation. At the beginning, they were advised only that the task they were about to engage in was about math, that they had to play for a while, and answer some questions at the end. When they had understood the task, four different ways of completing the task were introduced.

The two students (one boy and one girl) began by "playing" together for 1.5 h in the computer-based task manipulating a graph using sliders, dragging points or directly typing the values of 'a', 'b', 'c' and 'n' parameters. The way they started working showed that they had some experience with graphs and equations. For instance, the girl said: 'there it has the equation for that' when she was writing the algebraic expression, and it seemed that she referred to one of the graphs. Nevertheless, they did not appear to know, or at least they did not know precisely, what some of the terms were about. For example, the boy asked the girl in a lower voice 'what is a parameter?' or at an earlier moment, the girl wondered if would be possible to write down the values of 'x' directly. Another expression used by the student that shows the re-creation of past facts they considered related is when they said: 'I recognize that shape' referring to a specific n parameter value.

4.4 Math Meaningfulness and Three Modes of Manipulating the Blue Graph

4.4.1 The Adaptation Process: Dragging Points and Using Sliders

In this episode, the students' attention is guided by the task of matching the graphs. When the task was performed by slider manipulation, identification of the slider effect was easier. By this means, they matched the graphs several times: 16 matches in about 16 min. It took them three minutes to understand how to manipulate the sliders and then during the next 13 min achieved 16 matches. They showed evidence of having noticed the graphical representation of the parameters about one minute after they started the task, when they tried to drag point 'A' in the graph. The first element of the 'a' parameter they noticed was the 'A' point, which is a point in the graph defined by the coordinates (b + 1, a + c) in the Cartesian plane at minute $1'15''$. When they tried to drag it, trying to find out what a parameter was, seconds later they realised the sliders' functions, and the girl said: 'what is the punch with that point then?'—she had started to discover properties of the objects on the screen. Thirty seconds later, they clicked the check box that made a light blue arrow appear, representing the value of 'a' (see Fig. 4.1). During the next 70 s, they experimented moving this point until they realised they could also move 'c'. Ten seconds after the 'a' slider, the expression of the girl when she realised the effect of the slider movement on the graph was "oh my god" and kept moving for another ten seconds. At $3'45''$ they clicked the Test check box, and the graph to be matched appeared. The girl then referred to the 'a' slider and said: "ok, do 'a', and then, because that was the shape one". The boy decided to move the 'c' parameter first but seconds after he moved slider 'a' "approaching the shape", changing the parabola orientation twice, and said: "we can let it more like that". As of this moment, they manipulated parameter 'a' and easily matched 16 graphs in less than a minute per trial.

In general, it could be said that the effects of the parameters were on what students take as "the shape" and "the position" of the graph. During these first 16 trials, they could see the effect of the 'n' parameter on the shape with ten even positive numbers, two linear, two cubic, and two even negative numbers. They showed having understood what the difference in the effects of each parameter was well enough to accomplish the task several times. They were actually able to do each trial quickly. When they were doing trial 12 the girl said "I am going to get bored". In trial 15 they realized the slider changes levels and moved to level 2, where they matched two quadratic graphs. At the end of trial 16, the teacher interrupted them and explained that there are three different methods to accomplish the task. They had been using the slider method but it could be done by dragging the graph by the point 'V' and point 'A' (in this method as well, the 'n' parameter has to be manipulated by the slider) or by directly typing in the parameter values. The teacher asked them to try to achieve the task using the three methods.

4.4.2 Typing the Parameters Values

At the beginning of this new condition, it seemed that the understanding of the parameters was still the same; they continued matching the graphs easily, one per minute. Having to alternate methods, they faced new challenges. Using points seemed to be the same in terms of what they understood about the effect of the parameters. They started using the typing method and in the first two goes everything seemed easy: they got it in their first attempts. But before the third typing trial, confusion appeared when they were trying to match a linear graph and they established ‘n = 0’. They did not know how to change the slope. First, they moved the ‘n’ slider several times but returned to n = 0. Then they moved the ‘a’ slider until both ‘A’ points coincided. At the end, they moved ‘n’ again, indistinctly until the graphs matched. The third time they used the typing method and the confusion continued. Both graphs, the one to match and the one they manipulated, were linear. They typed ‘b’ and ‘c’ correctly, but they did not notice that the graph they manipulated was linear and start changing ‘n’ values. Before getting the right ‘n’ value, they started to think about the ‘a’ value and first tried a = 0. They then typed correctly a = 1, and finally returned to ‘n’. After three goes, they got it.

4.4.3 Perceiving the ‘a’ Parameter and Its Properties

In previous part of the episode, it became evident that the students during the adaptation period had no difficulty in associating the function of the parameters ‘b’, ‘c’ and ‘n’ with numerical values. However, they still had no clear understanding of the function of the ‘a’ parameter.

What happened in the next typing trial brought up the first explicit question about what ‘a’ was and made evident that the typing method was urging them to pay attention to the numerical values of the parameters. The equation for the graph to find was $f(x) = 1(x + 3)^7 + 5$. As usual they established ‘b’ and ‘c’ with no problems. Regarding ‘n’, they first tried n = 2 and then n = 3; they noticed the shape was similar and tried to look at the ‘A’ point. The boy zoomed the screen and asked the girl ‘can you see where ‘a’ got to?’ Point ‘A’ was at 6 on the Y-axis; both said 6 and typed it. When they saw the effect, they said ‘no wait… ahmm’, moved the graph to the center so they could see; the shape was similar and they concentrated on ‘a’, thinking that was the only incorrect value. It seemed they had noticed a smaller ‘a’ value was needed but did not stop to see what this quantity was about; all the earlier conjectures regarded the Y axis. Apparently, the objective was to match the points, not to understand; they probed 3, −1, 0 and when they typed a = 1, both ‘A’ points coincided but they seemed not to have noticed it. The girl typed a = 1 and the boy said: “yeah, I think it’s about right, it’s ‘n’ is wrong”. Meanwhile, he typed a = 0.5 but returned to a = 1, and they started looking for the shape through ‘n’, changing n = 4 to n = 5. As n = 5 approached the shape more closely, they again thought ‘a’ was wrong; the boy said: “and then maybe a = 2”, after seeing the effect, the girl suggested a = 6 and typed it, then returned to a = 1. The boy said: “I think ‘a’ is in the right place”. She suggested something about moving the crane up and down and then typed a = 0.75. It seems they suspected they needed continuous quantities, but when the position of the ‘A’ dot changed, the boy said: “no, I know ‘a’ is in the right place” and typed a = 1. Finally, he zoomed the screen, typed n = 7 and ‘got it’.

In this stage of the episode, the student began testing hypotheses regarding numerical values and topological characteristics of the parameters. They continue to arrive at conclusions with no clear evidence, and matching the graphs was the result of fortuitous actions. This last trial was important for them to start a more specific differentiation of the effects of the ‘n’ and ‘a’ parameters and illustrated the importance of an attitude of enquiry in the academic knowing process. In this trial, they had to pay more attention to the values of the ‘a’ parameter, so they started to realise the effects of different values on the graph. Their wanting to find out emerges through questions. The question ‘can you see where ‘a’ got to?’ refers to the attentional process while searching for the relation between values and position and shape of the graph. Even when they were able to match the graphs by directly manipulating parameters, they were not able to understand the relationship. After this, they had a last go at a typing trial, having the reference of the graph that corresponded to the values they were typing. In this trial they had no problem defining the ‘a’ or the rest of the parameters; they correctly typed all the parameters in the first go with confidence.

4.4.4 Typing Values Without Immediate Feedback

By that moment, the two students had accomplished 35 trials, of which 5 were typing trials. A new condition was then introduced: they had to type the values again but now without seeing the values in the corresponding graph. That is, in this new condition there was no immediate feedback of the effect of the parameters. Regarding the ‘a’ parameter, after the confusion occurred in the 4th typing trial, it seemed they first related the value with the position on the graph relative to the Y axis, and then returned to identify the ‘A’ point relative to the ‘V’ point. Nevertheless, when they started to do the typing without the graph visualization, for the first two goes, they did not need to type the ‘a’ value because it was already established, as it was needed at the start of the trials. But in the third trial, the ‘A’ point of the target graph was settled over the Y-axis and crossed the Y-axis with the ‘A’ point exactly at minus five. The target graph equation was $f(x) = -4(x - 1)^3 - 1$. They correctly typed the ‘b’, ‘c’ and ‘n’ parameters, and after that boy said “…we have to change ‘a’ because ‘a’ is in the wrong place”. He hesitated and typed $a = -5$. Since no ‘got it’ label appeared, he said: “and so $n = 4$, not 5, wait yeah…”. He typed five, but no ‘got it’ label appeared, and the boy said: “we are lost now”. Confusion came up again. Even when the boy previously had said: “the odd ones give you like that weird curve and the even ones give you…”. Here, the boy said: “$n = 1, 2, 3$ or 4”, but he also said “I think what goes wrong is ‘a’. I’m not quite sure why”. The girl said: “It’s because the dot is there”. The boy said: “yeah, but I don’t know why there is an ‘a’ dot”. The new task constraint (not being able to see the graph) directed their attention to past facts and made questions come up about the objects and their relationships. Once they started playing, they gradually became aware of the relations among the screen elements. They started matching the graphs by using the sliders. At that moment for them it was just as important to understand what happened when they moved the slider. In the typing mode, numbers as order and as magnitude became important. Somehow, they knew the difference among parameter effects but could not explain it. They no longer had feedback, but expressed being sure that ‘a’ was the wrong thing. At this moment, they seemed not to have the means to find out what was wrong, so teacher told them: “if you want, show the graph, and then hide it later”. They did it, and when the graph appeared, the girl said: “‘a’ is wrong”. They hid it again, typed $a = -2$, showed the graph again, and the girl said: “it’s closer now, it’s like $a = -3$”. The boy said: “no, but .... we got to…what is ‘a’!? because we’ve got to work it out without seeing it”. They discussed what could be done, and the girl said: “that’s the dot that would be there if we had the ‘c’ thing, and then it would have shown us that one (the ‘a’ dot)”. This suggests that the confusion arose because the part of the graph with the ‘a’ bit was over the Y axis. The boy hid the graph and typed $a = -5$ again, typed $n = 1$, showed the graph and concluded ‘a’ is the wrong thing. They typed $a = -5$ again and kept thinking ‘a’ is the point where the graph crosses the Y axis. They tried $a = -5$, $= -6$ and $= -7$ and showed the graph again, saying “I think ‘a’ is, must be the Y intersection”.

This part of the episode illustrates the metacognitive mechanism of seeking the experience of understanding. It is in this sense that it could be stated that the objective of the object knowledge is this experience. The students are driven by the need to understand (“because we’ve got to work without seeing [the graph]”), which could be interpreted as the need to be able to explain by modifying previous schemata. Nevertheless, the process of objectivization is still not a conscious process. Up to now, the process has been guided by intuition.

4.5 Discussion

4.5.1 Metacognitive Enactivism

It is important to notice that during the task, students self-regulate their actions in order to accomplish fitting two graphs, and the solution is attached to the math ideas regarding the enactment of the corresponding algebraic expression. In this sense, the self-regulated process has at least two levels regarding intentional behaviour when this learning episode took place. The first level refers to the problem-solving commitment: matching the graph. The second one relates to the academic learning process: making up the math ideas that underlie the process [19, 31].

When the student said “…we got to work it out without seeing it”, he realized how the academic knowing process is also attached to the task constraints. The boy asked again, more emphatically, “yeah, but what is ‘a’?” The girl, pointing to the ‘a’ parameter in the equation said: “‘a’ is that one! I mean, how can you work out where it is? Zoom in the screen,” The evidence supported his theory. He said: “I am sure it must be −5”, and he again tried $a = -5$ unsuccessfully. They gave up and clicked ‘next’; a new graph came up. This time the graph crossed the Y axis at 3 and the 'A' point was where the graph crossed the X axis at −1. They typed 'c', 'b', and 'n' parameters, first typing a = 3 and expressed bewilderment "uhh, I don't know where 'a' goes anymore". The girl noticed the 'A' dot and said: "there's the dot". She suggested and wrote minus one, the distance to the X axis, but he said: "no, no because all you do with 'a' is move it along that, vertically". After thinking for 30 s, the boy typed a = 0, showed the graph and they saw a horizontal line. Again confused, they hid the graph and typed n = 4 and showed the graph again. The horizontal line was still there; the boy said: "I think it's because 'a' is zero". The teacher suggested dragging sliders again, which they did with the graph visible; they moved the 'a slider' until the 'A' points matched. He said "uh, 'a' is how many above that is, how 'a' crosses X, because 'a' is relative to that (pointing to the 'A' point) (see Fig. 4.2); it is not relative to any line there, because it has its own zero, plus one, and I think…um". He hid the graph typed n = 2 and the 'got it' label appeared.

Clicking 'next', a cubic graph appears as the target graph ($f(x) = -1(1x - 2)^3 + 0$. The manipulated algebraic expression was $f(x) = 1(1x - 2)^2 + -1$. He said: "see what I mean" (it seems that he said this in relation to the previous trial) "Ok, so…" they typed all the parameters right. Point 'V' was over the X axis; they did not hesitate to write minus one, it seemed they had understood. Clicking 'next bottom', a linear graph appeared ($f(x) = -1(1x - 4) - 0$ with a 'V' point over the X axis again. The algebraic expression they manipulated remained the same: $f(x) = -1(1x - 4)^3 - 0$. And again, she said confidently: "Oh, a = −1" (…), while the boy typed a = −1. They 'got it' with no problem. He clicked the 'next' check box. The green graph changed to a third degree function, whose algebraic expression was $f(x) = -3*(x - 3)^3 + 1$. This time neither point 'V' nor 'A' coincided with the axes. When he was deciding 'a' the confusion with 'a' properties and axes became evident in their exchanges. The boy said: "and a…"; she said: "a = 1"; he: "I think it is minus" (typed a = −1). [pause] He said: "It should be…". She said: "ok" [long pause], clicked 'start' button to show the graph and the two remained silent while observing. She said: "'a' is wrong" [pause] 'umm' [pause]; he: "ahh, no", clicked 'start', the blue graph disappeared. She said: "no 'a' is one, minus one"; he said: "oh no, I see, that's what 'a' is, goes down from…, and it's from that line to where it crosses, and how many down is it? so 'a' is minus three." He typed a = −3, clicked 'enter' and the 'got it' label appeared. "Ok…yeah, ok I think I understand the whole 'a' thing!"

4.6 As a Conclusion

4.6.1 Objectification as a Condition for Academic Knowing

In the learning task, students had to have the intention of finding out what was involved in the solution to the problem, but the explanation was conditioned to the experience of understanding. The possibility of this occurred when an ontological question was posed: "what is this?", meaning "what should I understand by 'this'? With this question the student was seeking to experience an interaction among perceived objects, not the 'object itself' because the object itself is just a signal. Think of a dog. A dog can see a sidewalk or a traffic light, but cannot conceptualize their functionality. Of course, there are dogs that learn to react in accord with traffic light signals in a functional way, but it is impossible to say whether the dog knows the meaning of the traffic signals. Knowledge of traffic lights is a theoretical explanation that goes beyond the functional interaction. This metacognitive process is not easily verifiable in a dog.

In contrast with the dog, the students consciously sought to transform the subjective experience into knowledge. Theoretical explanation is the goal in school learning, and solving problems does not necessarily mean that understanding of knowledge schemata has been acquired. The process of solving problems gives students the opportunity to construct an experience toward understanding, but it could happen that they cannot objectify their experience.

Two actions are needed to recreate academic knowledge, which are related to the object of knowledge. First, it must be built as an external object and experienced as a subject-independent object. It is not what the mind automatically builds but what the context experience promotes and constrains. The latter would be the objectivization process. Second, objectification of the subjective experience, meaning the concrete interpretation of this object, where concretion is the use of terms, which are assumed to be technical or scientific terms. In this way, knowledge is just a status we assign to certain kind of experience elicited by terms.

In this sense, math terms represent the very first objectification mechanism elements since they are the trigger elements of particular ways of recreating the knowing process of specific objectivization facts. In these terms, the process is not a construction of objects but an identification of ways of knowing.

Our students knew a bit about graphs, they had heard some about equations, but this was the first time they tried to match two graphs by modifying parameter values, which they could 'know' only at the end of the task. Is there anything behind the perceptual experience, something that is not available for the senses? It seems that there is something else; the teacher 'knows it' and waits for the student to discover it. What occurred with our two students during the task suggests that this something also belongs to the perceptual sphere, in a subjective sense, to their inner perception. They arrived at conjectures through specific yet 'unknown' terms, known words that elicit past experiences and facts, inquiries, expectancies, subjective abstract stuff and, in an inter-subjective sense, through identification of social rules that constrain effective actions. Ontologically, objectivization as a metacognitive process of objectification emerges as knowing how to look for these experiences.

The possibility of acquiring academic knowledge depends on the student's awareness of her behavior toward herself in a context that is guided by the behavior of others. Consciousness of how things work is the precursor of objective knowledge schemata. However, the possibility of generating a learning result in accord with the expectations of the educational institution depends on being able to construct her own experience as the object of knowing. It is the voluntary intentional act that is the first element in the generation of academic learning. Therefore, attitude determines the possibility of its development. However, it is the attention placed on her own experience that allows it to become objective knowledge. The adequate characterization of the metacognitive process implicated in the development of academic learning thus becomes fundamental, and the role of awareness of the nature of the academic learning process is the articulating element. This element is knowing how to know, from subjectivity to objectivity, by objectifying the learning experience.

References

1. Hofer, B.K., Pintrich, R.P.: The development of epistemological theories: beliefs about knowledge and knowing and their relation to learning. Rev. Educ. Res. **67**(1), 88–140 (1997)
2. Hofer, B.K.: Personal epistemology research: implications for learning and teaching. J. Educ. Psychol. Rev. **13**(4), 353–382 (2001)
3. Chan, K., Elliot, R.G.: Relational analysis of personal epistemology and conceptions about teaching and learning. Teach. Teach. Educ. **20**(8), 817–831 (2004)
4. Kuhn, D.: The development of epistemological understanding. Cogn. Dev. **15**(3), 309–328 (2000)
5. Kuhn, D.: Education for Thinking. Harvard University Press, Cambridge (2005)
6. Miller, D.: (compilador) Popper Escritos Selectos. Fondo de Cultura Económica. México, D.F. (1995)
7. Richter, T., Schmid, S.: Epistemological beliefs and epistemic strategies in self-regulated learning. Metacogn. Learn. **5**, 47–65 (2010)
8. Tugendhat, E.: Autoconciencia y Autodeterminación una interpretación lingüístico-analítica. Fodo de Cultura Económica, España (1993)
9. Bandura, A.: Social cognitive theory: an agentic perspective. Asian J. Soc. Psychol. **2**, 21–41. mayo 2018, De. https://onlinelibrary.wiley.com/toc/1467839x/1999/2/1 (1999)
10. Castañeda, S.: Educación, aprendizaje y cognición. In: S. Castañeda, Educación, aprendizaje y cognición. Teoría en la práctica. UNAM/U de G/Manual Moderno, México (2004)
11. Weinstein, C.E., Powdrill, L., Husman, J., Roska, L.A., Dierking, D.R.: Aprendizaje estratégico: un modelo conceptual, instruccional y de evaluación. En S. Castañeda (ed.). Evaluación y fomento del desarrollo intelectual en la enseñanza de ciencias, artes y técnicas. Perspectiva internacional en el umbral del siglo XXI, pp. 197–228. CONACYT, UNAM y Miguel Angel Porrúa, México D. F (1998)
12. Entwistle, N., Kozeki, B.Y., Tait, H.: Pupils perceptions of school and teachers II-relationships with motivational approaches to learning. J. Educ. Psychol. **59**, 340–350 (1989)
13. Manassero, M.A., Vázquez, A.: Atribuciones causales de alumnado y profesorado sobre el rendimiento escolar: Consecuencias para la práctica educativa. Rvta. Interuniversitaria de Formación del Profesorado, 24, sep-dic. 125–141 (1995)
14. Weiner, B.: A theory of motivation for some classroom experiences. J. Educ. Psychol. **71**, 3–25 (1979)
15. Wigfield, A., Eccles, J.S.: The development of achievement task values: a theoretical analysis. Dev. Rev. **12**, 265–310 (1992)
16. Helmke, A.: The impact of student self-concept of ability and task motivation on different indicators of effort at school. Int. J. Educ. Res. **13**(8), 281–295 (1989)
17. Pintrich, P.R., Conley, A.M., Kempler, T.M.: Current issues in achievement goal theory and research. Int. J. Educ. Res. **39**, 319–337 (2003)
18. Boekaerts, M.: Personality and the psychology of learning. Eur. J. Pers. **10**, 377–404 (1996)
19. Santos, D.: Objetivación de información en aprendizaje matemático. Revista Mexicana de Psicología **27**(1), 103–110 (2010)

20. Smith, M., Siegel, H.: Knowing, believing, and understanding: what goals for science education? Sci. Educ. **13**, 553–582
21. Varela, F., Thompson, E., Rosch, E.: The Embodied Mind: Cognitive Science and Human Experience. The MIT Press, Massachusetts (1991)
22. Hamer, D., Elby, A.: Tapping epistemological resources for learning physics. J. Learn. Sci. **12**(1), 53–90. Lawrence Erlbaum Associates, Inc (2003)
23. Hofer, B.: Introduction: paradigmatic approaches to personal epistemology. Educ. Psychol. **39**(1), 1–3. Lawrence Erlbaum Associates. Inc (2004)
24. Mintchik, N.M., Farmer, T.A.: Associations between epistemological beliefs and moral reasoning: evidence from accounting. J. Bus. Ethics **84**, 259–275 (2009)
25. Paulsen, M.B., Feldman, K.A.: The conditional and interaction effects of epistemological beliefs on the self-regulated learning of college students: motivational strategies. Res. High. Educ. **46**(7) (2005)
26. Mason, L., Bromme, R.: Situating and relating epistemological beliefs into metacognition: studies on beliefs about knowledge and knowing. Metacogn. Learn. **5**, 1–6 (2010)
27. Freudenthal, H.: Mathematics as an Educational Task. D. Reidel Publishing Company, Dordrecht, Holland (1973)
28. Peñalva, R.: Las matemáticas en el desarrollo de la metacognición. Política Y Cultura, 33, 135–151. Retrieved from http://www.scielo.org.mx/scielo.php?script=sci_arttext&pid=S0188-77422010000100008&lng=es&nrm=iso&tlng=es (2010)
29. Papert, S.: Microworlds: transforming education. En Lawler, R., Yazdani, M. (eds.) Artificial Intelligence and Education volumen one. Learning Environments and Tutoring Systems. Ablex Publishing 355, Chestnut St. Norwood, NJ 07648 (1987)
30. Santos, D., Landa, A.: Topologic and topographic features of parameters of functions within a microworld–microidentity interaction (in press)
31. Santos, D.M., Castañeda, S.: Objetivación de información en aprendizaje matemático autorregulado: Validez empírica de constructo. Revista Mexicana de Investigación Educativa **13**(38), 713–736 (2008)

David Martín Santos Melgoza Doctor in Psychology by National University of Mexico, professor at Chapingo Autonomous University. His work concerns self-regulated behaviour. He is also concerned with metacognitive learning processes in the academic context, especially regarding personal epistemology.

Part II
Learning Analytics to Predict Student Performance

Chapter 5
Learning Feedback Based on Dispositional Learning Analytics

Dirk Tempelaar, Quan Nguyen and Bart Rienties

Abstract The combination of trace data captured from technology-enhanced learning support systems, formative assessment data and learning disposition data based on self-report surveys, offers a very rich context for learning analytics applications. In previous research, we have demonstrated how such Dispositional Learning Analytics applications not only have great potential regarding predictive power, e.g. with the aim to promptly signal students at risk, but also provide both students and teacher with actionable feedback. The ability to link predictions, such as a risk for drop-out, with characterizations of learning dispositions, such as profiles of learning strategies, implies that the provision of learning feedback is not the end point, but can be extended to the design of learning interventions that address suboptimal learning dispositions. Building upon the case studies we developed in our previous research, we replicated the Dispositional Learning Analytics analyses in the most recent 17/18 cohort of students based on the learning processes of 1017 first-year students in a blended introductory quantitative course. We conclude that the outcomes of these analyses, such as boredom being an important learning emotion, planning and task management being crucial skills in the efficient use of digital learning tools, help both predict learning performance and design effective interventions.

Keywords Blended learning · Dispositional learning analytics · E-tutorials · Learning feedback · Learning dispositions · Learning strategies

5.1 Introduction

Dispositional Learning Analytics (DLA) represents the pendulum of a clock, returning to its neutral position. During many decades, the educational theory advanced

D. Tempelaar (✉)
School of Business and Economics, Maastricht University, Maastricht, Netherlands
e-mail: d.tempelaar@maastrichtuniversity.nl

Q. Nguyen · B. Rienties
Institute of Educational Technology, The Open University, Walton Hall, Milton Keynes, MK7 6AA, UK

M. Virvou et al. (eds.), *Machine Learning Paradigms*, Intelligent Systems Reference Library 158, https://doi.org/10.1007/978-3-030-13743-4_5

by carefully observing learners, using surveys or think-aloud protocols, to reveal preferred modes of learning, or to investigate what learning conditions contribute mostly to efficient learning. The digital age brought Learning Analytics (LA), aiming to advance learning theory by systematically collecting trace data describing learning episodes in digital learning platforms, and moved the pendulum a full swing away from survey data to trace data. In the context of this metaphor, DLA corresponds to the pendulum in the neutral position, where both learning systems-based trace data and survey-based disposition data feed into our models describing learning behaviours.

Buckingham Shum and Deakin Crick [2] defined the DLA infrastructure as a combination of learning data (i.e. generated in learning activities through traces of an LMS) with learner data (i.e. student dispositions, values, and attitudes measured through self-report surveys). The surveys applied in the first applications of DLA, see, e.g. Crick [4], justified the characterization of learning dispositions: they were focusing on trait-like facets of learning antecedents, such as learner attitudes and values that are of generic nature, not depending on the specific learning context. However, the use of surveys is not restricted to these learning antecedents of a "true" disposition type. As for example clarified in Matzavela et al. [9], questionnaire data can cover the full range of learning antecedents, including cognitive and non-cognitive predictors, learning styles, affective states, learning motivation, satisfaction and curriculum aspects. Examples of empirical studies combining trace and survey data in the area of self-regulated learning are, e.g. Azevedo et al. [1] and Gašević et al. [6].

With this development, several distinct and overlapping niches in LA seem to converge. The first refers to DLA in relation to Multimodal LA [13]. Multimodal LA is defined as LA combining learning management system (LMS) or intelligent tutoring system (ITS) trace data with data of another mode to derive learning feedback. Although most empirical research focusses on gazing behaviour, body language, action recording, facial expressions, speech, writing and sketching as such alternative modalities [13], information achieved by administering surveys is another straightforward example of combining LMS/ITS trace data with data of other modality.

A second parallel is between DLA and the area of student or learner modelling. A DLA based prediction model uses preferred learning approaches to understand the choice of learning activities, uses attitudes as interest and affects as boredom and enjoyment to understand the intensity of learning activities. But that is exactly what the discipline of student modelling in expert systems is aiming at [3]: use aspects of students' characteristics to design a student model to provide adaptivity and personalisation in computer-based educational software. One of the issues in student modelling is to distinguish domain dependent from domain-independent students' characteristics, to distinguish static characteristics that can be measured one time, before the learning process takes place, from dynamic features that result from students' interactions with the learning systems [3]. The same considerations are leading in the design of a DLA application: what individual students' learning facets are dispositional in the strict sense, and can be measured in a single survey; what facets are best seen as students' characteristics that develop over time, and might be measured with repeated surveys, and what facets are that strongly context-dependent that continuous measurement, such as by log based trace variables, is appropriate?

In this contribution, we aim to convince the reader of the merits of adding a new dimension to conventional LA data sources. And to demonstrate the added value of students' disposition data beyond the predictive power of LMS or ITS trace data. We will do so in one specific context: first-year university students, learning introductory mathematics and statistics, in a large scale type of education. We choose for this context since it provides very rich data, both from the perspective of the availability of large samples and from the perspective of large diversity in the subjects. Because of this combination of large-scale education with strong diversity in students, the application of LA to derive learning feedback has a lot of potential added value.

The next section describes related research applying a similar learning context, followed by detailed sketch of the characteristics of that learning context in the third section. In the empirical fourth section of this contribution, we analyze data from the current cohort of students, followed by discussion and conclusions in the last section.

5.2 Related Work

In this section, we provide a description of related investigations applying dispositional learning analytics in blended contexts. The first subsection characterizes the context of the learning blend, followed by a discussion of predictive power and availability in time of different types of data in the second subsection. The third subsection focuses on the role of cultural values as an example of a data type that represents a purely fixed trait. Subsection four discusses different types of assessment data: assessment of, assessment for and assessment as learning. The last subsection discusses the relatively recent development of including affective learning dispositions along with dispositions of cognitive and behavioural nature: the role of learning emotions.

5.2.1 Educational Context

The learning context investigated in previous research by the authors is best described as a large-scale introductory mathematics and statistics course, using 'blended' or 'hybrid' learning, in a business and economics university program in the Netherlands. The main learning component is face-to-face: Problem-Based Learning (PBL), in small groups (14 students), coached by a content expert tutor [12, 37]. Participation in these tutorial groups is required. Optional is the online component of the blend: the use of the two e-tutorials SOWISO and MyStatLab (MSL) [25, 34]. This choice is based on the philosophy of student-centred education, placing the responsibility for making educational choices primarily on the student. Since most of the learning takes place in self-study outside class, using the e-tutorials or other learning materials, and class time is used to discuss solving advanced problems, the instructional format is best characterized as a flipped-class design [37]. The use of e-tutorials and achieving good scores in the practising modes of both e-tutorials is stimulated by making bonus points available for good performance in the quizzes: the formative assessments. Quizzes are taken every two weeks, and consist of items that are drawn from the same item pools applied in the practising mode. We chose this particular constellation as it stimulates students with limited prior knowledge to make intensive use of the e-tutorials. The bonus is maximized to 20% of what one can score in the exam.

The student-centred nature of the instructional design requires, first and foremost, adequate actionable feedback to students so that they can monitor their study progress and topic mastery. The provision of relevant feedback starts on the first day of the course when students take two diagnostic entry tests for mathematics and statistics. Feedback from these entry tests provides a first signal of the importance of using the e-tutorials. Next, the SOWISO and MSL-environments take over the monitoring function: at any time, students can see their performance in the practice sessions, their progress in preparing for the next quiz, and detailed feedback on their completed quizzes, all in the absolute and relative (to their peers) sense.

Subjects of our studies are subsequent cohorts of first-year students, participating in course activities: typically between 1000 and 1100 students each year. A large diversity in the student population is present: only about 20% are educated in the Dutch high school system. Regarding nationality, the largest group, about 40% of the students, is from Germany, followed by about 20% Dutch and between 15–20% Belgian students. In most cohorts, no less than 50 nationalities are present, but with a large share of European nationalities: no more than 5% of students are from outside Europe. High school systems in Europe differ strongly, most particularly in the teaching of mathematics and statistics (with, e.g. the Dutch high school system having a strong focus on the topic statistics, whereas that topic is completely missing in high school programs of many other countries). Therefore, it is crucial that the first module offered to these students is flexible and allows for individual learning paths [12, 37]. In the investigated cohorts, students work an average of 25–30 h in SOWISO and a similar amount of time in MSL, 30–40% of the available time of 80 h for learning on both topics.

Learning dispositions measured at the start of the course were of affective, behavioural, and cognitive types [16, 17]. The surveys had a prime role to supply students with an individual data set required for doing a statistical project, resulting in a full response.

5.2.2 The Crucial Predictive Power of Cognitive Data

Early LA applications focused on the development of predictive models, with the central question: what is the predictive power of the data at hand, can we signal students at risk with sufficient reliability by, e.g. LMS learning activity data. The best context to answer such question about predictive power is the context where a wide range of alternative learning data is available, allowing for comparative analyses of the predictive power of different types of data. We did so in a couple of studies [25, 27, 30–32], where we analysed LMS student activity data, e-tutorial trace data of both process and product types [1], formative assessment data, and learning disposition data. The conclusions of these studies can be adequately summarized as cognitive formative assessment data dominating all other types of data in terms of predictive power. Whether signalling students at risk or predicting course performance: as soon as quiz data became available, learning activity data or dispositions do not add explained variation anymore. However, that brings a timing issue: the availability of such formative assessment data is typically restricted to later moments, limiting the opportunity to use that data for learning interventions (in our case: the first assessment data became available in the fourth week of an eight-week course). The second outcome of our studies was that early intervention is best based on the combination of e-tutorial trace data and learning dispositions, available early in the course. LMS activity trace data has similar availability, but did not add any predictive power beyond e-tutorial trace data.

5.2.3 An Unexpected Source of Variation: National Cultural Values

In a discussion on the antecedents of learning processes and the trait/state nature of these antecedents, one group of antecedents takes the most polar position one can think of: national cultural values. These values, as is clear from their name, represent dimensions of preferences that distinguish countries, rather than individuals. In their influential work, Hofstede et al. [7] identified six major dimensions on which cultures in the workplace differ: power distance, uncertainty avoidance, individualism versus collectivism, masculinity versus femininity, long-term versus short-term orientation, and indulgence versus restraint. Power distance refers to the extent to which less powerful members of organisations and institutions accept and expect unequal distribution of power. Uncertainty avoidance refers to society's tolerance for uncertainty and ambiguity, indicating the extent to which members of a culture feel threatened by ambiguous and uncertain situations. Individualism versus collectivism signals the degree to which individuals are integrated into groups: from loose ties between individuals, and everyone expected to look after oneself and immediate family, to people being integrated into strong, cohesive in-groups. In masculine societies, emotional gender roles are rather distinct, whereas in feminine societies, these roles overlap. The fifth culture dimension of long-term orientation distinguishes societies in being directed towards future rewards, or the fulfilment of present needs and desires. The sixth and most recently added culture dimension is that of indulgence versus restraint and signals the degree to which a culture allows or suppresses gratification of needs and human drives related to hedonism and consumerism. And although these national cultural values are defined at the country level, assigning these country scores on the six dimensions to individual subjects in an attempt to investigate has proven to be an effective way to model country differences in a wide range of applications. In our context, dealing with the large diversity in European national cultures at the one hand, and small national subsamples at the other hand, it is an adequate solution to include more than 50 nationalities into one parsimonious prediction model.

In a series of studies [10, 19, 28, 29, 35], we investigated the role of national cultural values in learning processes, assigning national dimension scores from the Hofstede et al. [7] study to individual students. The effects we found are nowhere larger than medium-sized, explaining up to 5% of the variation in outcome measures, but the effects were quite generic. Two national culture dimensions tended to have positive impacts on learning: Long-Term Orientation and Masculinity, with the strongest role for orientation. Two other dimensions tended to have negative impacts: Power Distance and Indulgence (implying that Restraint has a positive impact). Weak or absent impacts were found for Individualism and Uncertainty Avoidance. Those impacts do not restrict to the prediction of learning performance and learning activity but extend to the prediction of other student characteristics that act as antecedents in our prediction model. For instance, masculinity, uncertainty avoidance, orientation and restraint are predictors of several learning emotions: boredom, hopelessness, and enjoyment. And of learning motivation and engagement variables, both adaptive and maladaptive types. That is: the relationships between cultural values and learning activity and performance is both of direct type, and of indirect type, through the mediation of learning dispositions. In a sample of such international composition as ours, cultural values thus serve two different functions: to create parsimonious prediction models, and to better understand the nature of country differences.

5.2.4 LA, Formative Assessment, Assessment of Learning and Feedback Preferences

LA is about having rich data, and in many cases, richness is about the cognitive nature of the available data: see the second subsection. Formative assessments, or 'assessments for learning', are the first source of such cognitive data about student mastery in relevant topics. There are, however, two issues with formative assessment: a timing issue, and an incentivisation issue. The first issue is discussed before: formative assessment data is often available only late in the course, limiting its use for educational interventions. That late availability is related to the issue of incentivisation: to get a reliable impression of student mastery; one needs to get rid of any non-committal nature. That requires incentivising the assessment, making it a kind of midterm test. But midterm feedback is indeed late feedback.

'Assessment as learning' data replacing formative assessment data suggests being an alternative. In our studies [11, 18, 19, 22–24, 26, 30, 33], we analysed the roles of both types of assessment data, assessment for and assessment as learning, and linked these with students' preferences for feedback. From an LA perspective, the great advantage of assessment as learning data is that these data are derived from trace data generated by test steered e-tutorial or intelligent tutoring systems, and beyond registering student mastery in these learning environments, these systems also log revealed learning approaches by students. Such as learning feedback modes students use most often when the choice is theirs: worked-examples, tutored problem-solving or untutored problem-solving [11, 30]. Another facet of revealed learning preferences refers to timing decisions: to what extent learn students just in time, and what events (tutorial session, midterm, final exam) are most important to learn for [33]. Enabled by the DLA nature, the last step of this analysis is to connect these revealed preferences with learning dispositions, to derive learning feedback of the nature of: 'learning as a preparation for tutorial sessions represents the most effective timing of learning; learning emotions are strongly related with timing decisions'.

5.2.5 LA and Learning Emotions

A relatively recent development in LA applications is the integration of affective antecedents of learning, along with the more standard behavioural and cognitive antecedents [15–17]. That development is stimulated by the availability of wearables that allow continuous measurement of emotions. Nonetheless, even more traditional surveys generating cross-sectional affect data offer great opportunities to account for trait-like learning emotions in the provision of learning feedback. In several studies [21, 31–33], we investigated the role of two different types of learning emotions: epistemic emotions and activity emotions [14]. Epistemic emotions represent real traits: what affects do students encounter when confronted with academic disciplines. Activity emotions are dependent on the learning context, on the learning tasks that shape the learning process. We found strong interrelations between both types of learning emotions and activity of students in the learning environments. Those interrelations should impact the type of learning feedback and learning interventions we derive from our prediction model. For instance, we found that learning boredom is one of the affects most strongly related (in a negative manner) to the learning activity. Where in general a message telling a student that (s)he is lagging behind peers, and is advised to catch up by doing some specific learning task, might be effective, such a message will have little impact when the reason of lagging behind is feeling bored about the typical learning activity. So another type of feedback may be needed, such as offering alternative learning activities.

5.3 The Current Study

In the empirical part of this contribution, we will investigate the potentials of DLA applied to the current '17/'18 cohort of first-year students in our program, who just finished their introductory mathematics and statistics course. It is best seen as a replication study: are the several empirical findings we distilled from previous research as reviewed in the second section, invariant over time? To what extent do they repeat themselves in new cohorts of international students, with the somewhat different composition of nationalities? These are the research questions we will focus on in the remainder of this section.

The first subsection defines the participants of the current study, whereas the next three subsections describe the different types of data: trace data in subsection two, learning performance data in subsection three, and disposition data in subsection four. We close the section with a description of the statistical methods in subsection five.

5.3.1 Participants

We included 1017 first-year students in this study: students in the introductory mathematics and statistics course who have been active in both digital learning platforms SOWISO and MSL (30 students chose to concentrate their learning outside one or both platforms). Of these students, 42% were female, 58% male, 21% had a Dutch high school diploma, and 79% were international students (including a small group of students of Dutch nationality but high school education of international type).

5.3.2 E-tutorial Trace Data

In both e-tutorial systems, we investigated one process variable: connect time in the tool, and one product variable: mastery in the tool. Average values of *MathTime* is 28 h, *StatsTime* 24 h. Crucial differences exist in the way both e-tutorials measure connect time, resulting in noisy measures for *StatsTime*: the tool does not correct for the idle time. Mastery, expressed as the percentage of learning activities successfully finished, is on average: *MathMastery*: 69%, *StatsMastery*: 77%. These are mastery levels at the very end of the course when writing the final exam. To investigate the timing decisions of students, we also looked at two intermediate mastery levels: the tutorial session and the quiz. These mastery levels were on average: *MathTutS*: 21%, *MathQuiz*: 41%, *StatsTutS*: 40%, *StatsQuiz*: 71%.

5.3.3 Performance Data

Two different performance indicators, Exam and Quiz for both academic topics, result in four performance variables: *MathExam*, *StatsExam*, *MathQuiz*, *StatsQuiz*. The course starts with a diagnostic entry test, producing *MathEntry* and *StatsEntry* measures of prior knowledge.

5.3.4 Disposition Data

Several sources of disposition data have been applied, all documented in full detail in previous studies [25, 31]. For space limitations, we limit the current description to the identification of survey scales adopted and refer to the above sources for a full elaboration.

National cultural values are adopted form Hofstede et al. [7]. We use six dimensions: power distance (*PowerDist*), uncertainty avoidance (*UncertAvoid*), individualism–collectivism (*Individual*), masculinity-femininity (*Masculine*), long-term–short-term orientation (*LongTermOrient*), and indulgence–restraint (*Restraint*; this last scale is reverted, to have its direction in line with the other national values).

Individual approaches to cognitive learning processing strategies and metacognitive learning regulation strategies are based on Vermunt's [36] learning styles instrument. Processing strategies can be ordered from surface to deep learning approaches: *Memorising* and rehearsing, *Analysing*, *Relating* and structuring, and *Critical* processing, with *Concrete* processing as a separate category. Regulation strategies are decomposed into self and external regulation: Self-regulation of learning processes and results (*SelfRegProc*), Self-regulation of learning content (*SelfRegCont*), External regulation of learning processes (*ExtRegProc*), and External regulation of learning results (*ExtRegRes*), with Lack of regulation (*LackReg*) indicating lack of regulation of any type.

Attitudes and beliefs toward learning quantitative topics are assessed with the SATS instrument [20]. It distinguishes *Affect*, cognitive competence (*CognComp*), *Value*, expected difficulty in learning, reversed (*NoDifficulty*), *Interest* and planned *Effort*.

Measurements of learning emotions, both of epistemic and activity type, are based on the research by Pekrun [14]. Epistemic emotions are composed of positive emotions *Curiosity* and *Enjoyment*, negative emotions *Confusion*, *Anxiety*, *Frustration*, and *Boredom*, and neutral emotion *Surprise*. Three activity emotions share the same focus as a corresponding epistemic emotion: *Enjoyment, Anxiety* and *Boredom*. A fourth activity emotion is the negative emotion *Hopelessness*. Academic control (*AcadControl*) is hypothesised being the main direct antecedent of activity emotions.

The instrument Motivation and Engagement Wheel [8] breaks down learning cognitions and learning behaviours into four categories of adaptive versus maladaptive types and cognitive versus behavioural types. *Self-belief*, value of school (*ValueSchool*), and learning focus (*LearnFocus*) shape the adaptive, cognitive factors, or cognitive boosters. *Planning*, task management (*TaskManagm*), and *Persistence* shape the behavioural boosters. Mufflers, the maladaptive, cognitive factors are *Anxiety*, failure avoidance (*FailAvoid*), and uncertain control (*UncertainCtrl*), while self-sabotage (*SelfSabotage*) and *Disengagement* are the maladaptive, behavioural factors or guzzlers.

A recently developed 4×2 achievement goal framework by Elliot et al. [5] was applied to include self-perceived goal setting behaviour of students. The instrument distinguishes two valence dimensions: approach and avoid, and four goal definition dimensions: task-based, self-based, other-based and potential-based competence, resulting in eight scales: *TaskApproach*, *TaskAvoid*, *SelfApproach*, *SelfAvoid*, *OtherApproach*, *OtherAvoid*, *PotentApproach* and *PotentAvoid* achievement goals.

5.3.5 Analyses

The main aim of the analyses is to demonstrate the role different learning dispositions may have in the explanation of learning activities and learning outcomes. For that reason, rather than deriving simultaneous prediction models, we will focus on bivariate relationships between learning antecedents and their consequences, and apply correlational analyses. Given the sample size in this study, correlations of the absolute size of 0.11 and beyond are statistically significant at the 0.01 level.

5.4 Results

In the results section, we will follow the same route as in section two, and describe in several subsections the relationships between e-tutorial trace variables of both product and process type, and different types of other learning related variables. We start by describing relationships between trace variables and performance variables in the first subsection and continue with the relationships between trace variables and national culture dimensions in subsection two. Subsections three and four continue with both facets of learning strategies: processing strategies and learning regulation. Followed by learning attitudes (subsection five), epistemic and activity type learning emotions (subsections six and seven), and closing with adaptive and maladaptive motivation and engagement (subsections eight and nine).

5.4.1 Performance

In order to find out what role learning in the e-tutorials had played in gaining mathematical and statistical knowledge, we investigated relationships between eight trace variables from the two e-tutorials, and six performance variables: the two quiz results (*MathQuiz* and *MathStats*), the two final exam results (*MathExam* and *StatsExam*), and the outcomes of the two diagnostic entry tests administered at day 1 (*MathEntry* and *StatsEntry*). Figure 5.1 gives insight into these bivariate relationships.

Quiz performance has by far the strongest relationship with the e-tutorial product and process data, followed by exam performance. Entry test scores are only weakly related to e-tutorial trace data. The dominant role of quiz scores is not surprising: quizzes share the same item bank as the materials students see in the practising mode.

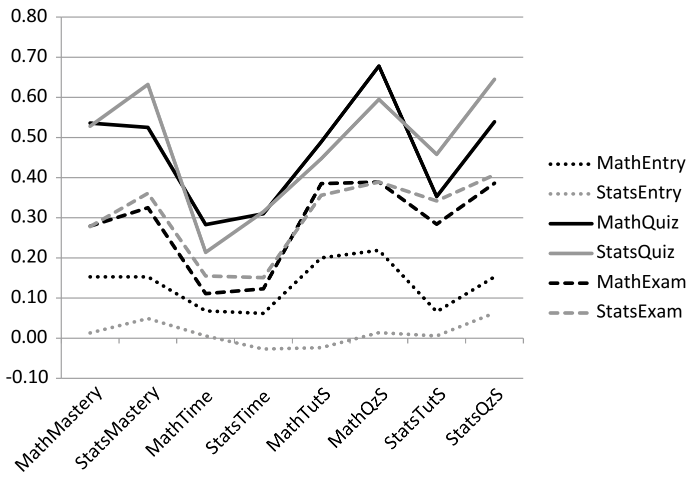


Fig. 5.1 Correlations between e-tutorial trace data, and performance indicators

With regard to the two types of e-tutorial data, tool mastery and tool time: the cognitive product variable mastery is a much stronger predictor of course performance than the process variable connect time in the tool. Regarding the timing of learning, we do not find any differences between the exam performance of students with different timing strategies. That is not true for quiz performance: the highest correlations are achieved by students who prepare just in time for the quiz sessions, not for students who prepare timely for the tutorial sessions.

5.4.2 National Cultural Values

Three of the cultural dimensions interrelate e-tutorial trace data, as visible from Fig. 5.2: *Masculine*, the *Restraint* pole of the indulgence-restraint dimensions, and the *Long-Term Orient*ation pole of the long-term versus short-term orientation dimension. Different from the performance correlations discussed above, correlations of e-tutorial time data and e-tutorial mastery data are not very far apart.

5.4.3 Cognitive Learning Processing Strategies

The processing strategies demonstrate a clear picture: deep learning, the composition of *Critical* processing and *Relating* and structuring, is uncorrelated to the use of the e-tutorials. Against the strict benchmark of 0.01 significance, the strategy of *Concrete* learning also is unrelated to learning in the digital mode; if anything, these

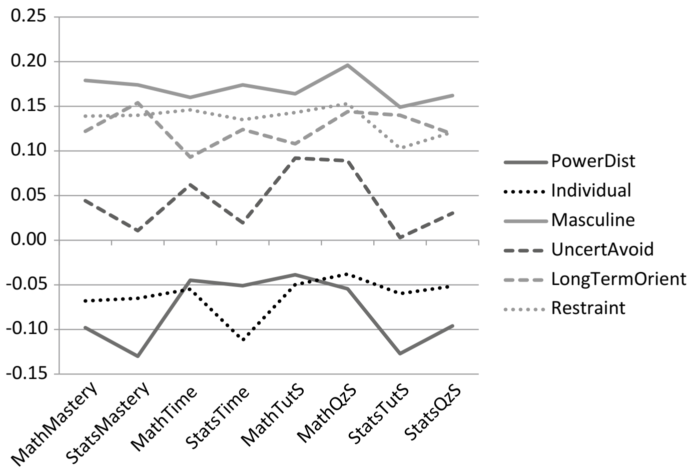


Fig. 5.2 Correlations between e-tutorial trace data, and national cultural values

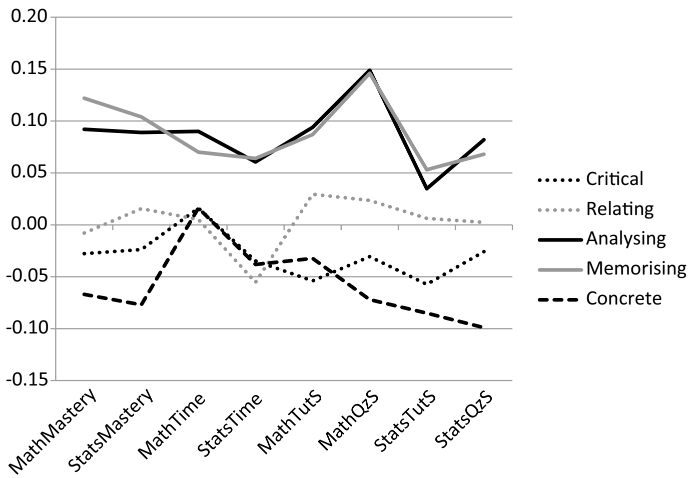


Fig. 5.3 Correlations between e-tutorial trace data, and cognitive learning processing strategies

correlations tend to be negative. Positive correlations show up for the two stepwise or surface learning strategies: *Memorising* and rehearsing, and *Analysing*. Correlations are of limited size, and beyond final math mastery and quiz math mastery, not significant beyond 0.01: see Fig. 5.3.

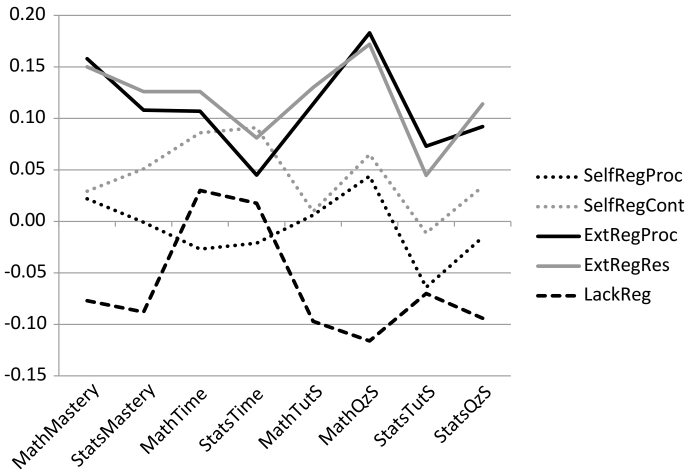


Fig. 5.4 Correlations between e-tutorial trace data, and metacognitive learning regulation strategies

5.4.4 Metacognitive Learning Regulation Strategies

The patterns in the regulation strategies are quite similar to those in the processing strategies: see Fig. 5.4. The two self-regulation scales, the self-regulation of the process (*SelfRegProc*) and the content (*SelfRegCont*), are uncorrelated to the several indicators of e-learning, as were the two deep-learning processing scales. The absence of learning regulation, represented by the *Lack* of *Reg*ulation scales, tends to be negatively related, without reaching the 0.01 benchmark of statistical significance, and except the two time-related traces variables. Positive correlations are there for the two external regulation scales, external regulation of the learning process (*ExtRegProc*) and learning results (*ExtRegRes*). The effect is again strongest for final math mastery and quiz math mastery, but more correlations go beyond the 0.01 significance benchmark.

5.4.5 Attitudes and Beliefs Towards Learning Quantitative Methods

Three of the attitudinal variables are basically unrelated to learning in the digital mode: *Value*, the absence of expected difficulty, *NoDifficulty*, and *Interest*, with two exceptions: the correlations of interest with the timely preparation of mathematics, *MathTutS* and *MathQzS:* see Fig. 5.5. Stronger correlations exist for *Effort*, *Affect*, and *CognComp*, the self-perceived level of quantitative competence. The three attitudes share that time correlations are dominated by mastery correlations, and that correlations for math dominate those for stats. They differ regarding the impact on the

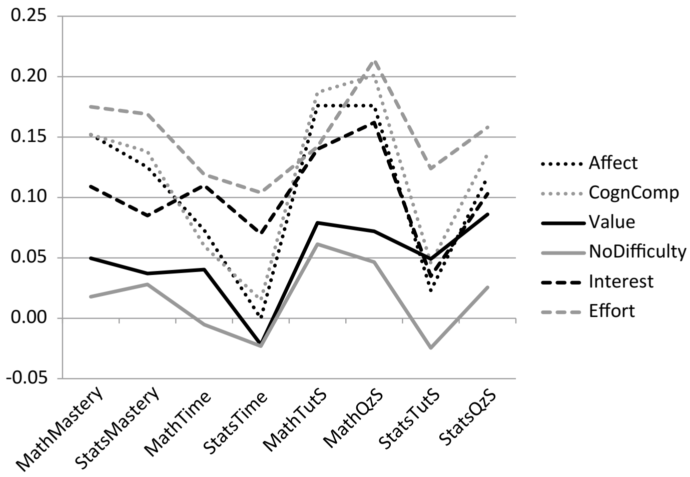


Fig. 5.5 Correlations between e-tutorial trace data, and attitudes and beliefs towards learning quantitative methods

timing of learning. Correlations between *Affect*, *CognComp* and *MathTutS*, *MathQzS* are higher than correlations with *MathMastery*. That is, students who like mathematics, and feel more competent, prepare their sessions more timely. That is not true for statistics: correlations with *StatsMastery* are higher than correlations with *StatsTutS*, *StatsQzS*, implying that positive attitudes do not help students to opt for timely learning of stats in the same way as it does for math.

5.4.6 Epistemic Learning Emotions

The valence dimension of epistemic emotions splits the correlational outcomes into two mirrored patterns. Positive emotions *Curiosity* and *Enjoyment* are positively related to all trace variables, be it that correlations are weak, and only significant beyond the 0.01 level for timely preparation of math: *MathTutS* and *MathQzS*. *Surprise*, hypothesized as a neutral emotion, acts as a positive emotion, be it nowhere passing the 0.01 level of significance: see Fig. 5.6.

Negative emotions *Frustration*, *Anxiety*, and *Confusion*, all demonstrate negative correlations (except for *StatsTime*), of modest size, except again the two correlations indicating timely preparation of math: *MathTutS* and *MathQzS*. Strongest correlations overall are for the negative emotion *Boredom*, indicating that this learning emotion forms an obstacle for both the amount of digital learning and the proper timing of digital learning.

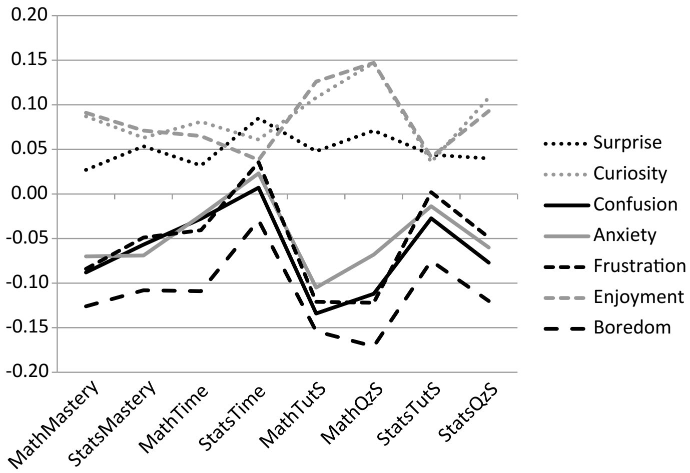


Fig. 5.6 Correlations between e-tutorial trace data, and epistemic learning emotions

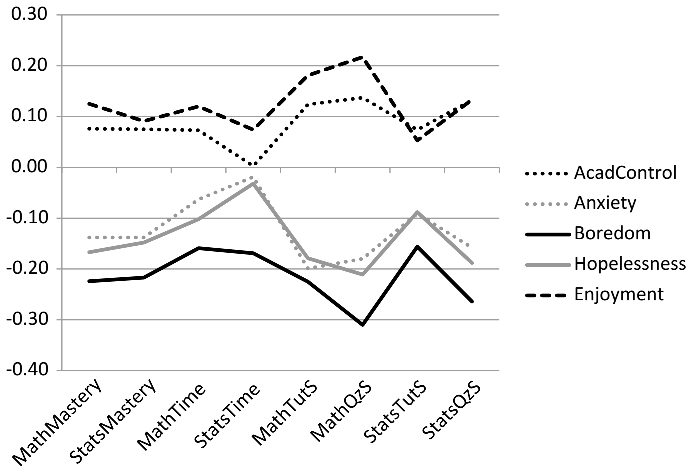


Fig. 5.7 Correlations between e-tutorial trace data, and activity learning emotions

5.4.7 Activity Learning Emotions

Patterns in epistemic emotions repeat in activity emotions, and academic control (*AcadControl*), the self-efficacy variable acting as a direct antecedent of the activity emotions: see Fig. 5.7.

It is again timely preparation for mathematics, represented by *MathTutS* and *MathQzS*, where the largest correlations are found. *Anxiety*, hypothesised as an activating negative emotion, follows the same pattern as the other negative emotions: no acti-

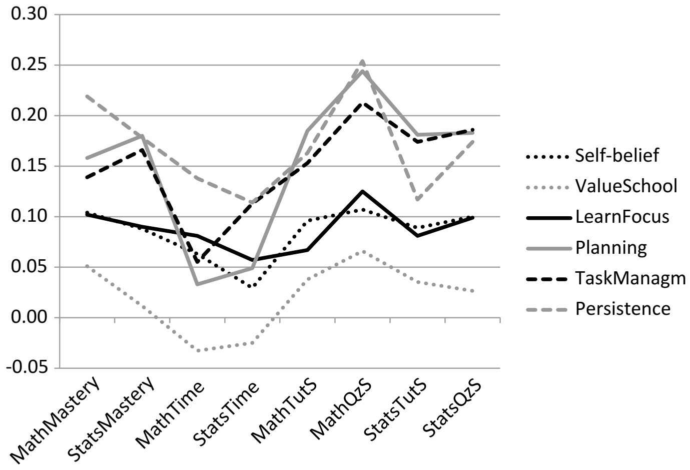


Fig. 5.8 Correlations between e-tutorial trace data, and adaptive motivation and engagement scales

vation is visible, neither with regard to time and mastery. Regarding the size of the effect, it is again *Boredom* dominating the other emotions.

5.4.8 Adaptive Motivation and Engagement

Cognitive and behavioural motivation and engagement constructs demonstrate different correlational patterns. The cognitive scales *Self-belief*, *Value School*, and *LearnFocus* are no more than weakly related to the trace variables. The behavioural constructs *Planning*, *TaskManagm*, and *Persistence* are much stronger positively related to learning in the digital platform: see Fig. 5.8.

It is again timely learning for math, but this time also timely learning for stats, that profits from planning and task-management skills of the students. Remarkably, students having those skills can achieve these high mastery levels in a very efficient way: they hardly need more time on average to reach much higher mastery levels than on average. Apparently, self-perceptions on planning and task-management do provide a reliable impression of actual skills.

5.4.9 Maladaptive Motivation and Engagement

The same breakdown of cognitive and behavioural correlations is visible in Fig. 5.9, providing patterns for maladaptive motivation and engagement constructs. The impacts of the maladaptive cognitive constructs, *Anxiety*, *FailAvoid*, and *UncertainCtrl*, tend to be negative, but small in size. The sign of the Anxiety correlations

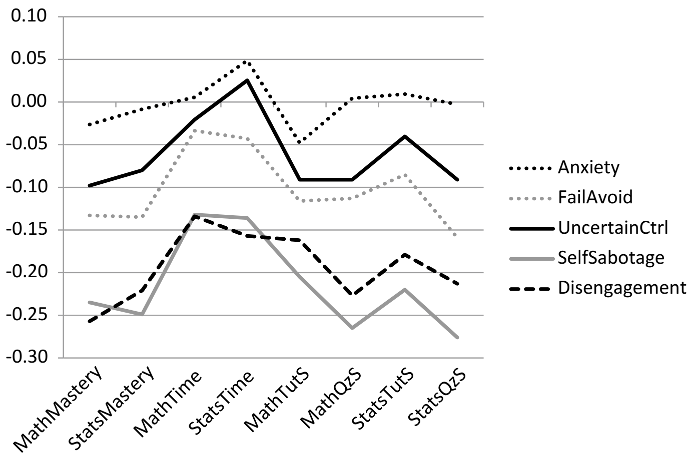


Fig. 5.9 Correlations between e-tutorial trace data, and maladaptive motivation and engagement scales

is even undetermined, tending to be positive for the two time variables, negative for the mastery variables. The behavioural constructs have a much stronger, consistently negative, impact: *SelfSabotage* and *Disengagement* predict both final mastery as well as timely preparation. Their impact on learning time is much smaller, implying that these are the students making inefficient use of their learning time, mirroring the positions of students high in planning and task-management.

5.5 Discussion and Conclusion

By and large, the outcomes of the empirical analyses reproduced the findings from previous studies. LA needs rich data: measuring student activity in a learning management system may not be the best data set to build a prediction model. In all our studies, we find formative assessment data being the key facet of rich data. This immediately gives rise to the dilemma of timely data versus informative data. It takes time to collect formative assessment data, maybe too much for being in time to intervene aiming the prevention of dropout or improve study success. So we might have to opt for somewhat less informative, but timelier data. In our context, assessment as learning data, trace data from e-tutorial systems representing mastery of students in the practice modes, in combination with learning disposition data collected through surveys, suggest being alternative data sources for LA applications: a good "second best" with regard to predictive power, early available in the course as to allow ample time for intervention.

In answering the question of what type of intervention is most helpful in assisting students, we find another advantage of including dispositions into an LA application.

If a traditional LA application using click and connect time type of trace data derived from LMS use comes to a prediction of drop-out, it is not that obvious what type of intervention is adequate. If the prediction results from low levels of student activity, a simple call to become more active is likely to have little effect, if boredom is the underlying cause of low activity. Or in case the student lacks planning and/or task management skills, offering a training to improve those skills may be a more productive intervention than again this simple call to become more active in the LMS.

The availability of such a broad range of disposition measurements as available in our study will be the exception rather than the rule. From that perspective, this study serves more as a showcase of what can be done with rich disposition data, where the way of getting such rich data may not be easily generalizable. An important facet of the richness of the data is having a full response of all students, where typically response rates of self-report surveys tend to be low and, typically, the missed cases represent students low in motivation and high in drop-out risk, exactly those students it is crucial to have data on. A less crucial facet of the richness of data is the multitude of different disposition surveys. Disposition data tends to be collinear, that is, students with less favourable attitudes will tend to follow less adaptive learning strategies, or depend strongly on external types of motivation. The availability of specific interventions will govern in such a situation the choice of what type of survey instruments to apply: the ultimate goal is to prevent drop-out, rather than predict drop-out.

References

1. Azevedo, R., Harley, J., Trevors, G., Duffy, M., Feyzi-Behnagh, R., Bouchet, F., et al.: Using trace data to examine the complex roles of cognitive, metacognitive, and emotional self-regulatory processes during learning with multi-agents systems. In: Azevedo, R., Aleven, V. (eds.) International Handbook of Metacognition and Learning Technologies, pp. 427–449. Springer, Amsterdam (2013)
2. Buckingham Shum, S., Deakin Crick, R.: Learning dispositions and transferable competencies: pedagogy, modelling and learning analytics. In: Buckingham Shum, S., Gasevic, D., Ferguson, R. (eds.) Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, pp. 92–101. ACM, New York, NY, USA (2012). https://doi.org/10.1145/2330601.2330629
3. Chrysafiadi, K., Virvou, M.: Student modeling approaches: a literature review for the last decade. Expert Syst. Appl. **40**, 4715–4729 (2013). https://doi.org/10.1016/j.eswa.2013.02.007
4. Crick, R.: Learning analytics: layers, loops and processes in a virtual learning infrastructure. In: Lang, C., Siemens, G., Wise, A., Gašević, D. (eds.) Handbook of Learning Analytics, Chap. 25, pp. 291–308. Society for Learning Analytics Research, Solar (2017) https://doi.org/10.18608/hla17
5. Elliot, A., Murayama, K., Kobeisy, A., Lichtenfeld, S.: Potential-based achievement goals. Brit. J. Educ. Psychol. **85**, 192–206 (2015). https://doi.org/10.1111/bjep.12051
6. Gašević, D., Jovanović, J., Pardo, A., Dawson, S.: Detecting learning strategies with analytics: links with self-reported measures and academic performance. J. Learn. Anal. **4**(1), 113–128 (2017). https://doi.org/10.18608/jla.2017.42.10
7. Hofstede, G., Hofstede, G.J., Minkov, M.: Cultures and Organizations: Software of the Mind. Revised and Expanded, 3rd edn. McGraw-Hill, Maidenhead (2010)

8. Martin, A.J.: Examining a multidimensional model of student motivation and engagement using a construct validation approach. Br. J. Educ. Psychol. **77**(2), 413–440 (2007). https://doi.org/10.1348/000709906X118036
9. Matzavela, V., Chrysafiadi, K., Alepis, E.: Questionnaires and artificial neural networks: a literature review on modern techniques in education. In: Proceedings 2017 IEEE Global Engineering Education Conference (EDUCON), 25–28 April 2017, Athens, Greece (2017). https://doi.org/10.1109/educon.2017.7943077
10. Mittelmeier, J., Rienties, B., Tempelaar, D.T., Hillaire, G., Whitelock, D.: The influence of internationalised versus local content on online intercultural collaboration in groups: a randomised control trial study in a statistics course. Comput. Educ. **118**(1), 82–95 (2018). https://doi.org/10.1016/j.compedu.2017.11.003
11. Nguyen, Q., Tempelaar, D.T., Rienties, B., Giesbers, B.: What learning analytics based prediction models tell us about feedback preferences of students. In: Amirault, R., Visser, Y. (eds.) e-Learners and their data, part 1: conceptual, research, and exploratory perspectives. Q. Rev. Distance Educ. **17**(3) (2016)
12. Non, A., Tempelaar, D.: Time preferences, study effort, and academic performance. Econ. Educ. Rev. **54**, 36–61 (2016). https://doi.org/10.1016/j.econedurev.2016.06.003
13. Ochea, X.: Multimodal learning analytics. In: Lang, C., Siemens, G., Wise, A., Gašević, D. (eds.) Handbook of Learning Analytics, Chap. 11, pp. 129–141. Solar: Society for Learning Analytics (2017). https://doi.org/10.18608/hla17
14. Pekrun, R., Linnenbrink-Garcia, L.: Academic emotions and student engagement. In: Christenson, S.L., Reschly, A.L., Wylie, C. (eds.) Handbook of Research on Student Engagement, pp. 259–282. Springer US (2012). https://doi.org/10.1007/978-1-4614-2018-7_12
15. Rienties, B., Alden Rivers, B.: Measuring and understanding learner emotions: evidence and prospects. In: LACE Review Papers, vol. 1. LACE, Milton Keynes (2014)
16. Rienties, B., Cross, S., Zdrahal, Z.: Implementing a learning analytics intervention and evaluation framework: what works? In: Kei Daniel, B. (ed.) Big Data and Learning Analytics: Current Theory and Practice in Higher Education, pp. 147–166. Springer International Publishing, Cham (2017). https://doi.org/10.1007/978-3-319-06520-5_10
17. Rogaten, J., Rienties, B., Sharpe, R., Cross, S., Whitelock, D., Lygo-Baker, S., Littlejohn, A.: Reviewing affective, behavioural, and cognitive learning gains in higher education. In: Assessment & Evaluation in Higher Education (2018). https://doi.org/10.1080/02602938.2018.1504277
18. Tempelaar, D.T.: Learning analytics and formative assessments in blended learning of mathematics and statistics. Innov. Infotechnologies Sci. Bus. Educ. **2**(17), 9–13 (2014)
19. Tempelaar, D.T., Cuypers, H., Van de Vrie, E., Heck, A., Van der Kooij, H.: Formative assessment and learning analytics. In: Suthers, D., Verbert, K. (eds.) Proceedings of the 3rd International Conference on Learning Analytics and Knowledge, pp. 205–209. ACM, New York (2013). https://doi.org/10.1145/2460296.2460337
20. Tempelaar, D.T., Gijselaers, W.H., Schim van der Loeff, S., Nijhuis, J.F.H.: A structural equation model analyzing the relationship of student achievement motivations and personality factors in a range of academic subject-matter areas. Contemp. Educ. Psychol. **32**(1), 105–131 (2007). https://doi.org/10.1016/j.cedpsych.2006.10.004
21. Tempelaar, D.T., Niculescu, A., Rienties, B., Giesbers, B., Gijselaers, W.H.: How achievement emotions impact students' decisions for online learning, and what precedes those emotions. Internet High. Educ. **15**(2012), 161–169 (2012). https://doi.org/10.1016/j.iheduc.2011.10.003
22. Tempelaar, D.T., Rienties, B., Giesbers, B.: Who profits most from blended learning? Ind. High. Educ. **23**(4), 285–292 (2009). https://doi.org/10.5367/000000009789346130
23. Tempelaar, D.T., Rienties, B., Giesbers, B.: Computer assisted, formative assessment and dispositional learning analytics in learning mathematics and statistics. In: Kalz, M., Ras, E. (eds.) Computer Assisted Assessment. Research into E-Assessment, vol. 439, pp. 67–78. Springer International Publishing (2014)
24. Tempelaar, D.T., Rienties, B., Giesbers, B.: Computer assisted, formative assessment and dispositional learning analytics in learning mathematics and statistics. In: Kalz, M., Ras, E. (eds.)

Computer Assisted Assessment. Research into E-Assessment, pp. 67–78. Communications in Computer and Information Science, vol. 439. Springer, Berlin (2014). https://doi.org/10.1007/978-3-319-08657-6_7
25. Tempelaar, D.T., Rienties, B., Giesbers, B.: In search for the most informative data for feedback generation: learning analytics in a data-rich context. Comput. Hum. Behav. **47**, 157–167 (2015) (Special Issue Learning Analytics). https://doi.org/10.1016/j.chb.2014.05.038
26. Tempelaar, D.T., Rienties, B., Giesbers, B.: Understanding the role of time on task in formative assessment: the case of mathematics learning. In: Ras, E., Joosten-ten Brinke, D. (eds.) Computer Assisted Assessment—Research into E-Assessment. Communications in Computer and Information Science, vol. 571, pp. 120–133. Springer, Zug, Switzerland (2015). https://doi.org/10.1007/978-3-319-27704-2_12
27. Tempelaar, D.T., Rienties, B., Giesbers, B.: Verifying the stability and sensitivity of learning analytics based prediction models: an extended case study. In: Zvacek, S., Restivo, M.T., Uhomoibhi, J., Helfert, M. (eds.) Computer Supported Education, pp. 256–273. Communications in Computer and Information Science, vol. 583. Springer, Switzerland (2016). https://doi.org/10.1007/978-3-319-29585-5_15
28. Tempelaar, D.T., Rienties, B., Giesbers, B., Schim van der Loeff, S.: How cultural and learning style differences impact students' learning preferences in blended learning. In: Jean Francois, E. (ed.) Transcultural Blended Learning and Teaching in Postsecondary Education, pp. 30–51. IGI Global, Hershey, PA (2013). https://doi.org/10.4018/978-1-4666-2014-8.ch003
29. Tempelaar, D.T., Rienties, B., Giesbers, B., Schim van der Loeff, S.: Cultural differences in learning approaches. In: Van den Bossche, P., Gijselaers, W.H., Milter, R.G. (eds.) Facilitating Learning in the 21st Century: Leading through Technology, Diversity and Authenticity, pp. 1–28. Springer, Dordrecht (2013). https://doi.org/10.1007/978-94-007-6137-7_1
30. Tempelaar, D.T., Rienties, B., Mittelmeier, J., Nguyen, Q.: Student profiling in a dispositional learning analytics application using formative assessment. Comput. Hum. Behav. **78**, 408–420 (2018). https://doi.org/10.1016/j.chb.2017.08.010
31. Tempelaar, D.T., Rienties, B., Nguyen, Q.: Towards actionable learning analytics using dispositions. IEEE Trans. Educ. **10**(1), 6–16 (2017). https://doi.org/10.1109/TLT.2017.2662679
32. Tempelaar, D.T., Rienties, B., Nguyen, Q.: Adding dispositions to create pedagogy-based learning analytics. Zeitschrift für Hochschulentwicklung, ZFHE **12**(1), 15–35 (2017)
33. Tempelaar, D., Rienties, B., Nguyen, Q.: Investigating learning strategies in a dispositional learning analytics context: the case of worked examples. In: Proceedings of the International Conference on Learning Analytics and Knowledge, Sydney, Australia, March 2018 (LAK'18), pp. 201–205 (2018). https://doi.org/10.1145/3170358.3170385
34. Tempelaar, D., Rienties, B., Nguyen, Q.: A multi-modal study into students' timing and learning regulation: time is ticking. In: Interactive Technology and Smart Education (2018) (in press)
35. Tempelaar, D.T., Verhoeven, P.: Adaptive and maladaptive emotions, behaviours and cognitions in the transition to university: the experience of international full degree students. In: Jindal-Snape, D., Rienties, B. (eds.) Multi-Dimensional Transitions of International Students to Higher Education, Chapter 12, pp. 334–358. Routledge, New York (2016)
36. Vermunt, J.D.: Metacognitive, cognitive and affective aspects of learning styles and strategies: a phenomenographic analysis. High. Educ. **31**(25–50) (1996). https://doi.org/10.1007/bf00129106
37. Williams, A., Sun, Z., Xie, K., Garcia, E., Ashby, I., Exter, M., Largent, D., Lu, P., Szafron, D., Ahmed, S., Onuczko, T., Smith, J., Tempelaar, D.T., Bitting, K.S., Olcott Marshall, A., Christensen, E., Tseng, H., Walsh, J.: Flipping STEM. In: Santos Green, L., Banas, J., Perkins, R. (eds.) The Flipped College Classroom, Conceptualized and Re-Conceptualized, Part II, pp. 149–186. Springer International Publishing, Switzerland (2017). https://doi.org/10.1007/978-3-319-41855-1_8

Dr. Dirk T. Tempelaar is an associate professor at the Department of Quantitative Economics at the Maastricht University School of Business and Economics. His research interests focus on modelling student learning, and students' achievements in learning, from an individual difference perspective. That includes Dispositional learning analytics: 'big data' approaches to learning processes, with the aim to find predictive models for generating learning feedback, based on computer-generated trace data, and learning dispositions.

Quan Nguyen is a Leverhulme funded Ph.D. candidate in Learning Analytics at the Institute of Educational Technology, The Open University, UK. He graduated with a Master (cum laude) of Economics and Information Management at Maastricht University. Quan had considerable experience in teaching Quantitative Methods and Management of Information System, and working as a data analyst in several projects. In his Ph.D. (2016–2019) under the supervision of Prof. Bart Rienties, Prof. Denise Whitelock, and Prof. Zdenek Zdrahal, he is focusing on the use of Learning Analytics to understand and improve how teachers design their course in Virtual Learning Environment.

Dr. Bart Rienties is Professor of Learning Analytics at the Institute of Educational Technology at the Open University UK. He is programme director Learning Analytics within IET and head of Data Wranglers, whereby he leads a group of learning analytics academics who conduct evidence-based research and sense-making of Big Data at the OU. As an educational psychologist, he conducts multi-disciplinary research on work-based and collaborative learning environments and focuses on the role of social interaction in learning, which is published in leading academic journals and books. His primary research interests are focussed on Learning Analytics, Computer-Supported Collaborative Learning, and the role of motivation in learning.

Chapter 6
The Variability of the Reasons for Student Dropout in Distance Learning and the Prediction of Dropout-Prone Students

Christos Pierrakeas, Giannis Koutsonikos, Anastasia-Dimitra Lipitakis, Sotiris Kotsiantis, Michalis Xenos and George A. Gravvanis

Abstract The adult education that is provided by Universities that use distance learning methods is without doubt inseparable from high dropout rates, frequently higher than those in conventional Universities. Dropping out in a University that provides distance education is caused by professional, academic, health and family and personal reasons. Limiting dropout is crucial and therefore, the aptitude to predict students' dropping out could be very useful. We try to identify the most appropriate comprehensive learning algorithm using the most informative attributes for the prediction of students' dropout. Additionally, we have explored the reasons of dropping out in order to examine on a large scale whether they are affected over time and study these changes. The data used was provided by the Student Registry of the Hellenic Open University and additional data was collected by an interview-based survey. It was found that the most informative attributes are the student gender, the participation at the first face to face meeting and the marks on the first two written assignments.

C. Pierrakeas · G. Koutsonikos
Department of Business Administration, Technological Educational Institute of Western Greece, 1 M. Alexandrou str. Koukouli, 263 34 Patras, Greece
e-mail: pierrakeas@eap.gr

G. Koutsonikos
e-mail: gkoutson@gmail.com

A.-D. Lipitakis
Department of Informatics and Telematics, Harokopio University of Athens, Kallithea, Greece
e-mail: adlipita@hua.gr

S. Kotsiantis (✉)
Department of Mathematics, University of Patras, 265 04 Rio, Greece
e-mail: sotos@math.upatras.gr

M. Xenos
Department of Computer Engineering & Informatics, University of Patras, 265 04 Rio, Greece
e-mail: xenos@ceid.upatras.gr

G. A. Gravvanis
Department of Electrical and Computer Engineering, Democritus University of Thrace, University Campus, Kimmeria, 67 100 Xanthi, Greece
e-mail: ggravvan@ee.duth.gr

M. Virvou et al. (eds.), *Machine Learning Paradigms*, Intelligent Systems Reference Library 158, https://doi.org/10.1007/978-3-030-13743-4_6

A web-based application, which is based on these attributes and can automatically recognize students with high probability of dropping out, was constructed in order to help tutors detect students at risk even at the beginning of the academic year.

Keywords Adult learning · Distance education and telelearning · Lifelong learning · Machine learning

6.1 Introduction

Dropout is a key indicator of the quality of an educational system that highlights the subsistence of severe failures in the processes of direction, transition, adaptation and student promotion. For this reason, in the frame of the European Space of Higher Education, a lot of universities take into account in their strategic plans as main objectives to reduce the rate of students' dropout.

It is a fact that student dropping out occurs fairly regularly in institutions that provide education using distance learning methods. Dropout rates in universities providing distance learning education are without doubt higher than those in conventional universities. Dropout is caused by professional, academic, health, family and personal reasons and varies depending on the education system implemented by the institution that provide distance learning, as well as on the selected theme of studies [1].

Poor academic performance is frequently an indicator of difficulties in adjusting to studies and makes dropping out more probable [2]. For students, dropping out before earning a degree represents untapped human potential and a low return on their investment in studies [3].

Students with weak educational strategies and without perseverance to attain their aims in life have low academic performance and low success rates and this implies a high risk of abandoning their studies [4]. Tutors in a distance-learning course, regardless of the distance between them and their students, must continuously support them. A tool that could automatically recognize students with high probability of dropping out (dropout-prone students) is very important so as tutors can take precautions and thereby reduce student dropping out. Doherty [5] reports that the United States Commission on the Future of Higher Education verified that college and university retention rates were analyzed as part of a review on federal funding.

The authors of [6] found that the main reason of dropping out in the Hellenic Open University is a combination of adult learners' obligations, specifically balancing their academic workload with their employment commitments and family obligations (primarily for female students). The second reason for dropping out is students' miscalculation of the available time for studying and their underestimation of the effort required for effective learning while an equally important reason that led students to discontinue their studies was the wrong selection of the enrolling course.

The aim of this study was twofold:

- To study the dropout reasons in Hellenic Open University by an interview-based survey.
- To identify the most informative attributes for the early dropout prediction in order to be used by a suitable learning algorithm. A support tool could then be constructed to be used by tutors for the early prediction of dropout students.

For this aim, data along with a number of learning algorithms [7] was used into the data set provided by the 'Computer Science' course of the Hellenic Open University. Indeed, it was proved that learning algorithms could enable tutors, even from the beginning of an academic year locate with satisfying accuracy the dropout-prone students. Of course, this accuracy is increased as new academic performance data come during the academic year.

The research papers that use statistical, machine learning and data mining techniques for predicting dropping out are reviewed in Sect. 6.2. Section 6.3 describes in brief the Hellenic Open University (HOU) distance learning methodology and the data set of this study. Section 6.4 presents the reasons, as they are being expressed by the dropout students, for discontinuing their studies. Section 6.5 presents the machine learning techniques that were tested and the results of our experiments. Finally, Sect. 6.6 present and discuss the reasons, as they are being expressed by the dropout students, for discontinuing their studies while also discuss the rest of our results along with the limitations of our study. Finally, in Sect. 6.7 the conclusions of this study are referred and some future research directions.

6.2 Literature Review

Dupin-Bryant [8] determined pre-entry variables to be used in the prediction of learner completion and non-completion in university-level online distance education courses. This study agrees with the study of [9] which reports that prior academic performance in terms of past educational experience and earlier computer training are the most helpful criteria in differentiating completers and dropouts.

Predictive discriminant analysis was used by [10] to develop a classification rule to predict undergraduate students' withdrawal from online courses based on data from 11 student cases. The study reports that a correct classification ratio of 74.5% was achieved using the variables of financial aid and locus of control. Internal locus of control is evidenced to be a predictor of academic persistence in distance education in many other studies [10, 11]. The satisfaction with the course and the academic locus of control that e-learning students demonstrate is examined by [12]. That study uses time invariant student data to observe whether the two aforementioned attributes affect the decision of students to drop out.

Herzog [13] examined the predictive accuracy of back-propagation neural networks, rule-induction and multinomial logistic regression, over the problem of predicting college freshmen retention. The author used three sources to produce the data set: the institutional student information system for student demographic; the American College Test (ACT)'s Student Profile Section for parent income data; and the National Student Clearinghouse for identifying transfer-out students. The results specify that all the examined methods achieve similar classification accuracy of approximately 75% in the middle and 84% at the end of the year.

The authors of [14] used University of Central Florida's student demographic and High School data from Academic Year 2001–2002 to study the retention problem with the help of data mining. The authors of [15] applied neural networks, discriminant analysis, decisions trees and random forests on survey data at the University of Belgium to classify new students in low-risk, medium-risk, and high-risk categories. The authors found that the scholastic history and socio-family background were the most significant predictors of students at risk. A study that uses logistic regression but focuses on a different variable, not related to demographic characteristics or prior academic performance, is the study of [16]. In that study, the effectiveness of the attribute of leisure boredom was investigated as a predictor of high school dropout.

The authors of [17] used the Answer Tree package from SPSS for predicting who would drop out of nursing courses. Two sorts of data were used. There were data known on entry: age, gender, entry qualifications, branch of nursing. There were other time-varying items, largely to do with the student's performance, gross and net attendance records.

Lin [18] uses alternative decision tree (ADT) learning algorithm to generate predictive models for student retention management on campus. The raw data set is a collection of 5943 records including information about the gender, age, financial need, loan received, class rank etc. The authors of [19] presented a dropout prediction method for e-learning courses, based on three machine learning techniques: neural networks, support vector machines and probabilistic ensemble simplified fuzzy ARTMAP. From demographic attributes, this study incorporates gender, residency (in the place of ethnicity) that receives values capital or province, and working experience in the field of the course. As far as prior academic performance is concerned, this study used the educational level of the students in the value range of basic to Ph.D. degree, as well as their level of fluency in the English language. The rest attributes were time-varying characteristics depicting the students' progress during the courses, as well as their level of engagement with the e-learning procedure.

Moreover, the authors of [20] used five years of institutional data along with several data mining techniques (both individuals as well as ensembles), in order to build models to predict and to explain the reasons behind student drop-out. The data contained variables related to student's academic, financial, and demographic characteristics. To predict students' dropout from online courses, various factors related to learning environment, learner characteristics, and institutional support were studied by [21]. For the aim of predicting if students still remain for the first three years of an undergraduate degree, the authors of [22] found as informative factors: family background and family's social-economic status, high school GPA and test scores.

The purpose of [23] study was to investigate premature dropping out of university study at Prince of Songkla University, Pattani Campus in Southern Thailand. The factor were about being enrolled in a non-preferred field of study, lifestyle, security, problems with time management as well as problems caused by a break or change in an intimate relationship.

The authors of [24] used five years of institutional U.S. data along with several data mining techniques, they developed analytical models to predict and to explain the reasons behind freshmen student attrition. The sensitivity analysis of the tested models revealed that the educational as well as financial variables are the most important predictors of the student attrition. The authors of [25] analyzed various sources of "e-students" feedback from the logging and feedback collecting point of view. They used a classifier based on the log data collected from their web-based education system ALEF during three-year period for the prediction of "stay or leave?" question.

The authors of [26] used data gathered from 419 high schools students in Mexico. They carried out experiments to predict dropout at different steps of the course, to select the best indicators of dropout. Results showed that their classifier could predict student dropout within the first 4–6 weeks of the course. Moreover, a recent survey of the general usage of data mining methods in educational data can be found in [27].

6.3 HOU Distance Learning Methodology and Data Description

Students are not required to take entry exams in order to register in the Hellenic Open University (HOU). Prospective students have to complete an application form. Subsequently, in case demand is greater than the actual available spaces, an open to the public draw takes place. In addition, courses are not free and thus, students should pay part of their student fees and tuition in advance. Therefore, it can be assumed that students enrolled in HOU have programmed their studies choosing their subject of preference. In the framework of this research work, the data used was provided by the 'Computer Science' course of the Hellenic Open University. Hellenic Open University offers university level education using the distance learning methodology. The basic educational unit of the 'Computer Science' course as well as for any other graduate or postgraduate course of the HOU is the module, which is equivalent to 3 or 4 semestral academic lessons. The 'Computer Science' course (PLI) is composed of 12 modules and leads to a Bachelor Degree.

Students of the PLI10 module during an academic year have to hand in 4 written assignments, participate in 5 optional face-to-face consulting meetings with their tutors and sit for a final examination. A student has to submit at least three of the four assignments. Tutors should evaluate these assignments according to the 10-grade marking system of the Hellenic Universities. A total mark greater than or equal to 20 should be obtained so as a student to be able to sit for the final examination test.

A total of 3882 students' records have been collected for the module 'Introduction to Informatics' (PLI10). Students were divided in 4 categories:

- Students who registered but never started their studies and did not re-register in the following year (Group D1) and thus are considered as dropout students.
- Students who started their studies and successfully completed some assignments or even some modules but decided to drop out for various reasons (Group D).
- Students who did not successfully complete some or all of the modules but decided to continue their studies and repeat these modules in the following year (Group C).
- Students who successfully completed all the selected modules during their first year of their studies (Group S).

An interview-based survey was conducted among students of groups D1 and D, in order to investigate the reasons due to which students dropped out the Course of Computer Science. This interview was based on a structured questionnaire and there were interviewed more than 287 randomly selected students. The questionnaire contained closed questions to assist in determining the degree of the respondents' agreement. Moreover, questions based on a five point Likert scale were used and the five scales were scored from 1 (Totally Disagree) to 5 (Totally Agree) measuring the respondents' opinion. The structure of the questionnaire was quite simple so as not to cause any problem to the respondents. It consists of five parts. The first part contains general and introductory questions concerning the field of distance education. The second part was designed to measure the students responses regarding the reasons that led them to study at a distance and the third part dealt with their satisfaction level regarding course services. The fourth part referred to the quality of studies and finally the fifth part contains questions about demographic profiles of the respondents.

Students were contacted by telephone and were also asked to express their opinion on the reasons of dropping out of their studies. The average duration of an interview was 15 min during which the reasons for dropping out their studies emerged. Subsequently, a content analysis was performed for all open-ended questions in order to categorize students' responses. Data collected, was analyzed and interpreted where needed, using chi-square (χ^2) test and Spearman's rank-order correlation coefficient (Rho-ρ) in order to measure the strength of the correlation between two ranked variables.

Additionally, for all collected records, it is real important for tutors to recognize dropout-prone students before the middle of the academic year in order to be able to offer additional support to these students at risk. Thus, the number of attributes collected before the middle of the academic year was used in this study for predicting the dropout-prone students. The set of the attributes used, was divided in 2 groups: the 'Curriculum-based' group and the 'Students' performance' group.

The 'Curriculum-based' group represents attributes, concerning students' sex, age, marital status, number of children and occupation. The previous—post high school—education in the field of computer science and the association between students' job and computers were also taken into account. In detail, a student who has attended at least a seminar (of 100 h or more) on Computer Science would be characterized as having computer literacy. Furthermore, a student who uses software packages (such as word processor) at his job without having any deep knowledge

Table 6.1 ‘Curriculum-based’ group of attributes and their values

‘Curriculum-based’ group	
Sex	Male, female
Age	24–46
Marital status	Single, married, divorced, widowed
Number of children	None, one, two, three, four of more
Occupation	No, part-time, fulltime, over-time
Computer literacy	No, yes
Job associated with computers	No, junior-user, senior-user
New student	No, yes

Table 6.2 ‘Students’ performance’ group attributes and their values

‘Students’ performance’ group	
1st face to face meeting	Absent, present
1st written assignment	0–10
2nd face to face meeting	Absent, present
2nd written assignment	0–10

in computer science was considered as ‘junior-user’, while a student who works as a programmer was considered as ‘senior user’. In the remaining cases student’s job was listed as ‘no’ concerning association with computers (Table 6.1).

The ‘Students’ performance’ group represents attributes concerning students’ marks on the first two written assignments and their presence or absence in the first two face-to-face meetings (Table 6.2).

6.4 Interview Based Survey Results

As shown in Fig. 6.1, male students tend to drop-out (47.8%) statistically significant less ($\chi^2 = 6.75$; $p < 0.01$) than female students (52.5%), result that agrees with the previously reported at [9]. On the contrary, during recent years, it is noticed that male and female are equally persistent (17.4 and 17.6% respectively) during their studies and female do not tend to dropout at the beginning of the academic year as reported on [9] where female students appear to drop out with double frequency than males. Students from the larger cities of Greece (Athens and Thessaloniki) tend to drop-out (47.5%) less than students that attend groups in smaller cities around Greece (51.6%) but the differences are not statistically significant.

As shown in Fig. 6.2, married students tend to drop-out (31.0%) less than single students (45.8%). This statistical significant difference ($\chi^2 = 6.56$; $p < 0.05$) shows

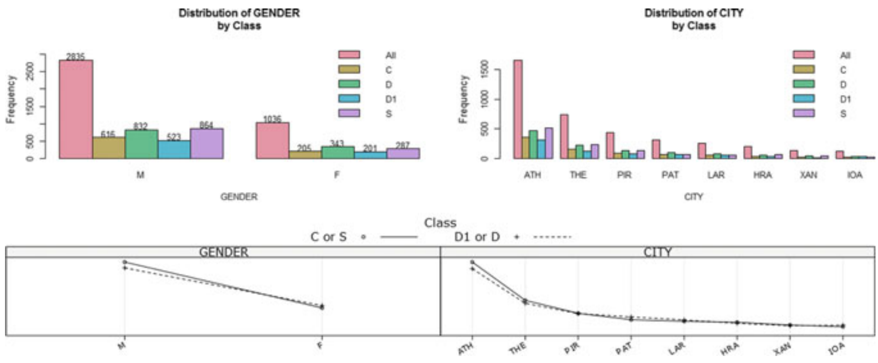


Fig. 6.1 Plots for attributes "gender" and "city" based on the whole data

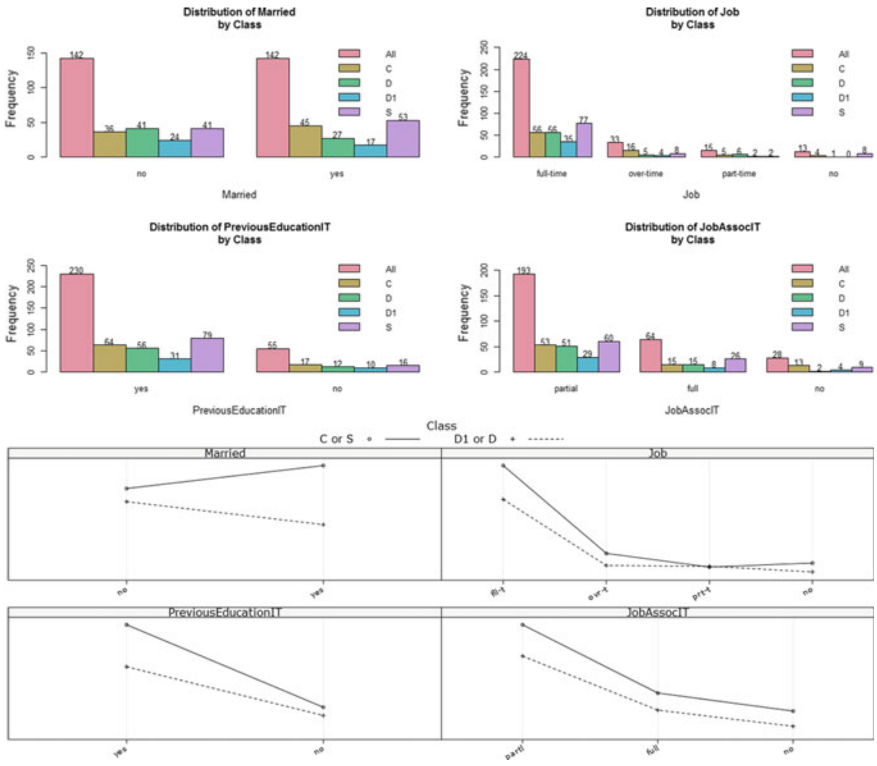


Fig. 6.2 Plots for the data from the interview-based survey

that the dropout rates are differentiated than those mentioned on [9], where dropout rates were independent of the students' marital status.

Students that do not work tend to drop-out (7.7%) statistically significant less ($\chi^2 = 14.32$; $p < 0.001$) than the working (either part-time, either full-time, or over-time)

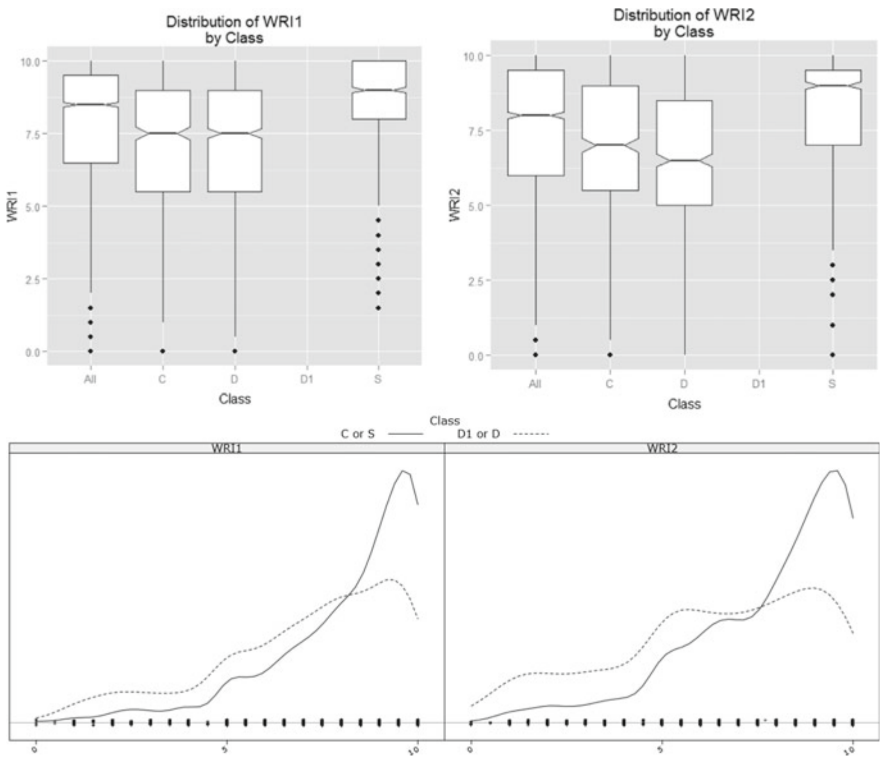


Fig. 6.3 Plots for the first two written assignments based on the whole data

ones (39.7%). Students that do not have a previous education in IT tend to drop-out (40.0%) more than the remaining students (37.8%), a result that is in agreement with the results reported by [9] (Fig. 6.2). Students that have a job associated with IT (either partial or full) tend to drop-out (38.9%) more than those whose job has no association with IT (35.9%) but this differentiation is not statistically significant. Additionally, if students believe they cannot succeed, or encounter difficulties, especially with the written assignments, they discontinue and do not choose to re-register in the following years as shown in Fig. 6.3, where the plots for the first two written assignments (WRI1 and WRI2) based on the whole data appear.

According to those findings, the average marks for students that will decide to drop out (Class D) and for those that will continue their studies (Class C) are almost equal (not statistical different) for the first written assignment (7.1 and 7.2 respectively). Unlike this, the average marks for students that will decide to drop out (Class D) are statistically significant lower ($p < 0.001$) than for those that will successfully complete the selected modules (Class S) (7.1 and 8.7 respectively) and thus these classes can be distinguished even from the first written assignment.

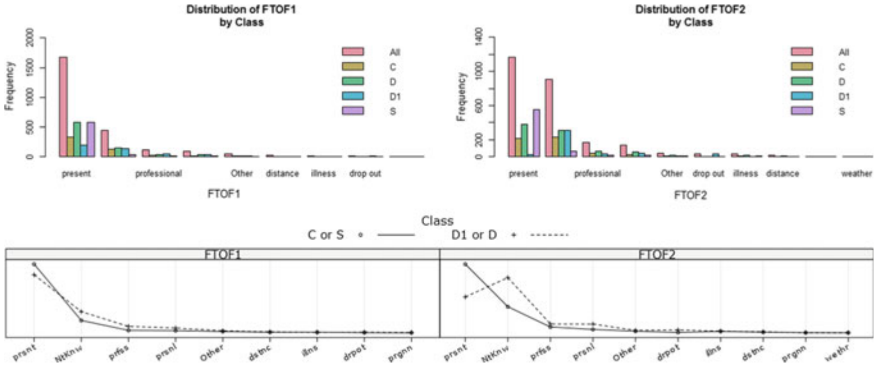


Fig. 6.4 Plots for the participation on 1st and 2nd face-to-face meetings ("FTOF1" and "FTOF2") based on the whole data

The average marks in the second written assignment are statistically significant lower ($p < 0.001$) for students that will decide to drop out (Class D) compared with those that will continue (Class C) (6.3 and 6.9 respectively). Similar results are also derived for the average marks in the second written assignment ($p < 0.001$) for students that will decide to drop out (Class D) compared with those that will successfully complete the selected modules (Class S) (6.3 and 8.2 respectively).

From the presence in the first face-to-face (FTOF1) meeting, there cannot be a clear distinguish between students that will decide to drop out and students that will continue their studies, a result that is fully expected since first face-to-face meeting takes place in the first week of the academic year. Unlike this, the student appearance in the second face-to-face (FTOF2) meeting is a key indicator as far as students that participate in the second face-to-face meeting tend to drop-out (34.3%) statistically significant less ($\chi^2 = 270.90$; $p < 0.0001$) than students (67.2%) that are absent of it (Fig. 6.4).

6.5 Machine Learning Techniques, Experiments and Results

Inductive machine learning is the process of learning from examples, a set of rules, or more generally speaking a concept or a classifier that can be used to generalize to new instances [28].

6.5.1 Machine Learning Techniques, Experiments and Results

In order to examine the usage of the learning techniques in this domain, the seven most common machine learning techniques namely Decision Trees [29], Rule learners [30], Bayesian algorithms [31], Instance-Based Learning Algorithms [32], Neural Networks [33], Logistic Regression [34] and Support Vector Machines [35] were used. For the purpose of this study, there was selected a representative algorithm for each described learning technique.

The C4.5 algorithm [29] was the representative of the decision trees in this study. The RIPPER algorithm [30] was the representative of the rule learners in this study. The Back Propagation (BP) algorithm [33]—was the representative of the ANNs. Naive Bayes classifier is the simplest form of Bayesian network [31]. The 3-NN algorithm was also used [32] as a representative of instance based learners. In addition, MLE (Maximum Likelihood Estimation) is the used statistical method for estimating the coefficients of the Logistic Regression model [34]. Finally, the Sequential Minimal Optimization (or SMO) algorithm was the representative of the SVMs as one of the fastest methods to train SVMs [36]. It must be also mentioned that the free available source code for these algorithms was used for the experiments [33].

6.5.2 The Experiments

The experiments took place in two distinct phases. During the first phase (training phase) the algorithms were trained using the data collected from the academic years 2008–10. As aforementioned, it is important for tutors to recognize dropout-prone students before the middle of the academic year, thus the attributes used were collected before the middle of the academic year along with the demographic attributes (Table 6.2). It must be mentioned that we did not have the demographic data for all the attributes for the full dataset presented in Sect. 6.4. Thus the machine learning algorithms were used in a subset (specifically in 103 students' records that dropout and in 197 students' records that continue) of the initial 3882 students' set.

The training phase was divided in 6 successive steps. The 1st step (DEMOG) included the demographic data and the resulting class (dropout or not). The 2nd step (FTOF-1) included both the demographic data along with the data from the first face-to-face meeting and the resulting class. The 3rd step (WRI-1) included data used for the 2nd step and the data from the first written assignment. The 4th step (FTOF-2) included data used for the 3rd step and the data from the second face-to-face meeting and the 5th step (WRI-2) included the available attributes described in Sect. 6.3.

Subsequently, 40 groups of data were collected each for every tutor for the new academic year (2010–11). Each one of these 40 groups was used to measure the prediction accuracy within these groups (testing phase). The testing phase also took

Table 6.3 The accuracy (%) of each algorithm in every step

Algorithm	Step				
	DEMOG (1st step)	FTOF-1 (2nd step)	WRI-1 (3rd step)	FTOF-2 (4th step)	WRI-2 (5th step)
Naive Bayes	50.52	55.47	67.04	69.62	73.45
C4.5	50.10	55.37	67.35	67.45	75.00
BP	50.52	55.78	68.18	68.69	74.48
SMO	50.21	57.43	67.35	67.45	75.20
3NN	50.00	55.78	65.70	66.11	72.31
Log. regression	51.44	55.88	68.80	68.80	76.13
Ripper	50.10	55.68	67.14	68.49	76.34

place in 5 steps in correspondence with the 5 steps of the training phase. During the testing phase each step was repeated 40 times (once for each tutor's dataset).

6.5.3 *Results*

In Table 6.3, the average accuracy of the algorithms in each testing step for these 40 datasets is presented. Indeed, it was found that learning algorithms could enable tutors, even from the beginning of an academic year to discover with satisfying accuracy the students at risk. The accuracy reaches 51% in the initial predictions based only on demographic data and exceeds 76% before the middle of the academic period.

As one can easily see from the comparison of the 7 algorithms, the produced classification accuracy is similar. A general tool that can be used for dropout prediction has been implemented. This classification tool can be fed with any subset of the attributes described, in order to be as general as possible. In the sequel, the process of the usage of the presented tool is described. The first step is the collection of the data set. Tutor selects the fields (attributes) that are the most informative. The simplest method is a 'brute-force', which indicates the measuring of everything available and only hopes that the right (informative, relevant) attributes are among them. Supposing the tutor has collected some data and wants to use them for prediction, a common situation is for the data to be stored in a spreadsheet. The tool expects the spreadsheet to be in CSV (Comma-Separated Value) file format. The CSV file format is often used to exchange data between disparate applications. The file format, as it is used in Microsoft Excel, has become a near-standard throughout the industry, even among non-Microsoft platforms. The tool assumes that the first row of the CSV file is used for the names of the attributes. There is no restriction on the attributes' ranking; however, the class attribute must be in the last column. After tutors' selection of the attributes that characterize the student for whom a prediction

Fig. 6.5 Selecting learning algorithm by the combo-box

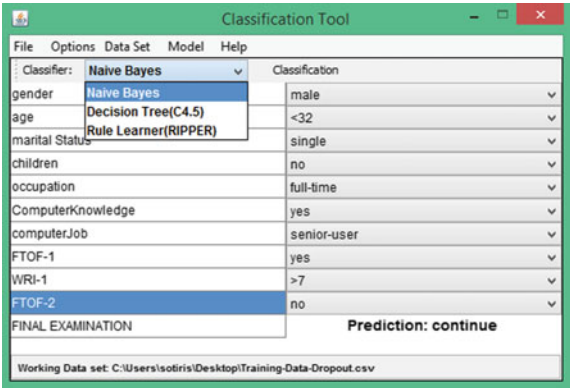
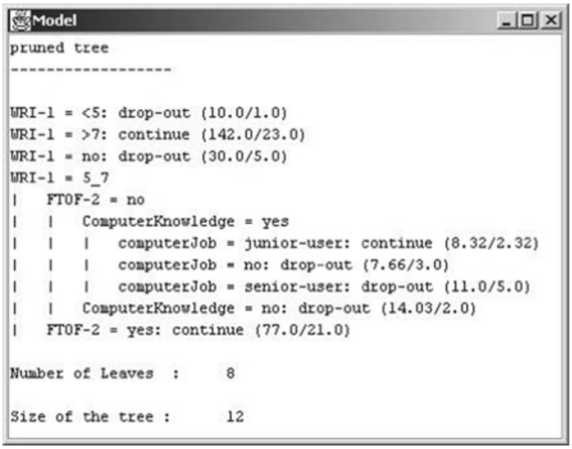


Fig. 6.6 Decision tree classifier



is needed, the tool automatically uses the corresponding attributes (training step) to train the learning algorithm. Independently of whether tutors want to predict values for one or a group of students they have to choose the most preferable algorithm to learn via the suitable combo-box (Fig. 6.5). Because in our case, it is important for tutors to generate understandable classifier, Naive Bayes, rule-based and a decision tree learning algorithm have been implemented.

After training the learning algorithm, the tutor is able to see the produced classifier. For example, the results obtained from the specific data set can be divided into rule groups using the embedded decision tree algorithm (Fig. 6.6). Subsequent, the tutor can identify the weak students and maybe select a special on-line course that each potentially weak student should be required to attend.

In our full dataset, it was found that the most informative attributes are student gender, the participation to the first face to face meeting and the marks on the first two written assignments.

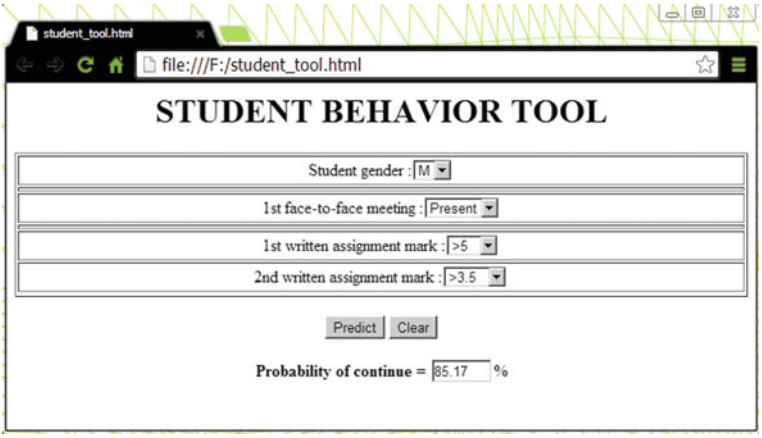


Fig. 6.7 The prototype web-based tool

6.5.4 Student Behavior Tool

A prototype web based support tool can automatically be constructed by the software tool using these informative attributes, which can help tutors in recognizing students with high probability of continue or dropout (Fig. 6.7). Naive Bayes classifier that can easily handle missing values is used for web based support tool. The HTML exporter of the tool is a component that enables tutor to export a dynamic html page that can be used by students to track their progress. This html page uses Javascript in order to support interaction.

6.6 Discussion

Student dropout has become a major problem for the academic community since it affects the university's reputation, ranking and financial robustness. According to the findings of this study, gender was proven as an attribute that could be associated to dropout according to the interview based survey. Marital status was also proven to be a factor that distinguishes dropout students from those who continue their studies ($p < 0.05$). Students that do not work tend to drop-out less ($p < 0.001$) than the working (either part-time, either full-time, or over-time) ones. The above results concerning the demographic data, have limited (as in the case of gender) or no contribution at all (as in the cases of marital status and employment) in the prediction accuracy of the learning algorithms. Additionally, the rest of the demographic data used, such as residency, previous education in IT and job association with IT, were not proven to be factors that could distinguish dropout students from those who continue and at the same time, had no contribution in the prediction accuracy of the learning algorithms.

According to the interview based survey and in the implemented machine learning algorithms, a few differentiations occurred in the result of the demographic attributes, something that was pretty much expected. It is well known that machine learning algorithms take into account all the attributes used, but because of the importance of the educational attributes used the demographic attributes were left out of the predictive model as proven in our study.

The above mentioned results are in accordance with previous researches as of Levy [12] who has proven that the majority of the demographic characteristics he used, including gender, age, residence and GPA could not distinguish between students that complete their studies and those that drop out in e-learning courses.

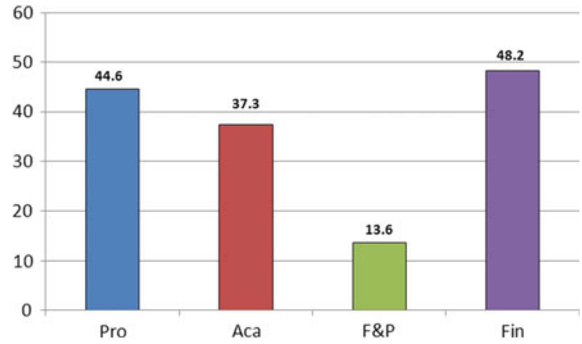
On the contrary, the participation in the face-to-face meetings was strongly connected with students' retention according to the interview based survey and at the same time was found to affect the results of the implemented learning algorithm. Specifically, the absence from the second face-to-face (FTOF2) meeting was proven to be a predictor with almost 70% overall accuracy for dropout students.

Furthermore, according to the interview based survey, the marks in the first two written assignments could perfectly distinguish between completer and dropout students. The marks for both first and second written assignments are statistically significant lower ($p < 0.001$) for students that will decide to drop out (Class D) compared to those that will continue (Class C). Previous mentioned results are in accordance with the results of the implemented learning algorithm while the marks in the first two written assignments were proven to be predictors for dropout students with almost 69% overall accuracy for the second written assignments and more than 76% for the second one.

The above mentioned results are also in accordance with previous researches as of [19] which found that the overall prediction accuracy achieved using time-invariant student data was less than 63%, while by using time-varying attributes (test and project grades, section activity etc.) the overall precision exceeded 70% in early course stages and reached nearly 100% for latter stages. They additionally found that time-invariant student data (gender, residency, working experience) are less accurate predictors of students' decision to drop out. Furthermore, the authors of [17] reported a rate of 31% as prediction accuracy using demographic data that reached 84% when they used time-varying data, while Delen [20], reported that educational and financial variables are among the most important predictors of the phenomenon. As the authors of [1] noted, the participation in face-to-face activities was found to be the most important factor in predicting subsequent enrollment. According to [4], students' average mark is highly associated with dropout. Thus, a poor academic performance is related to high probability of abandoning studies.

As far as, the reasons for dropout provided by the students that participated in the interview based survey, can be categorized in 4 major categories: (a) Professional (Pro), (b) Academic (Aca), (c) Family and Personal (F&P) and (d) Financial (Fin) reasons. Students were allowed to offer more than one reason for dropout but all of them offered only one or two reasons. As shown in Fig. 6.8, the majority of students claimed that their dropout caused by either financial (48.2%) or professional (44.6%)

Fig. 6.8 Dropout reasons—major categories



reasons, while many of them (37.3%) elected to discontinue due to academic reasons, followed by those who mentioned family and personal reasons (13.6%).

As stated by students, the specific reasons related to their Profession (Professional category) were: bad estimation of the time left for study due to professional obligations, unpredictable workload for study or change that occurred in the student's work (either a transfer to a new address or a promotion) that changed work requirements and so on. Reasons cited by students for dropping out related to academic reasons were: disappointment resulting from tutors' lack of willingness to help them understand assigned materials and written assignments, students' belief that they were not qualified enough for the specific course, their belief that although they were qualified enough they could not overcome the difficulty of the written assignments and a number of other reasons related to the students' "wrong choice" such as the dislike of the study (distance education) methodology or the erroneous course selection.

Students' or a family member's (husband, wife, children) health problem or decease, reasons related to child birth or child breeding and reasons which the students wouldn't like to discuss, constitute the main reasons in the Family and Personal (F&P) category that, as stated by students, led them discontinue their studies at the Hellenic Open University.

Financial reasons caused by the economic crisis of the recent years, is something that constitutes a very unpredictable factor nowadays. Financial reasons caused mainly either because a family member suddenly became unemployed or due to the reduction of personal or family income.

During past years there is a tendency for continuous reduction of dropout rates concerning professional reasons from over 60% [9], to 50% for the academic year 2008–9. This decline in dropout rates decreased further since 2008–9 and in the past academic year was approximately 30% (the previous mentioned differences are not statistically significant). The same result emerged for dropout rates associated to family and personal reasons from over 20% [9], to pretty much 14% for the academic year 2008–9, which tends to be stable since then (the previous mentioned differences are not statistically significant). Additionally, the authors of [1] found that the participation in face-to-face activities is the most important factor in predicting subsequent enrollment.

On the contrary, over the past years there has been an increment in dropout rates concerning financial reasons from less than 5% [9] to 30% for the academic year 2008–9. This increment in dropout rates for financial reasons was accelerated since then and was over 55% in the past academic year (the previous mentioned differences are not statistically significant). This is in accordance with prior literature as in [22] where income capacity was proven to be a key finding among the 52 attributes studied. Thus, third-year retention was higher for students with high income than for students with low income. Furthermore, the authors of [4] have proven in their study that socioeconomic status has correlation with students' dropout. Therefore, low socioeconomic status increases dropout probability.

During the past years, stability characterized the dropout rates related to academic reasons which fluctuated from almost 43% [9] to slightly less than 40% for the academic year 2008–9 and remained stable since then (the previous mentioned differences are not statistically significant). This is also in accordance with previous researches as in [4] where academic performance is connected with the probability of abandoning and as in Sittishai [23] where 50% of the interviewees' had abandoned their studies due to poor academic performance.

The above mentioned shift in students' opinion in dropout reasons is mainly due to the economic crisis of the recent years. Therefore, students are more cautious and choose curriculum after having carefully considered the field of study in order to minimize loss of money and finally choose to enroll in the Hellenic Open University after having settled their personal and family obligations in the best possible way. Thus, there is a drastic reduction of dropout rates regarding both professional reasons, such as erroneous estimation for the time they actually have available to study versus what is needed, and family and personal reasons such as child birth or child breeding and so on (see also findings in Fig. 6.3 for marital status). Unchanged (although slightly reduced) tend to be the dropout rates concerning unforeseeable specific reasons that belong to either family and personal reasons such as a death within the family, or professional reasons such as a promotion which changes the working demands or a change to their occupational address and so on.

Additionally, students tend to be more cautious. So, as students stated, if they believe they cannot succeed, or encounter difficulties, especially with the written assignments, they discontinue and do not choose to re-register in the following years. Results described above are consistent with prior literature concerning both predictive factors and reasons for dropout.

The present study has some limitations that are described below:

Firstly, the sample that was used for the survey can be characterized as convenient (sample members are chosen on the basis of being readily available). It cannot be considered representative for the whole student population. Our student population is significantly skewed towards first modules but in the case of successfully completing them, dropping out is minimized just as expected. Although the findings of the study cannot be generalized for the general population, they can be characterized as satisfactory.

Furthermore, in our study and also in cases of Open Universities, any prior educational performance of students is not so informative In order to be used by learning models. The Hellenic Open University offers a second chance for university studies in the adult population. To this end, for the majority of students there is a long period between graduation from secondary or post-secondary education and university level learning. As a result, building a classifier to predict student dropout in Hellenic Open University is by default based in less informative attributes than those that could be used in conventional universities. Therefore, prior educational performance of students cannot give valid information in our case.

6.7 Conclusion

Limiting dropout is crucial for a university that provides distance education and therefore, the aptitude to predict students' dropping out could be very useful. As a result, we tried to identify the most appropriate comprehensive learning algorithm using the most informative attributes for the prediction of students' dropping out. Thus, we explored the reasons of dropping out in order to examine on a large scale whether they were being affected over time and studied these changes. A total of 3882 students' records constituted the set of data used and were provided by the Student Registry of the Hellenic Open University. At the same time, additional data was collected by an interview-based survey on 297 dropout students.

It was proved that learning algorithms tend to predict the dropping out of students with satisfying accuracy and thus constitute a useful tool in an attempt to reduce dropouts. The accuracy reaches 51% in the initial predictions, which are based only on demographic data of the students, and exceeds 76% before the middle of the academic period, where the most informative attributes are the student gender, the participation at the first face to face meeting and the marks on the first two written assignments. A web-based application, which is based on these attributes and can automatically recognize students with high probability of dropout, was constructed in order to help tutors detect students at risk even at the beginning of the academic year.

It was also proved that the reasons students drop out are not constant, they change over time and are influenced by important external factors such as the economic crisis of the recent years. Therefore, the most significant reasons students cited for dropping-out were financial reasons caused by the economic crisis of the recent years, which was accompanied by the underestimation of the available time they have for studying due to their employment obligations, and the students' belief that the specific course was not suitable for them or that they were not qualified enough to attend it.

Additionally, it is shown that students tend to be more cautious, selecting a study course after great circumspection and, when possible, after having settled their personal and family obligations. Unchanged (although slightly reduced) tend to be the dropout rates concerning unforeseeable specific reasons that belong either to family and personal reasons, such as a death within the family, or to professional reasons such as a promotion which changes the working demands or a change to their occupational address and so on.

The above noticeable results that present a significant shift in students' opinion in dropping out reasons indicate that a continuous research on this important issue should be conducted. Additionally, remedial measures and other additional actions should be taken both by the academic and the authorities of the University. Furthermore, tutors and students should communicate more and even conduct an additional face to face meeting at the beginning of the academic year, where tutors can guide these students, explain the syllabus to them, answer their questions and clarify the incomprehensible concepts of the educational material. Respectively, the University authorities should intervene, in a different way, by providing financial-aid packages and financial support programs in the payment of the tuition for students with lower economic capacities and by reducing the cost of re-enrollment at the same module for a second year.

A further direction that refers to the applicability of the modeling approach to advanced modules, i.e. dealing with students close to the end of their studies, would be very interesting. Since our student population is significantly skewed towards first modules, and since dropping out is minimized after initial successes as expected, it is technically more difficult and at the same time more interesting to predict pass/fail in advanced modules using the proposed methodology, although less important from an educational point of view. In courses were Moodle is supported, data gathered from learners' interaction log files could be also used by a learning algorithm. Finally, when learning is performed online, the system using a learning algorithm could understand various traits of learner and deliver Learning Objects (LO) suitable for them to achieve personalization [37].

Appendix

The tool is available in the web page: http://www.math.upatras.gr/~sotos/tool1/.

References

1. Shin, N., Kim, J.: An exploration of learner progress and drop-out in Korea National Open University. Distance Educ. Int. J. **20**(1), 81–95 (1999)
2. Lau, L.K.: Institutional factors affecting student retention. Education **124**(1), 126–137 (2003)
3. Mannan, M.A.: Student attrition and academic and social integration: application of Tinto's model at the University of Papua New Guinea. High. Educ. **53**(2), 147–165 (2007)
4. Araque, F., Roldán, C., Salguero, A.: Factors influencing university dropout rates. Comput. Educ. **53**, 563–574 (2009)
5. Doherty, W.: An analysis of multiple factors affecting retention in web-based community college courses. Internet High. Educ. **9**(4), 245–255 (2006)

6. Pierrakeas, C., Xenos, M., Panagiotakopoulos, C., Vergidis, D.: A comparative study of dropout rates and causes for two different distance education courses. Int. Rev. Res. Open Distance Learn. **5**(2), 1–15 (2004)
7. Romero, C., Ventura, S.: Data mining in education. Wiley Interdiscip. Rev. Data Min. Knowl. Discovery **3**(1), 12–27 (2013)
8. Dupin-Bryant, P.A.: Pre-entry variables related to retention in online distance education. Am. J. Distance Educ. **18**(4), 199–206 (2004)
9. Xenos, M., Pierrakeas, C., Pintelas, P.: A survey on student dropout rates and dropout causes concerning the students in the course of informatics of the Hellenic Open University. Comput. Educ. **39**, 361–377 (2002)
10. Morris, L.V., Wu, S.S., Finnegan, C.L.: Predicting retention in online general education courses. Am. J. Distance Educ. **19**(1), 23–36 (2005)
11. Parker, A.: Identifying predictors of academic persistence in distance education. J. U. S. Distance Learn. Assoc. **17**(1), 55–61 (2003)
12. Levy, Y.: Comparing dropouts and persistence in e-learning courses. Comput. Educ. **48**(2), 185–204 (2007)
13. Herzog, S.: Estimating student retention and degree-completion time: decision trees and neural networks vs regression. New Dir. Inst. Res. **131**, 17–33 (2006)
14. Atwell, R.H., Ding, W., Ehasz, M., Johnson, S., Wang, M.: Using data mining techniques to predict student development and retention. In: Proceedings of the National Symposium on Student Retention, 9–11 Oct 2006, Albuquerque, New Mexico
15. Superby, J.F., Vandamme, J.P., Meskens, N.: Determination of factors influencing the achievement of the first-year university students using data mining methods. In: 8th International Conference on Intelligent Tutoring Systems (ITS 2006), Jhongli, Taiwan, pp. 37–44 (2006)
16. Wegner, L., Flisher, A.J., Chikobvu, P., Lombard, C., King, G.: Leisure boredom and high school dropout in Cape Town, South Africa. J. Adolesc. **31**(3), 421–431 (2008)
17. Moseley, L.G., Mead, D.M.: Predicting who will drop out of nursing courses: a machine learning exercise. Nurse Educ. Today **28**, 469–475 (2008)
18. Lin, S.H.: Data mining for student retention management. J. Comput. Sci. Colleges **27**(4), 92–99 (2012)
19. Lykourentzou, I., Giannoukos, I., Nikopoulos, V., Mpardis, G., Loumos, V.: Dropout prediction in e-learning courses through the combination of machine learning techniques. Comput. Educ. **53**, 950–965 (2009)
20. Delen, D.: A comparative analysis of machine learning techniques for student retention management. Decis. Support Syst. **49**, 498–506 (2010)
21. Lee, Y., Choi, J.: A review of online course dropout research: Implications for practice and future research. Educ. Technol. Res. Dev. **59**(5), 593–618 (2011)
22. Nandeshwar, A., Menzies, T., Nelson, A.: Learning patterns of university student retention. Expert Syst. Appl. **38**, 14984–14996 (2011)
23. Sittichai, R.: Why are there dropouts among university students? Experiences in a Thai University. Int. J. Educ. Dev. **32**, 283–289 (2012)
24. Hu, Ya-Han, Lo, Chia-Lun, Shih, Sheng-Pao: Developing early warning systems to predict students' online learning performance. Comput. Hum. Behav. **36**, 469–478 (2014)
25. Kassak, O., Kompan, M., Bielikova, M.: Student behavior in a web-based educational system: Exit intent prediction. Eng. Appl. Artif. Intell. **51**, 136–149 (2016)
26. Márquez-Vera, C., Cano, A., Romero, C., Noaman, A.Y.M., Mousa Fardoun, H., Ventura, S.: Early dropout prediction using data mining: a case study with high school students. Expert Syst. **33**(1), 107–124 (2016)
27. Peña-Ayala, A.: Educational data mining: a survey and a data mining-based analysis of recent works. Expert Syst. Appl. **41**(4) (Part 1), 1432–1462 (2014)
28. Williams, G.: Data Mining with Rattle and R: The Art of Excavating Data for Knowledge Discovery. Springer, New York (Use R!) (2011)
29. Quinlan, J.R.: C4.5: Programs for Machine Learning. Morgan Kaufmann, San Francisco (1993)

30. Cohen, W.W.: Fast effective rule induction. In: Twelfth International Conference on Machine Learning (ICML-95), Lake Tahoe, California, pp. 115–123
31. Domingos, P., Pazzani, M.: On the optimality of the simple Bayesian classifier under zero-one loss. Mach. Learn. **29**, 103–130 (1997)
32. Aha, D.: Lazy Learning. Kluwer Academic Publishers, Dordrecht (1997)
33. Witten, I.H., Frank, E., Hall, M.A.: Data Mining: Practical Machine Learning Tools and Techniques, 3rd edn. Morgan Kaufmann, San Francisco (2011)
34. Hosmer, D., Lemeshow, S.: Applied Logistic Regression, 2nd edn. Wiley, New York (2005). ISBN: 9780471356325
35. Burges, C.: A tutorial on support vector machines for pattern recognition. Data Min. Knowl. Discov. **2**, 1–47 (1998)
36. Platt, J.: Using sparseness and analytic QP to speed training of support vector machines. In: Kearns, M.S., Solla, S.A., Cohn, D.A. (eds.) Advances in Neural Information Processing Systems (NIPS). MIT Press, MA (1999)
37. Anitha, D., Deisy, C.: Proposing a novel approach for classification and sequencing of learning objects in E-learning systems based on learning style. J. Intell. Fuzzy Syst. **29**(2), 539–552 (2015)

Part III
Learning Analytics Incorporated in Tools for Building Learning Materials and Educational Courses

Chapter 7
An Architectural Perspective of Learning Analytics

Arvind W. Kiwelekar, Manjushree D. Laddha, Laxman D. Netak and Sanil Gandhi

Abstract Tools for learning analytics are becoming essential features of Learning Management Systems (LMS) and various course delivery platforms. These tools collect data from online learning platforms, analyze the collected data, and present the extracted information in a visually appealing manner. Representing the design-level concerns of such tools is one of the significant challenges faced by software developers. One way of overcoming this challenge is to adopt *architectural perspectives* which is a mechanism used by software architects to capture high-level design concerns. In this Chapter, we present an *architectural perspective* of such learning analytics tools and components. The primary objective of the chapter is to describe the functional elements and non-functional properties supported by such tools. Further, the chapter describes various techniques for realizing these functional and non-functional elements. Such an architectural perspective is useful in two different ways. First, the design knowledge represented through an architectural perspective is potentially useful to communicate the design and implementation of a learning analytics based system. Second, the architectural perspectives can also be used to evaluate the design of the tools in achieving their stated goals.

A. W. Kiwelekar (✉) · M. D. Laddha · L. D. Netak · S. Gandhi
Department of Computer Engineering, Dr. Babasaheb Ambedkar Technological University, Lonere, Raigad 402103, India
e-mail: awk@dbatu.ac.in

M. D. Laddha
e-mail: mdladdha@dbatu.ac.in

L. D. Netak
e-mail: ldnetak@dbatu.ac.in

S. Gandhi
e-mail: sanil.gandhi15@gmail.com

M. Virvou et al. (eds.), *Machine Learning Paradigms*, Intelligent Systems Reference Library 158, https://doi.org/10.1007/978-3-030-13743-4_7

7.1 Introduction

Technology is revolutionizing the field of education. The conventional scene of a teacher teaching a group of students in a walled classroom is increasingly replaced by students facing a computer screen in a virtual classroom. Students are preferring books available in digital media over conventional paper books. Ideas are getting exchanged through discussion forums and social networks rather than across the coffee table in a university canteen. Teachers are preferring online quizzes, exit tickets [31], and computer-generated adaptive testing [30] as methods of formative and summative assessments [24] over standardized tests delivered by educational institutes. Few concrete examples of technologies enabling the delivery of instructions are open learning platforms (e.g., Coursera[1]) and Learning Management Systems (e.g., Google Class room[2]).

One of the consequences of the widespread adoption of technology-enabled education is that these software systems are generating an enormous amount of data on a regular basis. This vast amount of data if appropriately harnessed gives significant insights about the learning behavior of students. The emerging discipline of **Learning Analytics** (LA) intends to collect, analyze, and report this data to understand learners and learning environments [22]. Researchers in this field have been developing techniques to extract relevant information from the data generated by learners and digital tools. They typically adopt *statistics* and *machine learning-based* approaches such as regression [2], and ANOVA [13]. The primary intentions behind these activities are to provide a decision framework for educational policymakers and offer better learning experiences to online learners. However, most of these efforts overlook the engineering issues such as design and development of tools for extracting, analyzing, and visualizing learning data.

In this chapter, we present an approach to understanding the domain of Learning Analytics. We present a set of concerns from the perspective of domain analysts and software architects. These are two crucial stakeholders defining the architecture of learning analytics based applications. The primary objective is to identify and comprehend the requirements and various alternatives to generate high-level design.

7.2 What is an Architectural Perspective?

An **architectural perspective** is a mechanism used by software architects to represent *high-level concerns* of engineering an application [28]. These concerns vary from identifying architecturally significant requirements to deployment of applications in an operational environment. Each of these concerns have a significant value to different stakeholders of an application. When architectural perspectives are developed at the early stages of life-cycle, they help to gain control over the complexity

[1] www.coursera.com.

[2] www.classroom.google.com.

Table 7.1 Architectural perspectives, concerns and stakeholder

Viewpoints	Concerns	Stakeholder
Functional viewpoint	To describe the functionalities of an application	Domain Analysts and End Users
Information viewpoint	To describe how system stores, distributes, and manages information	Data-base Administrator, System Integrator
Concurrency viewpoint	To describes and not to describes mapping of functional elements to concurrency units	Performance Analysts, System Administrator
Development viewpoint	To describe software development processes	Project Manager Software Developers, Testers
Deployment viewpoint	To describe the environment into which the system will be deployed	System Administrator
Operational viewpoint	To describe how the system will function in operational environment	End users, System Administrator

of the application, to identify the factors affecting software quality and to explore various implementation strategies. Such architectural perspectives can also be developed later in the software life cycle, i.e., when the application is deployed in an operational environment. In such scenario, they are primarily used to communicate design ideas.

In an emerging application domain such as Learning Analytics, development of architectural perspectives help to capture variabilities and similarities between different implementations [27]. They can act as a baseline to define reference architecture for an application domain i.e. Learning Analytics in our case.

Two main elements of architectural perspectives are viewpoints and tactics. First, an *architectural viewpoint* represents a single concern specific to a set of stakeholders. For example, *functional viewpoints* represent functionalities of an application which is specific to stakeholders such as domain analysts and end users. Second *architectural tactics* represent various alternatives to realize a quality attribute and tradeoffs among them. For example authenticating a user of the system is a non-functional requirement to ensure the quality attribute called security. The identity of end users can be confirmed by mechanisms such as simple text-based passwords, graphical patterns, bio-metric methods or combination of all these.

Table 7.1 enlists the various kinds of viewpoints, concerns addressed by them, and a set of associated stakeholders with it. Out of these viewpoints, functional viewpoints and information viewpoints deal with high-level design concerns in the early phases of software life-cycle. We discuss these viewpoints in greater detail in this chapter.

In Sect. 7.3, we present the functional viewpoint of learning analytics. Section 7.4 explains a set of quality attributes. In Sect. 7.5, we explain an information viewpoint for LA. Section 7.6 describes architectural patterns that will be useful to structure LA applications.

7.3 Functional Viewpoints

When software development is viewed as a problem-solving process; a functional viewpoint describes the understanding of the problem. This viewpoint includes the set of functions that a given software system is going to provide to its end users. In other words, it captures the most significant functional requirements of an application called *architecturally significant requirements*. This viewpoint is also known as *logical viewpoint* or *conceptual viewpoint*. In many cases, a functional viewpoint becomes the baseline to define the architecture of the proposed system. It is typically

Table 7.2 Architecturally significant functional requirements

FR-ID	Description	Source
Knowledge discovery functions		
KD-FR1	To learn pre-requisite skill structure	[2]
KD-FR2	To identify Boredom and Engagement	[6]
KD-FR3	To identify appropriate grouping of learners	[18]
Analytical functions		
ANA-FR1	To analyze the impact of students choices about content sequencing on their performance	[3]
ANA-FR2	To analyze the impact of student choices about content adoption on course outcomes	[5]
ANA-FR3	To analyze confidence level of student or Meta cognitive Analysis	[4]
ANA-FR4	To analyze natural language responses to course contents	[7]
ANA-FR5	To analyze multimodal data generated by biometric sensors	[8]
ANA-FR6	To analyze inclusiveness and accessability of Open Educational Resources	[9]
ANA-FR7	To map learning profiles to learning tasks	[19]
Generative functions		
GEN-FR1	To develop automated survey reporting system to provide formative and summative student feedback	[15]
GEN-FR2	To model the students learning trajectories	[17]
Predictive functions		
PRED-FR1	To predict student performance on post-requisite Skills	[2]
PRED-FR2	To predict academically at risk students	[25]

used to communicate the functionalities of a proposed system or to understand the services provided by an existing software system (Table 7.2).

To derive the functional view of an LA-based system, we envision an application that integrates loosely coupled services providing information about the learning experience to its essential stakeholders such as students, instructors, and course administrators. One can implement such an LA-based system as one single application or as a loose integration of separate functions embedded in an online learning platform.

Conventionally, a functional viewpoint is derived by interviewing various stakeholders, end-users, and by studying the working of existing users. However, in this chapter, we adopt a different approach.

We collected the functional requirements by surveying existing literature to understand how experts perceive the learning analytics. We analyzed about fifty recently published papers in the area of learning analytics. Fourteen most significant functional requirements were identified. These requirements are generic in the sense that these requirements ignore context specific variations. For example, the act of identifying pre-requisite skill structure can be done for various courses such as data structure, programming, and others.

These requirements are further grouped into four categories, i.e. (i) Knowledge discovery functions, (ii) Analytical functions, (iii) Predictive functions and (iv) Generative functions.

7.3.1 Knowledge Discovery Functions

The functions in this category analyze the existing data sets to discover the information that is not explicitly encoded in the data sets. We have listed three different such functions. One to discover the pre-requisite skill structure, second to identify boredom and third is to identify a grouping of the students to enhance their learning performance.

1. **To learn pre-requisite skill structure [KD-FR1]** It represents ordering among various skills to be acquired by learners during the course enrollments. One of the ways to relate skills is through a *pre-requisite relationships* [14]. For example, in a programming course, the skills that *apply arithmetic operators* and *comparison operators* are pre-requisites to master the skill of *correctly using a looping construct.* (e.g., for loops).
   The *pre-requisite structure* is emerging as a basic conceptual abstraction in learning analytics. The knowledge of pre-requisites skill structure for a given course is required to correctly sequence the instructions, and to design timely interventions for weaker students in a class [2].
   Partially Ordered Knowledge Structure (POKS) [20] is a variant of pre-requisite structure which relates *question items* from the test with an assumption that each item in a test evaluates specific skills.

2. **To identify Boredom and Engagement [KD-FR2]** One of the challenges faced by online course instructors and designers of Intelligent Tutoring Systems (ITS) is how to keep learners engaged and sustain their interest in learning activities. This functionality aims to early detect the symptoms of boredom by adopting techniques such as a sequence of keystrokes, number of active windows, and tracking eye movements.
3. **To identify appropriate grouping of learners [KD-FR3]** The impact of the grouping of students on their achievements yielded conflicting results. The cluster of students with similar abilities and past performance sometimes increases the individual performance because of high-degree of interactions and sharing learning resources. It has also found that mixing students with different skills are also used to enhance individual performance. Hence learning analytics tools should support this feature to identify an appropriate grouping of students in a particular context.

7.3.2 Analytical Functions

The functions in this category intend to give new insight into student's learning experiences and to explore the interdependencies of learning design parameters. The outcomes of these analyses are used to make instructional decisions and formulate new policies.

1. **To analyze the impact of students choices about content sequencing on their performance** [ANA-FR1] One of the goals for adaptive testing and intelligent tutoring is to provide personalized instruction. In such systems, the choice concerning sequencing content, assignments, and test plays the crucial role. So the impact of such choices on a student's performance needs to be analyzed to get insights into the student's learning experiences and build better student's model.
2. **To analyze the impact of student choices about content adoption on course outcomes** [ANA-FR2] This functionality aims to analyze the impact of students' choices on course outcomes. This analysis differs with last analysis in the sense that it gives insights about instruction delivery to course instructors. In case of Intelligent Tutoring System (ITS), it helps to build a useful pedagogical model. This functionality addresses the concerns of an instructor while previous one addresses the concerns of learners.
3. **To analyze confidence level of student or Metacognitive Analysis** [ANA-FR3] It has been observed that a student's performance is directly connected to his/her perception of own capabilities to do a learning task. This analysis is a reflective analysis aims to provide proper insights to learner about his/her capabilities. Most of the time, the confidence level of a student is monitored against the level of attainment in performing a task.
4. **To analyze natural language responses to course contents** [ANA-FR4] Many ITS and online learning platforms provide mechanisms to learners for expressing

their learning experiences in natural languages. Discussion forums, comments are some of the ways through which learners can share their learning experiences. Instructors, as well as system providers, can get better insights through analyzing these contents.

5. **To analyze multimodal data generated by biometric sensors** [ANA-FR5] The correlation between bodily movements (e.g., eye gaze, speech prosodics, hand gestures, facial expression) and human cognition is one of the continuously studied phenomena [8]. Recent advances in sensor technologies helping us to monitor these physical movements. This functionality aims to access the sensor data and analyze it to study the effect of bodily movements on human cognition.
6. **To analyze inclusiveness and accessibility of Open Educational Resources** [ANA-FR6] Most of the functionalities supported by learning analytics tools provide information about a student's learning behavior. The purpose of this functionality is to provide valuable information to course designers and instructors on the courses they design. This functionality offers insights on whether the content created by them is accessible to all kinds of user. This feature becomes important to expand the outreach of the course to all types of learners especially learners facing some physical challenges.
7. **To map learner's profile to learning task** [ANA-FR7] Online learning platforms store valuable personal information (e.g., social background, economic background, past academic data, etc.) about learners. This personal information can be referred to as *learner's profile*. Education policymakers need a mapping of this profile information to various learning activities and attainment of learning objectives.

7.3.3 Predictive Functions

These functions primarily intend to predict the outcome of learning activities based on historical data about past performance, and the current level of engagement. These functions warn about probable dropouts and students at risk. An instructor can use these predictions to design proper interventions.

1. **To Predict Student's performance on Post-Requisite Skills** [PRED-FR1] Knowing in advance what will be the student's performance at the term-end is one of the practical tools in instructor's repertoire. LA-based tools shall support this feature to predict the performance of post-requisite skills using either past performance data or learners' performance data on pre-requisite skills.
2. **To predict Academically at Risk Students** [PRED-FR2] Students drop out of a course or college, fail to get a high grade or employment. Such outcomes can be associated with their online learning activities, less engagement in class and failure to complete assignments, quizzes, and examinations on time. LA tools can use the available data on learner's behavior to predict such academically at-risk students at an early stage, and issue warnings recommend interventions.

7.3.4 Generative Functions

The purpose of functions included in this category is to generate reports, summarize data, create visuals so that users of data can easily draw inferences and interpret the data.

1. **To develop an automated survey reporting system** [GEN-FR1] Reporting is one of the prime functionality of the LA tools. Dashboards, recommender systems, and automatic feedback system are the conventional methods used to report the results of analytical activities. The reporting of result done in visually appealing manner provides formative feedback to students. The commonly used techniques for increasing visual appeal are bar charts, pie charts, and word clouds.
2. **To model Learning Trajectories** [GEN-FR2] A learning trajectory describes the learning progress over a period. It is an effective method to describe the levels of competencies and knowledge acquired by learners. Performance data in a formative assessment, successful completion of assignments, and other learning tasks can be used to generate learning trajectories. A learning analytics tool shall provide the features to generate learning trajectories for an individual as well as for a group.

7.4 Quality Attributes

The second most important component of the functional viewpoint is a set of significant quality attributes. These attributes define *how* the functionalities supported by an application are delivered to end users. These are also known as *non-functional requirements*.

Quality attributes play an important role in determining the architecture of an application and to select an architectural style to structure application functionalities [23]. For example, in case of operating system design, the *monolithic* architecture style is preferred when *performance* is the desired quality attribute while *microkernel* architecture style is preferred when *modifiability* is the desired quality attribute.

Some of the most significant quality attributes from the ISO/IEC 25022 quality model [12, 21] are identified and their relevance to the design of learning analytics tools are discussed below.

1. **Personalization** The quality attribute **Personalization** refers to delivering the content of e-learning platform, testing platform, and the results of analytical activities as per the needs and requirements of individuals. The utility and effectiveness of LA-based tools depend on the personalized insights offered by such tools. Personalized insights and functionalities speed up reflective thinking and decision making.
2. **Adaptability** The quality attribute **Adaptability** refers to delivering the content of e-learning platform and testing platform taking into consideration the progress

made by the learner and his/her current performance level. This feature becomes essential because of the diversity of learner's abilities. The learner community on any MOOC/ITS has varied social and educational background.

3. **Flexibility** It is the feature of software tools that characterizes easiness with which new functionalities can be added and how accessible it is to configure existing functionalities to meet the requirements of users. The learning analytics tools shall have enough flexibility to supporting different data formats and visualization models.
4. **Privacy** As more and more students, instructors, and educational institutes moving towards public platforms and cloud-based technologies, the privacy of information is becoming a critical issue. The quality attribute *privacy* refers not to disclose the profile data, and data shared by systems' users to the third party without making them aware of it. Further, it also refers to use the shared data only for agreed terms and conditions. Any learning analytics system shall ensure and protect the privacy of its users by formulating and enforcing privacy policies.
5. **Accessability** This feature characterizes the degree of accessing the web content to all kinds of users especially users with disabilities such as auditory, cognitive, neurological, physical, speech and visual. This feature becomes significant because learning analytics tools are commonly deployed in educational institutes which aims to provide personalized instruction to students. The high degree of content access guarantees inclusion of students with various kinds of disabilities. Typically LA-tools shall follow the Web Content Accessibility Guidelines (WCAG)[3] for design and development of learning contents as well as it should support monitoring mechanisms to evaluate the accessibility of learning resources continuously.
6. **Multimodality** One of the objectives of LA-based tools is to analyze learner's data on their behavior and provide accurate insight. This data is typically collected from learners interaction with systems such as learning platforms and ITS. With the advent of advanced sensors, now it is possible to receive data from different sources, like eye-tracking devices, data about their physical movements, their speech in group discussion and other modes. The quality attribute of **multimodality** specifies that an LA-based tool shall collect and analyze learners data from different sources to give proper insights about learner's behavior.

7.5 Information Viewpoint

One of the most crucial viewpoints in the early stage of development is the information viewpoint. Its purpose is to describe how system stores, manipulates and extracts information. This viewpoint is useful to stakeholders such as application developers, database administrators, and testers.

[3] https://www.w3.org/WAI/standards-guidelines/wcag/.

Table 7.3 Q-matrix: an example

Concepts	Q1	Q2	Q3	Q4
C1	1	0	1	0
C2	1	1	0	1
C3	0	1	1	0
C4	0	0	1	1

For our application, we have identified a set of external applications which generate data about learner's behavior, and their engagement in online learning platforms. These data producers are listed below.

1. **Adaptive Testing Systems [ATS]** These are computer-assisted tests delivery platforms. These platforms administer test based on a student's current performance in the test. The next item to be delivered depends on the correctness of the response given to the current test item. Such systems typically make use of pre-requisite skill structures [35]. PLACEment [2] is one example of adaptive testing systems to evaluate mathematical knowledge and skills. Adaptive testing systems generate data about students' strengths, and achievements of learning objectives. Responses given to test items can be analyzed in more than one way to gain insights on student's performance in an examination.
2. **Intelligent Tutoring Systems [ITS]** The goal of intelligent tutoring system is to provide the one-to-one teaching to students. The underlying principle is that personalized teaching is more effective as compared to the conventional one-to-many model of classroom teaching. Typically it consists of three sub-components called *domain model*, *pedagogical model* and *Student model* [29]. The *domain model* aims to store and retrieve course-specific knowledge base; *pedagogical models* deal with the sequencing of instruction such that student performance is enhanced and the *student model* represents student's attainment of learning objectives. The ASSISTment [5] is one example of ITS for acquiring personalized mathematical knowledge and skills.
3. **Q-matirx [QM]** This binary data structure aims to analyze the state of student's knowledge based on the performances in a test. The underlying principle of this data component is that a student acquires mastery over a concept or a skill when s/he correctly responds all the questions associated with a particular concept. Hence, Q-matrix data component is a matrix of concepts and questions. When a question and a concept are associated with each other, the corresponding entry in the particular cell of the Q-matrix is 1 otherwise not [11]. For example, in Table 7.3, $Q1$ and $Q3$ are related through the concept $C1$ while the questions $Q2$ and $Q4$ are not related to the concept $C1$. The Q-matrix has been found a useful data component to identify pre-requisite structures and to identify knowledge gaps in learners.

7.6 Architectural Patterns and Styles

In this section, we review different design alternatives that are available to group the functionalities discussed earlier. We have identified a set of *architectural styles* which realize the quality attributes listed above.

An architectural style specifies the *design solutions* to a recurring problem in terms of high-level components and interactions among them. Its main objective is to achieve design reuse. The architectural styles are well documented [16] and provide implementable solutions to realize a specific quality attribute or design concern. The architectural styles that we are going to review are: (i) Model-View-Controller, (ii) Publish-Subscriber and (iii) Microservices

These three architectural styles provide solutions to three frequently asked questions while developing learning analytics applications. (i) How do we provide rich visual interfaces to different kinds of users? (ii) How do we achieve effective communication across different processes? (iii) Which is the effective software development strategy for a continuously evolving application?

7.6.1 Model-View-Control (MVC)

This architectural style suggests decomposing the system functionalities into three broad components, i.e. (i) Model, (ii) View, and (iii) Controller. The element *Model* typically stores and distributes data, the component *view* represents various views to be generated from the data. The responsibility of continuously updating the view is assigned to the component *controller*.

This architectural style is typically preferred to design interactive applications when *flexibility* regarding representing data in various format is required. Many learning analytics applications are data-driven which need to visualize data in appealing formats such as pie-charts, bar-charts, and colored tables. In such cases, the MVC architectural pattern becomes the appropriate way to decompose an application. Conventionally, MVC patterns are used to design desktop applications. However, MVC has been found equally powerful to design web-based applications and various web application development frameworks such as Django[4] support MVC pattern [34].

7.6.2 Publisher-Subscriber

The second critical design parameter to consider is how to achieve communication between interacting components. Most of the learning analytics applications are driven by data where one element is a producer of the data, and some other parts are the consumer of the data. The producers generate data in asynchronous

[4] https://www.djangoproject.com/.

way or in other words the timing of data generation is uncertain. For example, an instructor's timing of posting grades or assignment is not fixed. In such scenario, the *publisher-subscriber* pattern effectively archives the communication among interacting components [26, 33].

In the publisher-subscriber pattern, one can achieve communication without knowing the identity of senders and receivers. Here, senders and receivers are loosely coupled via a mediator. This pattern is used to send notifications and alerts to more than one recipients. Few examples of notifications are uploading of an assignment, grades, and students at risks. Another advantage of publish subscriber pattern is that the task for enforcing data privacy policies can be assigned to the mediator component. This pattern realizes the quality attributes such as scalability and flexibility when application functionality is distributed over multiple locations.

7.6.3 Microservices

Microservices-based software development is increasingly becoming the most preferred way of developing enterprise applications [1, 32]. This architectural style offers seamless integration of various phases of software development, namely, code-build-test-deploy. In this architectural style, an application is developed as a suite of smaller services which are independently designed, tested, and deployed in an operating environment. Later these services can be integrated through well-defined API, preferably accessible through Web, to build a large-scale application.

Further, microservices support deployment over different kinds of platforms such as mobiles, desktops, and servers. The different services communicate with each other through message communication in which a service receiving a message responds by generating a response message. Hence they are loosely integrated in contrast through processes communicating through a call based mechanism such as remote procedure calls. From learning analytics point of view, one of the distinct and immediate advantages is that microservices-based architectural design offers one to develop functionalities as and when it is fully specified or needed and then integrate it with the rest of the services.

7.6.4 An Architecture for Learning Analytics

Based upon above requirements analysis and review of different system decomposition techniques, we suggest an architecture for learning analytics application which adopts a three layered decomposition as shown in Fig. 7.1 namely, data producer layer, analytics engine layer and dashboard layer. This architecture is structured around MVC pattern.

The data producer layer includes all data generating components such as adaptive testing system, intelligent tutoring system, and Q-matirx. This layer roughly corre-

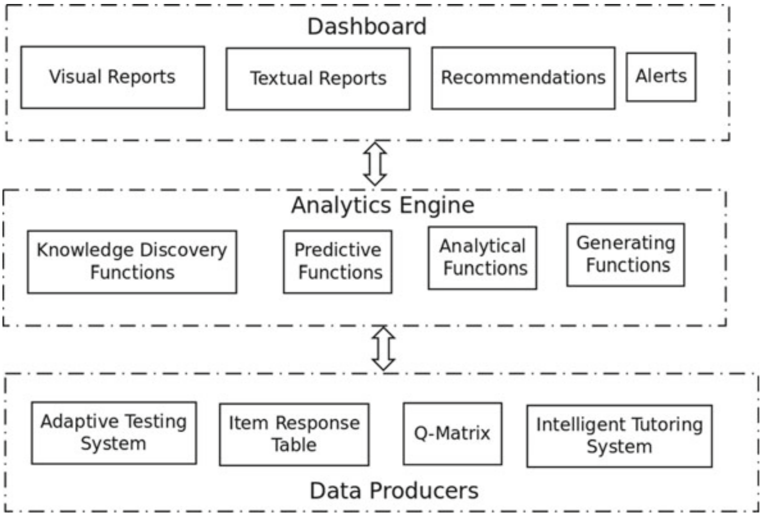


Fig. 7.1 A suggestive architecture for learning analytics

sponds to the *model* in MVC architectural style. It's prime responsibility is to store data that is generated by various platforms. In the second layer, we have included the system functionalities covered in the Sect. 7.3 on Functional Viewpoint. It typically includes knowledge discovery functions, analytical functions, predictive functions and generative functions. This is the main processing layer which corresponds to the *Controller* element of MVC pattern. The third and topmost layer includes various visual reports, textual reports, alerts and recommendations. It corresponds to the *View* element of MVC pattern. The same architecture can also be implemented through microservice architecture style. In such cases, the functions listed in Table 7.2 becomes individual services and they interact with each other through well-defined APIs.

7.7 Discussion

The emerging discipline of Learning Analytics is a sub-field of data analysis that applies automated techniques developed for data-driven decision making to the field of Education. In recent years, researchers have been successful in applying various statistical methods to analyze learners' data. One of the significant contributions of these efforts is that it has identified multiple analytical functions to get insights into the learners' behavior. The chapter goes beyond that and views the field of Learning Analytics from Software Engineering perspective.

We adopted the *architecture-centric* approach for specifying a generalized design of an LA-based system. Two critical architectural viewpoints called Functional, and

Information viewpoints are developed in this chapter. One of the contributions of this chapter is the identification of architecturally significant requirements and defining a set of quality attributes affecting the design of LA-based systems. The information viewpoint developed in this chapter enlists the external data generating applications upon which higher level analytical functions can be implemented. A three-tier generalized architecture is specified based upon the functional requirements and desired quality attributes. The potential benefit of the suggested architecture is that it can be reused in different usage scenarios by implementing specific use-cases around the suggested architecture.

We considered the state-of-the-art requirements that occurred regularly in the literature. It needs to be extended into an exhaustive list of functional and non-functional requirements. Various middleware platforms (e.g., zoomdata[5]) supporting data analytics applications are emerging which effectively separate the tasks of data processing from analytics and visualization. Use of such middleware for developing LA tools needs to evaluated for various quality attributes. Further, describing *architectural decisions and tactics* [10] affecting the software quality are also needed to develop because it facilitates selection of an implementation technique from multiple competing alternatives.

References

1. Aderaldo, C.M., Mendonça, N.C., Pahl, C., Jamshidi, P.: Benchmark requirements for microservices architecture research. In: Proceedings of the 1st International Workshop on Establishing the Community-Wide Infrastructure for Architecture-Based Software Engineering, ECASE '17, pp. 8–13, Piscataway, NJ, USA. IEEE Press (2017)
2. Adjei, S.A., Botelho, A.F., Heffernan, N.T.: Predicting student performance on post-requisite skills using prerequisite skill data: an alternative method for refining prerequisite skill structures. In: Proceedings of the Sixth International Conference on Learning Analytics & Knowledge, pp. 469–473. ACM (2016)
3. Adjei, S.A., Botelho, A.F., Heffernan, N.T.: Sequencing content in an adaptive testing system: the role of choice. In: Proceedings of the Seventh International Learning Analytics & Knowledge Conference, pp. 178–182. ACM (2017)
4. Aghababyan, A., Lewkow, N., Baker, R.: Exploring the asymmetry of metacognition. In: Proceedings of the Seventh International Learning Analytics & Knowledge Conference, pp. 115–119. ACM (2017)
5. Agnihotri, L., Essa, A., Baker, R.S.: Impact of student choice of content adoption delay on course outcomes. In: LAK, pp. 16–20 (2017)
6. Allen, L.K., Mills, C., Jacovina, M.E., Crossley, S., D'mello, S., McNamara, D.S.: Investigating boredom and engagement during writing using multiple sources of information: the essay, the writer, and keystrokes. In: Proceedings of the Sixth International Conference on Learning Analytics & Knowledge, pp. 114–123. ACM (2016)
7. Allen, L.K., Perret, C.A., Likens, A.D., McNamara, D.S.: What'd you say again?: recurrence quantification analysis as a method for analyzing the dynamics of discourse in a reading strategy tutor. In: LAK, pp. 373–382 (2017)

[5] www.zoomdata.com.

8. Andrade, A.: Understanding student learning trajectories using multimodal learning analytics within an embodied-interaction learning environment. In: Proceedings of the Seventh International Learning Analytics & Knowledge Conference, LAK '17, pp. 70–79, New York, NY, USA. ACM (2017)
9. Avila, C., Baldiris, S., Fabregat, R., Graf, S.: ATCE: an analytics tool to trace the creation and evaluation of inclusive and accessible open educational resources. In: Proceedings of the Seventh International Learning Analytics & Knowledge Conference, pp. 183–187. ACM (2017)
10. Bachmann, F., Bass, L., Klein, M.: Deriving architectural tactics: a step toward methodical architectural design. Technical report, Carnegie-Mellon University, Pittsburgh, PA, Software Engineering Institute (2003)
11. Barnes, T.: The q-matrix method: mining student response data for knowledge
12. Bøegh, J.: A new standard for quality requirements. IEEE Softw. **2**, 57–63 (2008)
13. Bos, N., Brand-Gruwel, S.: Student differences in regulation strategies and their use of learning resources: implications for educational design. In: Proceedings of the Sixth International Conference on Learning Analytics & Knowledge, pp. 344–353. ACM (2016)
14. Brunskill, E.: Estimating prerequisite structure from noisy data. In: EDM, pp. 217–222. Citeseer (2011)
15. Burns, S., Corwin, K.: Automating student survey reports in online education for faculty and instructional designers. In: Proceedings of the Seventh International Learning Analytics & Knowledge Conference, pp. 590–591. ACM (2017)
16. Buschmann, F., Meunier, R., Rohnert, H., Sommerlad, P., Stal, M.: Pattern-Oriented Software Architecture, Volume 1: A System of Patterns (1996)
17. Chen, L., Dubrawski, A.: Learning from learning curves: discovering interpretable learning trajectories. In: Proceedings of the Seventh International Learning Analytics & Knowledge Conference, pp. 544–545. ACM (2017)
18. Chiu, M.M., Chow, B.W.-Y., Joh, S.W.: How to assign students into sections to raise learning. In: Proceedings of the Seventh International Learning Analytics & Knowledge Conference, pp. 95–104. ACM (2017)
19. Corrin, L., de Barba, P.G., Bakharia, A.: Using learning analytics to explore help-seeking learner profiles in MOOCs. In: Proceedings of the Seventh International Learning Analytics & Knowledge Conference, LAK '17, pp. 424–428, New York, NY, USA. ACM (2017)
20. Desmarais, M.C., Maluf, A., Liu, J.: User-expertise modeling with empirically derived probabilistic implication networks. User Model. User Adapt. Interact. **5**(3-4), 283–315 (1995)
21. Esaki, K., Azuma, M., Komiyama, T.: Introduction of quality requirement and evaluation based on ISO/IEC square series of standard. In: International Conference on Trustworthy Computing and Services, pp. 94–101. Springer (2012)
22. Ferguson, R.: Learning analytics: drivers, developments and challenges. Int. J. Technol. Enhanc. Learn. **4**(5–6), 304–317 (2012)
23. Gorton, I.: Software quality attributes. In: Essential Software Architecture, pp. 23–38. Springer (2011)
24. Harlen, W., James, M.: Assessment and learning: differences and relationships between formative and summative assessment. Assess. Educ. Princ. Policy Pract. **4**(3), 365–379 (1997)
25. Jayaprakash, S.M., Moody, E.W., Lauría, E.J.M., Regan, J.R., Baron, J.D.: Early alert of academically at-risk students: an open source analytics initiative. J. Learn. Anal. **1**(1), 6–47 (2014)
26. Nabeel, M., Shang, N., Bertino, E.: Efficient privacy preserving content based publish subscribe systems. In: Proceedings of the 17th ACM Symposium on Access Control Models and Technologies, pp. 133–144. ACM (2012)
27. Paliwal, G., Kiwelekar, A.W.: A product line architecture for mobile patient monitoring system. In: Mobile Health, pp. 489–511. Springer (2015)
28. Rozanski, N., Woods, E.: Software Systems Architecture: Working With Stakeholders Using Viewpoints and Perspectives, 2nd edn. Addison-Wesley Professional (2011)
29. Sreenivasa Sarma, B.H., Ravindran, B.: Intelligent tutoring systems using reinforcement learning to teach autistic students. In: Home Informatics and Telematics: ICT for The Next Billion, pp. 65–78. Springer (2007)

30. Segall, D.O.: Computerized adaptive testing. Encycl. Soc. Meas. **1**, 429–438 (2005)
31. Sprague, A.: Improving the ESL graduate writing classroom using socrative: (re)considering exit tickets. TESOL J. **7**(4), 989–998 (2016)
32. Thönes, J.: Microservices. IEEE Softw. **32**(1), 116–116 (2015)
33. Trossen, D., Sarela, M., Sollins, K.: Arguments for an information-centric internetworking architecture. SIGCOMM Comput. Commun. Rev. **40**(2), 26–33 (2010)
34. Uram, T.D., Papka, M.E., Hereld, M., Wilde, M.: A solution looking for lots of problems: generic portals for science infrastructure. In: Proceedings of the 2011 TeraGrid Conference: Extreme Digital Discovery, TG '11, pp. 44:1–44:7, New York, NY, USA. ACM (2011)
35. Van der Linden, W.J., Glas, C.A.W.: Computerized Adaptive Testing: Theory and Practice. Springer (2000)

Chapter 8
Multimodal Learning Analytics in a Laboratory Classroom

Man Ching Esther Chan, Xavier Ochoa and David Clarke

Abstract Sophisticated research approaches and tools can help researchers to investigate the complex processes involved in learning in various settings. The use of video technology to record classroom practices, in particular, can be a powerful way for capturing and studying learning and related phenomena within a social setting such as the classroom. This chapter outlines several multimodal techniques to analyze the learning activities in a laboratory classroom. The video and audio recordings were processed automatically to obtain information rather than requiring manual coding. Moreover, these automated techniques are able to extract information with an efficiency that is beyond the capabilities of human-coders, providing the means to deal analytically with the multiple modalities that characterize the classroom. Once generated, the information provided by the different modalities is used to explain and predict high-level constructs such as students' attention and engagement. This chapter not only presents the results of the analysis, but also describes the setting, hardware and software needed to replicate this analytical approach.

8.1 Introduction

Sophisticated research approaches and tools can help researchers to investigate the complex processes involved in learning in various settings. As a research site, classroom settings are particularly complex and challenging to investigate, where multiple participants are involved, each with different levels and kinds of knowledge and experience and with an intricate, dynamic network of relationships between the participants. As pointed out by Hiebert et al. [31], video records allow fine-grained analysis of the complex classroom interactions through replaying the recording and examining the interactions from multiple dimensions or perspectives. Such records also allow cross-validation of observations and re-examination at a later time as new

M. C. E. Chan (✉) · D. Clarke
Melbourne Graduate School of Education, The University of Melbourne, Victoria, Australia
e-mail: mc.chan@unimelb.edu.au

X. Ochoa
New York University, New York, USA

M. Virvou et al. (eds.), *Machine Learning Paradigms*, Intelligent Systems Reference Library 158, https://doi.org/10.1007/978-3-030-13743-4_8

theories or perspectives emerge [13, 14, 18]. The use of video technology to record classroom practices therefore can be a powerful way for capturing and studying learning and related phenomena within a social setting such as the classroom [53]. However, the resulting video data can be time-consuming to process in terms of information extraction and to analyze.

The laboratory classroom at The University of Melbourne is able to generate high-resolution video records of classroom social interactions with a rich amount of detail. The facility was purposefully designed and built to allow simultaneous and continuous documentation of classroom interactions using multiple cameras and microphones. The facility has been utilized by several research projects since its launch in March 2015, one of which was the Social Unit of Learning project [12], which examined individual, dyadic, small group (four to six students) and whole class problem solving and learning in mathematics and the associated/consequent learning. This chapter presents several multimodal techniques to analyze the learning activities in such a laboratory classroom. Once generated, the information provided through the different modalities can be used to explain and predict high-level constructs such as students' attention and engagement.

The next section (Sect. 8.2) provides a brief history of the methodological and technological evolution of classroom research. The laboratory classroom setting (Sect. 8.3), the Social Unit of Learning project (Sect. 8.4), and the conceptualization of student engagement in this project (Sect. 8.5) are then outlined. An overview of multimodal learning analytics (Sect. 8.6) and the observation data used in this study (Sect. 8.7) are provided. Several multimodal features relevant to engagement are selected, extracted and evaluated. These features include student gaze direction (Sect. 8.8.1.1), student posture (Sect. 8.8.1.2), teacher position (Sect. 8.8.1.3), student talk (Sect. 8.8.1.4), and teacher talk (Sect. 8.8.1.5). The visualization of some of these features is illustrated in Sect. 8.8.2. To demonstrate how multimodal learning analytics can be applied in education research, Sect. 8.9 provides an illustration of the way particular high level constructs can be examined based on several multimodal features. These high level constructs include attention to teacher speech (Sect. 8.9.1), teacher attention (Sect. 8.9.2), concentration on individual task (Sect. 8.9.3), and engagement during pair- and group-work (Sect. 8.9.4). The chapter concludes by discussing the research and pedagogical implications of the multimodal learning analytics approach reported here (Sect. 8.10) and the significance of the methodological and technological advances made in the study so far (Sect. 8.11).

8.2 Classroom Research

Classroom research can be traced back to early investigations into learning and concept formation. Historically, investigations of learning were typically clinical experimental studies of a small number of individuals [16]. Microgenetic research, for example, examines concept formation, usually in the area of cognitive and language development (e.g., [24, 42, 54]). One of the major goals of microgenetic research is to capture in detail the processes involved in qualitative changes in a person's thinking, such as the process of solving a complex problem. With the early focus on the individual, learning studies were traditionally laboratory-based, where the researcher has a high level of control over the experimental conditions (e.g., [49]), and is well-placed to frame and test hypotheses. However, the experimental setting may limit the extrapolation of findings to natural or authentic (less artificial, contrived experimental) setting.

In the past 50 years, learning in classroom settings became increasingly the subject of research and this interest was accompanied by the development of onsite real-time observational techniques (e.g., [1, 3]). The process-product approach to education research (e.g., [6, 28]) sought to identify statistically significant associations between classroom process variables (e.g., number of teacher questions) and product variables (typically measures of student achievement or attitude). Limited by correlational logic, process-product studies suggested rather than proved any causal connection between variables (Antonakis et al. [2]). In contrast to experimental and process-product approaches, ethnography involves a family of diverse qualitative investigative approaches focusing on detailed description or the generation of deductive explanation (as opposed to hypothesis testing) [40]. Naturalistic case studies of student learning in authentic classroom settings (e.g., [15, 20, 22]) drew upon the practices of ethnographic research to understand the relationships between individuals, their practice, and their consequent learning in classroom settings.

The move towards fine-grained detailed analysis of classroom practice has facilitated the contemporary use of video (e.g., [32]. The affordability of video technologies and computer processing power has given rise to the increased use of video in classroom research. International comparative studies of classroom practice have been undertaken using video as a key data collection tool (e.g., [17, 51]). More recently, university-based and school-based classrooms equipped with video and audio facilities have been set up around the world, such as in the USA, the Netherlands, and China [12]. The Science of Learning Research Classroom at the University of Melbourne in Australia is one such facility.

The use of videos in classroom research has imposed additional processing demands associated with analyzing video data. The notion of processing demand is invoked in two senses: one involves the technical processing and configuration required to prepare the data suitably for analysis, and the other is the interpretive processing required for any coding process/activity. In this chapter, we consider both senses of processing demand. Qualitative analytical software, such as vPrism, NVivo, and Studiocode, has been developed and used to code video data or transcripts based on the video data [18]. Such software has assisted researchers to code and visually present coded video data, link these data to transcripts, and carry out textual searches of transcribed data more efficiently (see Fig. 8.1). Nonetheless, much of the coding and transcription process still needs to be carried out manually and this can be highly time-consuming and prone to inconsistency and error. The multimodal learning analytics technique developed for the Social Unit of Learning project provided much-needed automation for extracting visual and audio information from videos

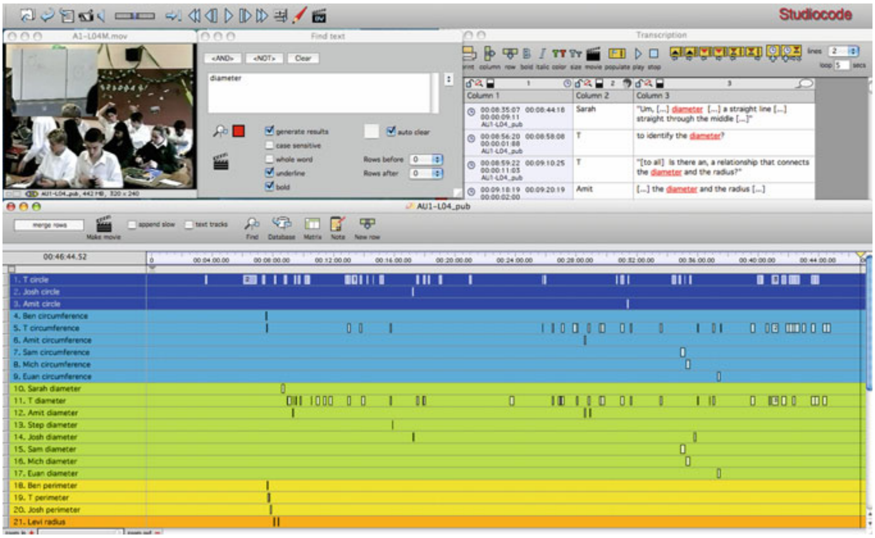


Fig. 8.1 Sample analytical display in Studiocode—video window (top left), transcript search screen (top middle), transcript window (top right), and time-line (bottom)

and processing the large volume of data that were being generated for the project using the Science of Learning Research Classroom.

8.3 The Science of Learning Research Classroom

The Science of Learning Research Classroom at the University of Melbourne (https://pursuit.unimelb.edu.au/articles/high-tech-classroom-sheds-light-on-how-students-learn) was set up through an Australian Government Special Research Initiatives Grant (ARC-SR120300015). The laboratory classroom is a 129 sq. m. teaching space that resembles a typical classroom, but is fitted with high definition audio-visual recording equipment and physically connected to an adjacent Control Room via a one-way window (Fig. 8.2). Lessons given in the research classroom can be recorded through up to 16 high-definition video channels and up to 32 fixed and portable microphones. In the Control Room are screen monitors and computer equipment that allow a technical team to control and monitor the data generated by the recording equipment in the research classroom. Researchers can also observe the activities within the research classroom from the Control Room as the lesson progresses, either by direct observation through the one-way viewing window or on any of the monitors displaying the images recorded by the different video cameras and by listening to any of the audio channels. Observation is also possible via live

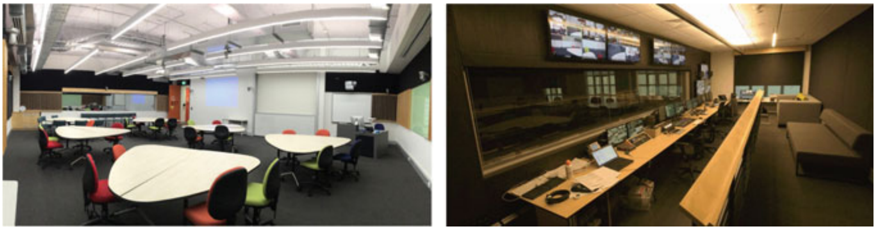


Fig. 8.2 Images of the Science of Learning Research Classroom (left) and the Control Room (right). Images reproduced from Chan and Clarke [9]

streaming of selected video outputs to remote locations. The laboratory classroom therefore affords a variety of collaborative research modes.

The Science of Learning Research Classroom offers education researchers a facility with cutting-edge technology that can document classroom activities at an unprecedented level of detail. The classroom can simultaneously record the activities of a single class of students working in small groups (e.g., six groups of four students) while tracking the movement and speech of the teacher throughout an instructional sequence. Researchers no longer need to be selective as to which group or groups of students they want to study in the classroom. Rather than inferring the experience of the whole class based on the observation of a few target students, the facility can capture in detail the activities of all students so that hypotheses regarding the behaviors of a few students can be tested against all other students who shared the same classroom activities and teacher instructions.

8.4 The Social Unit of Learning Project

The Social Unit of Learning project [12] investigated the social phenomena that characterize learning processes in a mathematics classroom. The development of the laboratory classroom has made possible a research design that combines better approximation to natural social settings with the retention of some degree of control over the research setting, task characteristics, and possible forms of social interaction. The project used the laboratory classroom facilities to record the interactions of an intact class of students (20–26 students per class) and their teacher as they engaged in researcher-developed mathematical activities. A typical investigative session took 50–60 min, where students attempted tasks individually, in pairs, and in groups of four to six. Figure 8.3 illustrates one of the activity configurations utilized in the project. The sessions were designed to facilitate recordable (visible and audible) social interactions, necessitated by the obligation to solve content-specific mathematical tasks collaboratively. The resulting data collected in the project included: all written material produced by the students; instructional material used by the teacher; video footage of all of the students during the session; video footage of the teacher

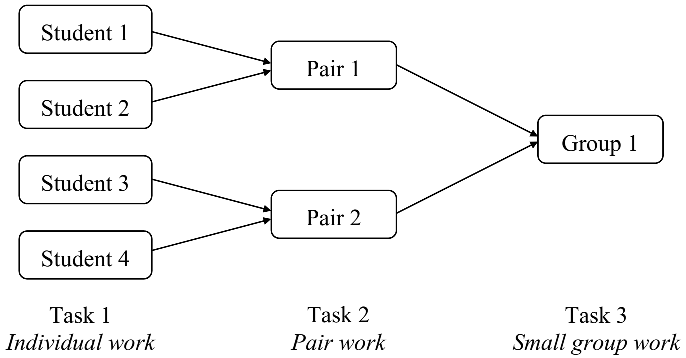


Fig. 8.3 Student grouping for three task conditions within a single investigative session. Image reproduced from Chan and Clarke [11, p. 956]

tracked throughout the session; transcripts of teacher and student speech; and pre- and post-session teacher interviews.

Compared to school-based classroom research, the research design of the Social Unit of Learning project allowd conclusions about connections between interactive patterns of social negotiation and knowledge products (learning) to be made with greater confidence. This allowd the examination of data from multiple perspectives by multiple researchers as well as the reciprocal interrogation of the different theoretical perspectives [10]. One line of inquiry in this project was the connection between student engagement and the process and consequence of learning during collaborative problem solving in mathematics. The identification of the form and function of student engagement within a classroom setting constituted the focus of this investigation.

8.5 Conceptualization(s) of Engagement

The construct of student engagement is seen both as a precondition for classroom learning and a school accountability outcome in many educational systems around the world [52]. However, measures of student engagement often rely on student self-report or teacher-report rather than direct observation of in-class student behaviors [8, 30]. The indicators of engagement also vary widely depending on the definition of engagement implicit in the measure (e.g., [25, 27, 48]. Student engagement essentially describes "a state of being when a person is cognitively, behaviorally and emotionally involved in learning activities and maintaining a heightened sense of concentration, interest and enjoyment during those activities" [8, p. 11]. It is a multifaceted construct that can involve behavioral (participation and involvement in academic or curricular activities), emotional (positive and negative reactions towards the school community including teachers and classmates), and cognitive (thoughtfulness and willingness to invest effort in learning activities) components [25]. Furthermore, engagement is a subjective experience of the learner, and such experience can occur inside or outside the classroom [48]. Unlike the concept of motivation, which places greater attention on the agency of an individual in terms of the energy or drive pertaining to the person [26], the concept of engagement places greater emphasis on the interactions and transactions between an individual and the environment, and is therefore always situated.

The data generated from the Social Unit of Learning project offer a unique opportunity to study student engagement in a classroom setting. The rich information allows the multifaceted nature of the construct to be examined. Helme and Clarke [30], in particular, distinguished between *participation* (i.e., behavioral engagement) and *active engagement* (i.e., cognitive engagement) and argued that the two are qualitatively different, and require different forms of evidence. Participation has been measured in terms of time-on-task (e.g., [29, 43]) while active engagement relates to indicators (e.g., linguistic and non-verbal cues) of students' cognitive and metacognitive activity.

Compared to cognitive engagement, which tends to require detailed linguistic or discourse analysis (e.g., [47]), multimodal learning analytics appears to be particularly suitable for examining the behavioral aspect of student engagement through the detection of observable behavioral indicators (e.g., student gaze, posture, and talking time). The technique can also be used to extract information about teacher behaviors during the class which may provide further pedagogical insights. In addition, as highlighted by the analysis of Helme and Clarke [30], the situatedness of engagement suggests that different indictors of engagement may be more relevant to some classroom activities or tasks than others. Asking and answering questions, for example, may be relevant as an engagement indicator for collaborative small group activities or whole class interactions with the teacher, but less likely to be evident during individual work. Instead, verbalizing thinking (e.g., self-talk) and self-monitoring could be more relevant as indicators of cognitive engagement when students are working individually. The application of different multimodal learning analytic techniques for examining engagement during different classroom activities based on the data generated from the Social Unit of Learning project forms the focus of this paper.

8.6 Multimodal Learning Analytics of Engagement in Classrooms

Learning Analytics has been defined as "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" [23, p. 305]. As such, it tries to tackle the same questions as traditional Educational Research, but by utilizing the analysis of data produced by the learner during the learning process. However, due to the abundance of readily available data from online learning systems, the initial focus of Learning Analytics has been the study of the learning process that happens on online learning systems such as Learning Management Systems (LMS) and massive open online courses (MOOCs) [38].

In recent years, there is a strong movement towards applying Learning Analytics in learning settings other than online learning systems, such as in face-to-face and other physical learning spaces. This is evident through the increased number of scientific papers that analyzed data captured from the physical world published in the Learning Analytics and Knowledge (LAK) conference and the *Journal of Learning Analytics* (JLA) [39], the main scientific venues for Learning Analytics research. This new line of research is generally known as Multimodal Learning Analytics (MMLA) [5].

MMLA attempts to incorporate different sources of learning data captured from the real world into Learning Analytics research and practice, focusing on understanding and optimizing learning scenarios where the interactions are not necessarily mediated through a computer or digital device [38]. In MMLA, the "learning traces" are extracted from different digitally accessed modalities (e.g., visual, aural, and written), such as video and audio records, text records from digital pens, and so on. These learning traces are combined to provide a more comprehensive view of the actions of the learner. This idea of fusing different modalities to study learning is shared by traditional experimental education research, where a human observer, that is by nature a multimodal sensor and analyzer, observes the learning process, extracts information (i.e., data) from the observation through coding or tagging, and formulates conclusions based on the analysis of the data. MMLA adopts the same research method but pushes this methodology forward through the use of more advanced and precise sensors than human eyes and ears. The technique expands the amount of data that can be captured and the speed at which they are analyzed through the use of automated tagging and machine learning-based and artificial intelligence-based analysis algorithms. If different modalities could be recorded and learning traces could be automatically extracted from these modalities, Learning Analytics tools could potentially be built and used to provide continuous, real-time feedback loops to improve learning as it is happening.

It is important to note that MMLA is (and needs to be) a multi-disciplinary field. Techniques developed in Computer Vision, Speech Processing, Sketch Recognition and other Computer Science fields need to be guided by the current learning theories provided by Learning Science, Education Research, and Behavioral Science to capture different modalities, extract relevant features, and fuse them to measure the construct needed to provide answer to pedagogical questions. This chapter illustrates how MMLA techniques can be used to operationalize and possibly quantify the construct of student engagement based on the multimodal data captured in the Science of Learning Research Classroom.

8.7 Observation Data

The observation data that the MMLA were applied to in this chapter consisted of multi-camera video and multi-channel audio recording captured in the Social Unit of Learning project. The activities recorded were the teacher-student and student-student interactions during a 60-min session where Year 7 students (12- to 13-year-olds) were involved in a set of six problem solving tasks facilitated by their regular teacher. A total of five groups of four students and a group of three students (23 students in total) and a teacher were part of the observation. All of the students carried out the first set of tasks individually. For the groups with four students, the next set of tasks were carried out in pairs, and the final set of tasks by the whole group. The group of three carried out the pair tasks as a group.

The multi-camera video data set consisted of eight standard quality videos of approximately one hour each. Six of those videos were captured by fixed cameras pointed to each of the student work groups (front view of the group). Two microphones were placed in the middle of the table of each work group providing stereo audio to each video for each student pair (in separate left and right audio channels) and group (left and right audio channels in stereo). The seventh video is a tracking shot of the teacher, captured by several cameras in the classroom. The audio of the video was printed from the lavalier microphone that the teacher wore during the session. The final video is a wide-angle shot of the whole classroom. The audio of the video came from the built-in microphone on the camera. A map of the research classroom was constructed to estimate the spatial relationships between the different video sources. These multimodal recordings and a map of the classroom were used to extract relevant features (Table 8.1).

Table 8.1 Summary of video and audio recordings analyzed

<table>
<tr><th>Video types</th><th>Number of videos</th><th>Camera view</th><th>Video specification</th><th>Audio feed</th><th>Audio specification</th></tr>
<tr><td>Student video</td><td>6</td><td>Fixed</td><td rowspan="3">Length: 3726 s
Resolution: 480 × 270 pixels
Frames per second: 25</td><td>2 microphones</td><td rowspan="3">Channels: Stereo
Length: 3726 s
Sampling frequency: 44100 Hz
Bitrate: 16 bit</td></tr>
<tr><td>Teacher tracking video</td><td>1</td><td>Composite (from multiple cameras including fixed and movable cameras)</td><td>1 lavalier microphone</td></tr>
<tr><td>Whole class video (teacher + students)</td><td>1</td><td>Fixed with wide angle</td><td>1 built in microphone</td></tr>
</table>

The video and audio recording were pre-processed in order to remove the initial technical instructions given by the researchers about the activity. The processed video and audio had a length of approximately 54 min for each video, totaling 432 recording minutes across all eight videos.

8.8 Features Selection, Extraction and Evaluation

8.8.1 Multimodal Behavioral Features

This section outlines the multimodal behavioral features that could potentially be used to operationalize and estimate the construct of student engagement. Traditional observational features related to engagement guided the feature selection process. Computer Vision and Audio Processing algorithms were to extract those features from the pre-processed video and audio recordings. An evaluation process was performed for each of the extracted features to determine the quality of the extraction. A total of four features were selected, extracted and evaluated. The following subsections detail the process for extracting each one of the features.

8.8.1.1 Student Gaze Direction

One of the main indicators used traditionally to suggest student engagement in a classroom is the gaze direction of the student [44, 45]. If the teacher is talking, it is expected that the student direct his or her gaze to the teacher. If the activity is individual student work involving solving an exercise on paper, it is expected that the student directs his or her gaze to the paper. If the activity is group discussion, it is expected that each student within the group directs his or her gaze to the other members of the group during the activity, especially to the person who is currently talking.

The data that were used to extract the gaze direction feature were the pre-processed videos with the front view of each student group. Due to the nature of the videos, it was not possible to track the eyes of the individual students (the eyes represented only a few pixels in the image). Given that we only needed the general direction of student gaze and not a precise measurement, gaze direction was estimated with the direction at which the head of a student is pointing. The direction of the head for each student was estimated using a Computer Vision library called HyperFace,[1] which uses deep learning to predict face/non-face, landmarks, pose and gender in an image. However, this implementation can only detect up to one face per image, if the face covers the majority of the image. As a pre-processing step, another library called DockerFace[2]

[1] HyperFace: Face landmarks and pose detection. https://github.com/takiyu/hyperface.

[2] DockerFace: Face detection https://github.com/natanielruiz/dockerface.

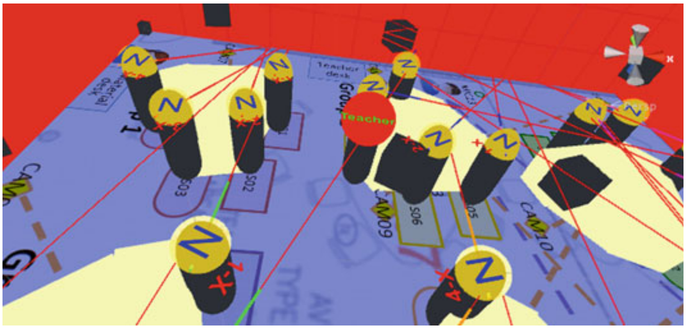


Fig. 8.4 Visualization of the student gaze direction

was used, which detects all the faces present in the images. DockerFace also uses deep learning algorithms, and returns a file with each face location per frame. This file generated by DockerFace was used to select the location of the students' faces in the video.

In the student work group videos captured in the Social Unit of Learning project, there were many faces found in each frame, not only the four student members of each group, but also other students in the background. Therefore, we developed an algorithm to keep track of the location of the students we were interested in. For this, we set the initial regions of interests (ROI) for each student face, and we matched these with the closest locations found by the face detection program. Afterwards, we used extracted images of the tracked locations of the faces, and these images were used as input to the HyperFace library. As a result, we obtained an estimation in Euler angles of the head direction for each image. These angles were converted to 3D vectors that indicated where the face of the student was directed. These vectors were stored in a comma separated values file (csv) at the frequency provided by the frame rate of the video to be later visualized. An example of these vectors can be seen in Fig. 8.4.

To obtain an estimation of the quality of the automatic extraction, the extraction was compared with the ground truth extracted by a human observer. Only two human observers were used to perform the tagging of the video frames due to the objective and mechanic nature of the feature being measured. Fifty random frames from the video feed were extracted from the six existing videos. The human observers had to determine if they agreed or disagreed with the estimation made by the extraction algorithm. The inter-rater reliability measure obtained was high (0.92). One evaluator agreed with the computer estimation 84% of the time, while the second evaluator agreed with the computer estimation 83% of the time. These numbers suggest that the feature of student gaze direction can be used with a high level of confidence.

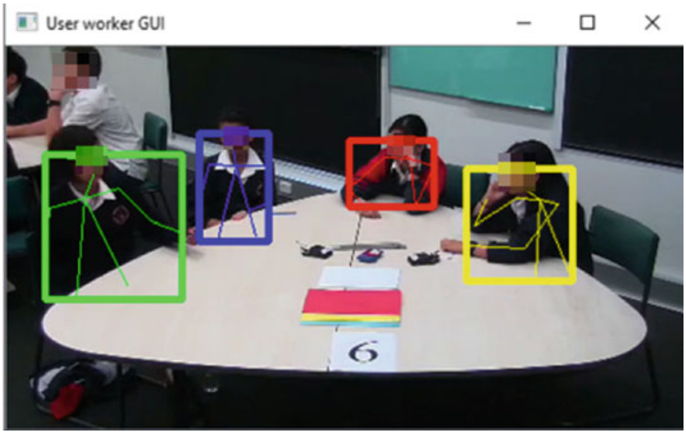


Fig. 8.5 Extracted body skeletons of the students

8.8.1.2 Student Posture

The link between posture and affect has been a well-researched area in psychology, giving rise to the field of affective computing (cf., [41]). Drawing from psychological studies, computer scientists are able to recognize the affective state of a person from body posture (e.g., [33]). During all of the activities in the recorded session in the Social Unit of Learning project, the students were sitting around the group table. The sitting posture that the students adopted could indicate their level of engagement in the activity [36], especially for activities that involved reading or writing [37]. The six student videos were used to extract the student posture feature. In these videos, there is a clear view of the upper and middle body of each of the students in the group.

To start the process of student posture detection, it was first necessary to identify the students belonging to the same group. As mentioned before, the videos not only contain images of the students in the focal group, but also students from groups beside and behind the focal group in the background. The specific student detection was solved using a general ROI that contained only the students of a same group. This ROI was set manually, and differs from each video depending on the location of the camera and the students. Once we had detected the students of the same group, it was also necessary to identify each student of the group, labeling them from 1 (leftmost student) to 4 (rightmost student). For this detection, a manual ROI was also used for each student in conjunction with the posture detection explained below.

For the posture detection, two Computer Vision libraries were used. The first one was OpenPose, which is a tool that detects all the body skeletons that appear on a video. Once the region of a student was established (student detection), OpenPose extracts only the body skeletons of the required students in each video. The results can be seen in Fig. 8.5.

Although OpenPose provides several key points from the skeleton, only a few of those body key points were used to detect the posture of the students (Nose, Neck, Right hip and Left hip). According to the combination of values of those key points, the posture detection algorithm classified the posture of a student as Inclined, Reclined and Neutral. The points were selected based on a human expert evaluation of the influence of the different points in distinguishing between those postures.

An algorithm based on fuzzy clustering [4] was used to create a model to predict the posture of a student based on the geometric relations of the position of the key points belonging to the extracted skeleton of the student posture. The first geometric relation used was the angle formed between the line that passes through the neck point and right or left hip point (depending on the position of the student with respect to the camera) and the x-axis. This can vary from 0° to 180°. The second geometric relation used was the angle formed between the line that passes through the nose point and the neck point and the x-axis and can vary from 0° to 360°. Based on these geometric relations and the position of the student, the algorithm classified the posture of a student as Reclined, Inclined and Neutral.

The extraction of the posture information was evaluated using the 50 random frames of the video from the six student videos. Two human observers were asked to specify the posture of the students based on three options: Reclined, Inclined, and Neutral. These values were compared to the postures detected by the algorithm. The inter-rater reliability coefficient was high (0.90). The first observer agreed with the algorithm for 67.5% of the postures, and the second one for 70%. These results suggest that this feature can only be used with a moderate level of confidence for coding automation.

8.8.1.3 Teacher Position

In the Social Unit of Learning project, the teacher played an important role as he or she was the person giving students the instructions to the activities, providing them with information about the activities, and ensuring productive student work. When determining the engagement level of the students during the problem solving activity, it is important to consider the physical position of the teacher with respect to the different groups. The information could be used in various ways, such as to understand the relationship between teacher attention (in terms of physical proximity to a student group) and student engagement, or where students' attention should be when the teacher is providing instruction.

In order to detect the physical position of the teacher, first, a general ROI was set manually for all the videos, which covered the area in the room where the students were working. Next, we used OpenPose to detect all the bodies within the ROI to avoid unnecessary processing. To facilitate the detection of the teacher among the skeletons detected in the image, we selected two physical characteristics that differentiated the teacher from the students: the body size and the clothing color.

To proceed with the teacher position recognition, we used a color detection and tracking library. First, thresholds were defined for each Red/Green/Blue (RGB) channel. Second, ROIs were obtained from the skeletons detected for each frame. All ROIs that did not correspond to the body size of the teacher were eliminated. From all the remaining ROIs that corresponded with an adult in the video, the average color of the pixels was compared with the detected color of the clothing of the teacher. If the color matched, the position of the teacher was estimated to be near the current group table. A visualization of the position of the teacher can be seen in Fig. 8.4 (red circle).

For evaluating the quality of the teacher position estimation, 163 random frames were obtained from each of the groups' videos. Two human observers were asked to view six frames (one per group) of the same moment in time, and specify near which group the teacher was. The evaluators agreed with each other 100% of the time. These values were compared to the automatic detection using the algorithm, and both evaluators agreed with 60% of the automatic detection. This suggests that this feature provides a low level of confidence for coding automation.

8.8.1.4 Student Talk

The activities conducted during the session had different levels of interaction between students. At certain moments, the students were silent listening to the teacher's instructions. At another moment, the students were engaging in conversation among themselves to solve a group activity. Obtaining a feature that reflects the noise level at each table could be used to estimate the level of conversation and social interactions in different activities.

To obtain this feature of student talk, first, the audio signal was extracted from the group videos. A preliminary analysis was performed to define three levels of volume in the audio files labeled as Silence, Low Talking and High Talking. A human evaluator listened to the audio files and segmented several samples for each level. The volume of the segmented samples was averaged and two thresholds were defined. A Python script was developed to automatically classify the audio levels according to the defined thresholds.

The accuracy of the student talk feature was evaluated through classifying a set of 60 audio samples by the computer system and two human observers. First, the human observers listened to three examples corresponding to each volume level. Second, they classified the 60 samples. The inter-rater reliability coefficient was medium (0.72). Accuracy was evaluated in terms of the number of matches between human evaluators and the extraction algorithm. Preliminary results showed poor accuracy (51% average) when comparing both human and machine classifications. The lack of agreement was especially notorious for the Low and High Talking levels. We concluded that this happened because humans do not rely on static thresholds to classify volume of the voice, but perform a more general estimation. Also, the microphones placed on each group table were omnidirectional. This led the student group's audio to record other voices from the teacher and classmates nearby from other groups. In a second approach, the levels Low and High Talking were merged into a single level called Talking. A new comparison was performed based on the two levels. Results reported an accuracy of 70%. This level of accuracy provides a high level of confidence in the use of the extracted feature.

8.8.1.5 Teacher Talk

Regardless of the pedagogical tradition of a classroom, it is reasonable to assume that teacher public talk is an important moment during a lesson, worthy of student attention [19]. Determining when the teacher is talking therefore could be useful to identify the moments when engaged students should be paying attention to the teacher.

The teacher audio was extracted from the teacher video and classified following the same technique used for student talk (Sect. 8.1.4). The audio from the teacher was automatically classified into three volume categories (Silence, Low Talking and High Talking), by the computer system prior to human evaluation.

Similar to the student talk feature, the same evaluation approach was carried out for teacher talk. The same classification problem was present when three audio levels were used (only 67% accuracy). Again, the Low and High Talking levels were merged into a single Talking level. The agreement between humans and the algorithm was 90%. The higher level of agreement in the evaluation of teacher talk was strongly associated with the placement of the microphone, which was closer to the mouth of the speaker throughout the session. This precision level provides very high confidence in the use of teacher talk as an extracted feature.

8.8.2 Feature Visualization

An interactive visualization of some of the extracted multimodal features was developed based on the top-view map of the classroom and the video and audio input sources. A simulation of the group dynamics is visualized as a 2D top-view replica of the classroom developed in the Unity game engine. Figure 8.6 shows the different elements of the visualization representing the extracted features. The teacher (red circle) and students (yellow circles) are dynamic elements that react according to the automatic analysis. Besides the teacher and students, this environment shows other virtual graphical object, such as tables (pale yellow trapezoids), cameras (black squares), room structures (red walls), and labels that identify the key elements in the simulation.

In this visualization, every student is shown as a circle with a straight line coming out from it. This line is intended to denote the viewing direction of each student. To estimate each student's viewing direction, a directional vector $\overrightarrow{v_d}$ was calculated to draw the desired line by using the given vector $\overrightarrow{V_x}$ from the file and rotating the vector regarding a reference which is the camera that is pointing to the group where the student is. The estimation of the posture of each student is represented in

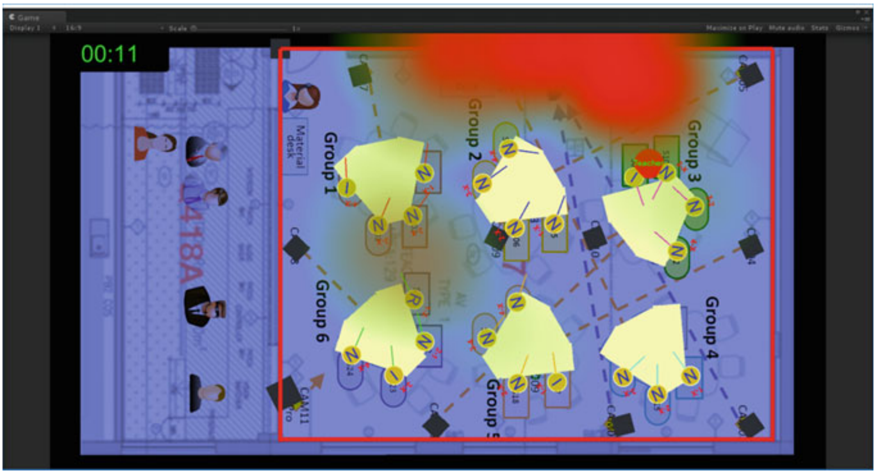


Fig. 8.6 Visualization of some of the extracted features. The elements in the image include the teacher (red circle), students (yellow circles), tables (yellow trapezoids), cameras (black squares), and the density of student attentional focus (red blobs)

this visualization as a letter on top of each student. The letters represent the three classified postures: Inclined (I), Reclined (R) and Neutral (N).

To better visualize the focus of the students' attention, a heatmap is embedded in the image representing the classroom areas which more students were looking at. A strategy with virtual collisions was implemented. The simulation tool has a built-in physics engine that was used to model a 3D representation of the room as virtual colliders, which are invisible elements that can interact with objects by using physical models from the real world. In our case, the physics engine provided a tool to use rays that can be thrown towards a given direction and obtains the position information from the object that intersected with one of these rays. The collision position of a ray with an object can then be obtained to calculate the location in the room with a high concentration of intersection points. The calculation involved considering the viewing directions of individual student as vectors to drive the rays, as can be seen in Fig. 8.6. A shader was then used to draw diffuse circles according to the density of points with the result shown in the figure. The intensity, radius, and color gradient depended on the accumulation of intersection points in an area. Also in Fig. 8.6, the heatmap appears in red color and it is easy to identify that the students were paying attention to the position where the teacher was at that moment in the session.

8.8.3 Feature Extraction Conclusions

Accordingly, the MMLA techniques applied were able to successfully extract relevant features to quantify and visualize teacher and student behaviors and activities related to student engagement based on the classroom video and audio recordings from the Social Unit of Learning project. Existing Computer Vision and Audio Processing libraries enabled the quantification of basic indicators of student and teacher behavior such the area where the students were looking, the posture of the students, the position of the teacher in the classroom, and the talk volume of both the students and the teacher. The medium to very high level of confidence in the estimation of the extracted features suggests the viable use of these features in place of human observation or manual coding. Although each of the features on its own may only provide a rudimentary indicator of student engagement, in combination, the extracted features may help to paint a better picture of the internal state of an individual. The combination of student gaze with posture and speech, for example, may provide a better indicator of student engagement than a single behavior or activity indicator. The combined use of these features is illustrated in the next section.

8.9 Illustration of High Level Construct Based on Features Extracted

To provide an example of the capabilities of MMLA to be used in education research, the features extracted in the previous section were combined to automatically detect evidence for behavioral and cognitive indicators of student engagement. Given the nature of the observation, this analysis was exploratory and only descriptive of the single session analyzed in the Social Unit of Learning project.

8.9.1 Attention to Teacher Speech

A common behavioral indicator of engagement is attention to the teacher during class, for example, when the teacher is explaining the instructions of a task. It is expected that a student who is paying attention to the teacher is looking at the teacher and is probably not talking to other people at the same time. Even though looking at the teacher and not talking do not directly suggest that a student is paying attention, the absence of these behaviors (i.e., a student not looking at the teacher while talking at the same time) can be considered as a clear indicator of lack of attention.

The gaze, teacher position, teacher talk and student talk features can be fused to obtain a general measurement of the level of student attention that the teacher is capturing during his or her interventions. The fusion strategy is straightforward: (1) Identify the moments when the teacher was actively talking to the classroom (High

Talking state in the teacher talk feature) were used to segment the whole recording. (2) From the moments identified in (1), determine the moments when the gaze of all the students (directional vectors) intersected with the extracted position of the teacher. A threshold-based comparison was used to account for inaccuracies in the gaze and position detection. (3) Calculate a first score (Visual Attention) as the simple count of the percentage of students who were looking at the teacher for each window of video (five frames or 200 ms). This sum was divided by the total number of analyzed windows to obtain an average Visual Attention score. (4) Calculate a second score (Auditory Attention) based on the student talk feature. A point was added to this score for each audio window (200 ms) when the student talk feature is in Silence or Low Talk for all student groups. The adjusted score is then divided by the total number of windows in which the teacher was talking to the whole group to obtain the average Auditory Attention score.

When applied to the test recording, the teacher obtained an average Visual Attention score of 0.34 and an average Auditory Attention score of 0.25. These numbers by themselves provide little pedagogical insight. The numbers suggest that the teacher was being watched by a third of her students while she was talking and only commanded the silence of the classroom a quarter of the time. These values, however, could be useful for comparison between teachers, pedagogical strategies, activities being performed, students groups, present distractors, time of the day, or so on.

In addition, the level of student attention could be estimated during different moments of the class. For example, the class period can be segmented into different activities and the scores can be calculated for each one of these segments. For the session studied, the whole session was divided into three moments. In the first moment which corresponded to individual student work, the average Visual Attention score was 0.72 and average Auditory Attention score was 0.49. During the second moment which corresponded to student pair work, the average Visual Attention score dropped to 0.22 while the average Auditory Attention score dropped to 0.08. During the last moment, student group work, the average Visual Attention score dropped to 0.02 and the average Auditory Attention score dropped to 0. This decomposition, based on time provides a better picture of the effectiveness of classroom-wide communication during the different activities. For instance, the teacher's attempts to announce a short message to the class during the group activity did not capture the attention of the students.

8.9.2 Teacher Attention

There is a known relationship between the behavioral patterns of the teacher and the engagement of students during class [50]. One of these behavioral patterns is the preferred physical position in the classroom that the teacher occupies during instruction [34]. In this study, the physical proximity of the teacher to each student group can be used as an indicator to estimate the attention that the teacher was paying towards each group.

Table 8.2 Percentage of time the teacher spent near each group

Group	Number of windows	Percentage (%)
1	957	7
2	4890	37
3	2967	22
4	874	7
5	2513	19
6	1028	8

To explore this indicator, the teacher position among the student groups was used to draw a simple statistic about the preferred groups visited during the whole session. To obtain this estimation, the number of times that the teacher was located close to a student group (teacher position feature) was divided into the total number of valid identifications of the teacher, that is, the frames in which the teacher was positively detected in the video image. Table 8.2 presents the results for the present case. It can be inferred from the table that the teacher often stood close to Groups 2, 3 and 5, while Groups 1, 4 and 6 were less attended to. The statistics does not imply appropriateness or inappropriateness of the teacher's position, as the teacher may have chosen not to intervene with a particular group because she thought that the group worked well, or that some of the groups did not seek help from the teacher as frequently as the other groups.

8.9.3 Student Concentration During Individual Task

A possible cognitive indication of engagement in individual activities is the level of concentration and avoidance of distractors [48]. A higher level of cognitive engagement can be inferred when students concentrate on the task at hand during an individual activity, even if the environment is noisy, compared to students who disengage from the task and talk to each other.

The estimation of the level of student concentration during the individual task was based on the student gaze and posture features. First, the data that corresponded to the individual task activity was segmented from the full dataset. Then, student posture and gaze were used to determine the level of concentration of each student at different noise levels at the table. Students who had an inclined posture and with gaze pointing to the table in front of them (looking down) were labeled as being concentrated in that analysis window. Finally, the number of windows in which each student appeared to be concentrating was divided by the total number of analyzed windows. The final number was the Concentration Score.

The distribution of the Concentration score can be seen in Fig. 8.7. In the case being studied, most of the students were in a high concentration state most of the

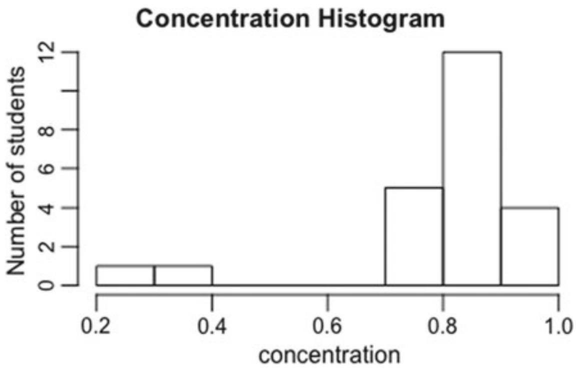


Fig. 8.7 Distribution of the Concentration score among the 24 students during the individual task

time during the individual task. However, two students focused much less on the activity compared to the other students.

8.9.4 Engagement During Pair and Group Work

Visual contact, shared attention, and peer conversation can be considered as behavioral indicators of engagement during pair- and group-work. A student who actively looks towards his or her interlocutor during a conversation can be seen as demonstrating a higher level of engagement than a student who is looking at the students in the other groups or at his or her own writing. Also, two students within the same group looking at the same object (for example, a piece of paper), while talking, may suggest a higher level of task engagement than two students looking at different places.

The student gaze feature was used to estimate the level of engagement during student-student conversation. For the pair work activity, the engagement of each pair of students was determined by the percentage of time during the activity when they were looking at each other (their gaze pointed at each other) or when they were looking at the same region of space (their gaze intersected at a given location inside the classroom), given that there was Low or High Talking in the work group. This percentage of time constituted their Pairwise Engagement score.

For group work, level of engagement was estimated based on two criteria. The first criterion was the attention paid to the current speaker, calculated by the percentage of the activity time that three students were looking at the position of a fourth student in the group. The second criterion was the shared attention to an object in the classroom, calculated by the percentage of the activity time that the gaze of the four students intersected at a single point inside the classroom.

Table 8.3 presents the results for the session analyzed. The level of pairwise engagement seems very uniform among sub-groups. However, the score can discriminate between highly engaged pairs (Pair 1 in Group 6) and less engaged ones

Table 8.3 Pairwise and group engagement scores

Group	1		2		3		4	5		6	
Pair	1	2	1	2	1	2	1[a]	1	2	1	2
Pair work scores	0.43	0.30	0.65	0.52	0.35	0.13	0.29	0.25	0.20	0.65	0.52
Group work scores	0.25		0.45		0.23		0.31	0.21		0.41	

[a]Group 4 only had 3 students and the pair work included all three students

(Pair 2 in Group 3). A human observer confirmed this difference. Also notable is that the level of group engagement is usually lower than the pairwise engagement, as the engagement level depends on the four individuals in the group. It is enough to have a disruptive student to lower the score of the whole group.

8.10 Implications

This chapter has illustrated in detail several multimodal techniques for analyzing the learning activities in a laboratory classroom (individual work, and pair, group, and whole class interactions). These techniques exemplify the different implications, both technical and pedagogical, that MMLA has for classroom research and education research in general.

- Scaling observational studies
  The main constraint of analyzing classroom video and audio recordings is the high cost related to the manual tagging and analysis of the recordings. MMLA expands the capacity of researchers to process and configure video and audio data for analysis, as well as to code the data available with improved reliability and consistency. The MMLA techniques described expand the analytical possibilities from a single subject observation to observation of the whole class involving multiple student groups. The same data can be aggregated at different levels to produce different indicators with minimal recoding effort.
  Instead of observing isolated sessions, data can be captured over weeks and months. Hours of videos can be processed and analyzed automatically at a very low cost. This makes comparison between multiple classes of students over multiple sessions feasible. Researchers can control certain variables (e.g., the students participating and the teacher(s) involved) while varying others (e.g., tasks involved, topic taught, or time of the day) to explore connections between the processes, conditions, and outcomes of learning and teaching.
- Multidimensional analysis
  The use of several modalities to better understand the learning process is at the heart of MMLA. It is difficult to estimate a complex mental state based only on a single behavioral feature. For example, we cannot confidently infer attentional

focus based on eye gaze alone. However, when gaze is combined with posture and speech, each modality helps to obtain a better indicator of the internal state of student. The combination of different features extracted from the different modalities can provide diverse indicators that enable a better understanding of higher level constructs such as engagement, teamwork, and self-regulation.

- Details difficult to be detected by human observers
  The main difference that MMLA sensors and techniques offer over the human observer approach is the level of detail at which the students and teacher actions and reactions can be measured and analyzed. For example, Raca et al. [46] detected meaningful location-based delays in student reactions over time intervals that will be very hard to detect for a human observer. MMLA techniques therefore enable the extraction of features from videos that are not previously possible.
- Visualizing the classroom
  Through the extraction of features continuously from the video sources, visualizations superimposed on the recording can be created to make visible indicators that may not be apparent from still images or manual viewing of the video data. For example, a heatmap can be generated of the locus of student attention or the physical position and movement of the teacher during instruction. These visualizations help researchers to document and examine the dynamics of classroom activities.
- Real-time data processing
  One clear advantage of automatic processing is the opportunity to gather and generate information as the class progresses. Real-time analysis can be conducted using the MMLA techniques detailed in this chapter. Although it is unclear whether such feedback could be of benefit to the teacher and the students in the classroom during a lesson or not, the reduction in data processing time would offer researchers an additional data source when conducting post-lesson interview with the teacher or students immediately after the lesson.
- Less obtrusive observation
  Compared to other data collection techniques such as wearable devices (e.g., mobile electroencephalography [EEG] or gaze tracking devices), videos are relatively unobtrusive for documenting classroom practices. Teachers and students often forget about the presence of the video cameras as the class progresses [9]. The ability to infer the general attention of the teacher and students without the need to alter their appearances helps to minimize disruption or distortion to the classroom interactions.

In terms of pedagogical implications, the indictors obtained in this study have different potential classroom uses. For example, the visualization of student attention and teacher physical position, as well as student engagement scores during different activities may provide useful feedback for teachers. A teacher may want to experiment with different teaching strategies and see which strategy captures students' attention better. A teacher may also want to find out which students work better as a pair or as a group to evaluate the effectiveness of group work compared to individual work.

Despite the potential value of MMLA in classroom research, we are also cautious about applications of the techniques that could create potential adverse effects to teaching and learning. We need to stress that we are not defining engagement only based on the features that we can extract using MMLA (e.g., student gaze and posture), but suggesting different ways in which aspects of engagement can be observed and quantified. The engagement scores presented in this paper are only one form of evidence of student engagement, particularly behavioral engagement. For example, to determine students' cognitive engagement would require other sources of evidence and possibly more interpretative analysis such as discourse analysis [30, 47]. The results from the MMLA could complement such analyses, which are currently being carried out as part of the larger Social Unit of Learning project [10].

We are acutely aware of the debates surrounding the uses of learning analytics techniques in education (cf. [21, 35]). Any classroom use of the MMLA results requires careful discussion and collaboration with all of the parties involved (i.e., teachers, students, caregiver, school administrators, etc.) to avoid misuse or misinterpretation of the results. Care must be taken to ensure that the extraction and quantification of the behavioral and activity features does not distort the teaching and learning process in an undesirable way (cf. [7]). Rather than treating the MMLA results as a holistic and comprehensive representation of the classroom interactions, the results should be recognized as one out of many possible sources of feedback for teachers and students. Such caution is necessary to realize the potential benefits of the MMLA techniques to improve teaching and student learning.

8.11 Conclusion

In conclusion, this chapter showed how MMLA techniques could expand the scope and scale of classroom and education research. In the digital era of powerful computers and easily accessible video technology, researchers can take advantage of the fast-developing MMLA techniques to reduce the time and effort required for video and audio coding. This is done through automating the previously laborious video coding process and improving the quality of the coding in terms of reliability and consistency through MMLA techniques. The techniques open up exciting research possibilities for investigating various classroom and pedagogical conditions for the optimization of classroom teaching and learning. Nonetheless, the automation of data processing does not remove the need for researchers and other potential data users to be aware of the limitations of the techniques and the results generated. With care and reflectiveness, MMLA provides a powerful tool for investigating and understanding learning processes.

Furthermore, the work reported in this chapter is an example of the benefits of joining efforts between education researchers and the emerging field of learning analytics. Existing research questions could be answered through the use of more detailed measuring and coding instruments and large-scale analysis. New hypotheses regarding the process of teaching and learning could be formulated utilizing the features that can be extracted through MMLA to better serve pedagogical interests. This is a first step forward for the collaboration between learning analytics and education research.

Acknowledgements This research was conducted with Science of Learning Research Centre funding provided by the Australian Research Council Special Initiatives Grant (SR120300015) and the Discovery Projects funding scheme (DP170102541). We would like to thank the students, parents, teachers, and school staff for their invaluable support of this project. We are also very grateful to our technical team, Cameron Mitchell and Peter (Reggie) Bowman, for their expertise in operating the Science of Learning Research Classroom facility for the project.

References

1. Amidon, E., Flanders, N.A.: The effects of direct and indirect teacher influence on dependent-prone students learning geometry. J. Educ. Psychol. **52**(6), 286–291 (1961). https://doi.org/10.1037/h0043674
2. Antonakis, J., Bendahan, S., Jacquart, P., Lalive, R.: On making causal claims: a review and recommendations. Leadersh. Q. **21**(6), 1086–1120 (2010). https://doi.org/10.1016/j.leaqua.2010.10.010
3. Beeby, T., Burkhardt, H., Fraser, R.: Systematic Classroom Analysis Notation. Shell Centre for Mathematics Education, Nottingham, England (1979)
4. Bezdek, J.C., Ehrlich, R., Full, W.: FCM: the fuzzy c-means clustering algorithm. Comput. Geosci. **10**(2), 191–203 (1984). https://doi.org/10.1016/0098-3004(84)90020-7
5. Blikstein, P.: Multimodal learning analytics. In: Suthers, D., Verbert, K., Duval, E., Ochoa, X. (eds.) Proceedings of the Third International Conference on Learning Analytics and Knowledge, Leuven, Belgium, pp. 102–106 (2013)
6. Bourke, S.F.: The teaching and learning of mathematics: national report of the second phase of the IEA Classroom Environment Study (ACER research monograph No. 25). Australian Council for Educational Research, Hawthorn, Victoria (1984)
7. Campbell, D.T.: Assessing the impact of planned social change (Occasional Paper Series No. 8). Western Michigan University, College of Education, Evaluation Center, Kalamazoo, MI (1976). https://eric.ed.gov/?id=ED303512
8. Chan, M.C.E., Baker, A., Slee, R., Williamson, J.: Educational engagement through the middle years of schooling: Report for the In2COmmuinity Applied Learning Project. Victoria Institute, Melbourne, Australia (2015). https://www.vu.edu.au/sites/default/files/victoria-institute/pdfs/Educational%20Engagement%20through%20the%20Middle%20Years%20of%20Schooling%20%28web-version2%29.pdf
9. Chan, M.C.E., Clarke, D.J.: Video-based research in a laboratory classroom. In: Xu, L., Aranda, G., Clarke, D. (eds.) Video-Based Research in Education: Cross-Disciplinary Perspectives. Routledge, New York (in press)
10. Chan, M.C.E., Clarke, D.J.: Learning research in a laboratory classroom: Complementarity and commensurability in juxtaposing multiple interpretive accounts. In: Dooley, T., Gueudet, G. (eds.) Proceedings of the Congress of European Research in Mathematics Education, Dublin, Ireland, pp. 2713–2720 (2017)
11. Chan, M.C.E., Clarke, D.J.: Structured affordances in the use of open-ended tasks to facilitate collaborative problem solving. ZDM Int. J. Math. Educ. **49**, 951–963 (2017). https://doi.org/10.1007/s11858-017-0876-2
12. Chan, M.C.E., Clarke, D.J., Cao, Y.: The social essentials of learning: an experimental investigation of collaborative problem solving and knowledge construction in mathematics classrooms in Australia and China. Math. Educ. Res. J. **30**(1), 39–50 (2017). https://doi.org/10.1007/s13394-017-0209-3
13. Clarke,D.J.: International comparative studies in mathematics education. Chapter 5 In: Bishop, A.J.,Clements, M.A.,Keitel, C.,Kilpatrick, J., Leung, F.K.S. (eds.) Second InternationalHandbook of Mathematics Education, pp. 145–186. Dordrecht, The Netherlands: Kluwer Academic Publishers (2003)

14. Clarke, D.J.: Studying the classroom negotiation of meaning: Complementary accounts methodology, Chapter 7. In: Teppo, A. (ed.) Qualitative Research Methods in Mathematics Education. Monograph Number 9 of the Journal for Research in Mathematics Education, pp. 98–111. NCTM, Reston, VA (1998)
15. Clarke, D.J. (ed.): Perspectives on Practice and Meaning in Mathematics and Science Classrooms. Kluwer Academic Publishers, Dordrecht, The Netherlands (2001)
16. Clarke, D.J.: Using cross-cultural comparison to interrogate the logic of classroom research in mathematics education. In: Kaur, B., Ho, W.K., Toh, T.L., Choy, B.H. (eds.) Proceedings of the 41st Conference of the International Group for the Psychology of Mathematics Education, vol. 1, pp. 13–28. PME, Singapore (2017)
17. Clarke, D.J., Keitel, C., Shimizu, Y. (eds.): Mathematics Classrooms in Twelve Countries: The Insider's Perspective. Sense Publishers, Rotterdam, The Netherlands (2006)
18. Clarke, D.J., Mitchell, C., Bowman, P.: Optimising the use of available technology to support international collaborative research in mathematics classrooms. In: Janik, T., Seidel, T. (eds.) The Power of Video Studies in Investigating Teaching and Learning in the Classroom, pp. 39–60. Waxmann, New York (2009)
19. Clarke, D.J., Xu, L.H., Wan, M.E.V.: Spoken mathematics as an instructional strategy: The public discourse of mathematics classrooms in different countries. In: Kaur, B., Anthony, G., Ohtani, M., Clarke, D. (eds.) Student Voice in Mathematics Classrooms Around the World, pp. 13–31. Sense Publishers, Rotterdam, The Netherlands (2013)
20. Cobb, P., Bauersfeld, H.: The Emergence of Mathematical Meaning: Interaction in Classroom Cultures. L. Erlbaum Associates, Hillsdale, NJ (1995)
21. Dringus, L.P.: Learning analytics considered harmful. J. Asynchronous Learn. Netw. **16**(3), 87–100 (2012)
22. Erlwanger, S.H.: Case studies of children's conceptions of mathematics. J. Child. Math. Behav. **1**(3), 157–283 (1975)
23. Ferguson, R.: Learning analytics: drivers, developments and challenges. Int. J. Technol. Enhanc. Learn. **4**(5–6), 304–317 (2012)
24. Ferreiro, E., Teberosky, A.: Literacy before schooling (K. Goodman Castro Trans.) [Los sistemas de escritura en el desarrollo del niño]. Heinemann Educational Books, Exeter, NH (Original work published 1979) (1982)
25. Fredricks, J.A., Blumenfeld, P.C., Paris, A.H.: School engagement: potential of the concept, state of the evidence. Rev. Educ. Res. **74**(1), 59–109 (2004)
26. Frydenberg, E., Ainley, M., Russell, V.J.: Student motivation and engagement. Sch. Issues Dig. **2** (2005)
27. Gibbs, R., Poskitt, J.: Student Engagement in the Middle Years of Schooling (Years 7–10): A Literature Review. New Zealand Ministry of Education, Wellington (2010). http://www.educationcounts.govt.nz/publications/schooling/student-engagement-in-the-middle-years-of-schooling-years-7-10-a-literature-review/introduction
28. Good, T.L., Grouws, D.A.: Teaching effects: a process-product study in fourth-grade mathematics classrooms. J. Teach. Educ. **28**(3), 49–54 (1977). https://doi.org/10.1177/002248717702800310
29. Hart, L.E.: Classroom processes, sex of student, and confidence in learning mathematics. J. Res. Math. Educ. **20**(3), 242–260 (1989). https://doi.org/10.2307/749514
30. Helme, S., Clarke, D.: Cognitive engagement in the mathematics classroom. In: Clarke, D. (ed.) Perspectives on Practice and Meaning in Mathematics and Science Classrooms, pp. 131–153. Kluwer Academic Publishers, Dordrecht, The Netherlands (2001)
31. Hiebert, J., Gallimore, R., Garnier, H., Givvin, K.B., Hollingsworth, H., Jacobs, J., et al.: Teaching Mathematics in Seven Countries: Results from the TIMSS 1999 Video Study (NCES 2003–013 Revised). U.S. Department of Education, National Center for Education Statistics, Washington, DC (2003). http://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2003013
32. Janík, T., Seidel, T. (eds.): The Power of Video Studies in Investigating Teaching and Learning in the Classroom. Waxmann, Münster, Germany (2009)

33. Kleinsmith, A., Bianchi-Berthouze, N.: Recognizing affective dimensions from body posture. In: Paiva, A., Prada, R., Picard, R.W. (eds.) Proceedings of the Affective Computing and Intelligent Interaction Conference, Lisbon, Portugal, pp. 48–58 (2007)
34. Lim, F.V., O'Halloran, K.L., Podlasov, A.: Spatial pedagogy: mapping meanings in the use of classroom space. Camb. J. Educ. **42**(2), 235–251 (2012)
35. Marshall, S.: Exploring the ethical implications of MOOCs. Distance Educ. **35**(2), 250–262 (2014). https://doi.org/10.1080/01587919.2014.917706
36. Mota, S., Picard, R.W.: Automated posture analysis for detecting learner's interest level. In: Martinez, A.M., Tan, H.Z. (eds.) Proceedings of the Conference on Computer Vision and Pattern Recognition Workshop, Madison, WI, vol. 5, pp. 49–54, June 2003
37. Ochoa, X., Chiluiza, K., Méndez, G., Luzardo, G., Guamán, B., Castells, J.: Expertise estimation based on simple multimodal features. In: Proceedings of the 15th ACM on International Conference on Multimodal Interaction, pp. 583–590. ACM, Dec 2013
38. Ochoa, X.: Multimodal learning analytics. In: Lang, C., Siemens, G., Wise, A.F., Gaševic, D. (eds.) The Handbook of Learning Analytics, pp. 129–141. Society for Learning Analytics Research (SoLAR), Alberta, Canada (2017)
39. Ochoa, X., Worsley, M.: Augmenting learning analytics with multimodal sensory data. J. Learn. Anal. **3**(2), 213–219 (2016)
40. Overholt, G.: Ethnography and education: limitations and sources of error. J. Thought **15**(3), 11–20 (1980)
41. Paiva, A., Prada, R., Picard, R.W. (eds.): Conference Proceedings of the Second Affective Computing and Intelligent Interaction Conference. Springer, Lisbon, Portugal (2007)
42. Piaget, J.: The Language and Thought of the Child. Routledge & Kegan Paul, London (1926)
43. Peterson, P.L., Fennema, E.: Effective teaching, student engagement in classroom activities, and sex-related differences in learning mathematics. Am. Educ. Res. J. **22**(3), 309–335 (1985). https://doi.org/10.2307/1162966
44. Raca, M., Dillenbourg, P.: System for assessing classroom attention. In: Proceedings of the Third International Conference on Learning Analytics and Knowledge, pp. 265–269. ACM, Apr 2013
45. Raca, M., Dillenbourg, P.: System for assessing classroom attention. In: Suthers, D., Verbert, K., Duval, E., Ochoa, X. (eds.) Proceedings of the Third International Conference on Learning Analytics and Knowledge, Leuven, Belgium, pp. 265–269, Apr 2013
46. Raca, M., Tormey, R., Dillenbourg, P.: Sleepers' lag-study on motion and attention. In: Proceedings of the Fourth International Conference on Learning Analytics and Knowledge, Indianapolis, IN, pp. 36–43, Mar 2014
47. Sfard, A., Kieran, C.: Cognition as communication: Rethinking learning-by-talking through multi-faceted analysis of students' mathematical interactions. Mind Cult. Act. **8**(1), 42–76 (2001). https://doi.org/10.1207/s15327884mca0801_04
48. Shernoff, D.J.: Optimal Learning Environments to Promote Student Engagement. Springer, New York (2013)
49. Skinner, B.F.: The science of learning and the art of teaching. Harv. Educ. Rev. **24**, 86–97 (1954)
50. Skinner, E.A., Belmont, M.J.: Motivation in the classroom: reciprocal effects of teacher behavior and student engagement across the school year. J. Educ. Psychol. **85**(4), 571–581 (1993)
51. Stigler, J.W., Hiebert, J.: The Teaching Gap: Best Ideas from the World's Teachers for Improving Education in the Classroom. Free Press, New York (2009)
52. Taylor, L., Parsons, J.: Improving student engagement. Curr. Issues Educ. **14**(1) (2011)
53. Ulewicz, M., Beatty, A.: The Power of Video Technology in International Comparative Research in Education. National Academy Press, Washington, DC (2001)
54. Vygotsky, L.S.: Mind in Society: The Development of Higher Psychological Processes. Harvard University Press, Cambridge, MA (1978)

Chapter 9
Dashboards for Computer-Supported Collaborative Learning

Arita L. Liu and John C. Nesbit

Abstract In the field of learning analytics, dashboards are visual displays that help instructors and students monitor performance, track goals and modify learning-related activities and plans. Student-facing dashboards provide visualizations of the data students need to take responsibility for their own learning, while instructor-facing dashboards help instructors guide and orchestrate student learning. After summarizing the spectrum of learning analytics research on dashboards, we critically review dashboards designed to support collaborative learning and examine research on student-facing and instructor-facing dashboards for problem-based learning, project-based learning, collaborative argumentation, and various team-based learning activities. We explain key concepts such as group awareness, shared mental models, and group cognition, and review tools including shared mirroring systems, ambient displays, and learning dashboards. We then identify opportunities and challenges in the burgeoning field of learning analytics dashboards for computer-supported collaborative learning and argue that learning dashboards can be a useful aid in facilitating collaborative learning but only when designed with a clear pedagogical purpose informed by research and theory will learning dashboards be able to foster effective teaching and learning strategies.

9.1 The Emergence of Learning Analytics and Dashboards

Digital technologies generate plentiful data as people engage in online activities and use web-based platforms. From practitioners of the "quantified self" movement [97] who monitor their daily activities to improve their health and fitness, to marketers who track user interests to personalize advertising, many are seeking ways to exploit the arrival of big data. For educational researchers, teachers, and students, "data trails offer an opportunity to explore learning from new and multiple angles"

A. L. Liu (✉) · J. C. Nesbit (✉)
Simon Fraser University, Burnaby, Canada
e-mail: arita_liu@sfu.ca

J. C. Nesbit
e-mail: jcnesbit@sfu.ca; nesbit@sfu.ca

M. Virvou et al. (eds.), *Machine Learning Paradigms*, Intelligent Systems Reference Library 158, https://doi.org/10.1007/978-3-030-13743-4_9

[79, p. 1381]. Learning analytics (LA) researchers have investigated how data generated as students learn can be used to predict performance [4, 6], improve student success and retention [11, 15, 53], create learner profiles [68, 78], recommend learning resources [55, 91], provide tailored feedback [3, 65], improve pedagogical and instructional practice [52, 95], provide real-time teaching and learning support [16, 17], and build personalized learning environments [34, 43, 49]. LA researchers recognize that to meaningfully extend the boundaries of educational inquiry, they must produce actionable knowledge and pedagogical insights, and do so through processes of data collection, measurement, analysis, reporting, and interpretation that are grounded in learning science research [27].

The learning dashboard, a user-facing reporting tool, has received much attention from LA researchers. A learning dashboard is "a single display that aggregates different indicators about [learning] into one or multiple visualizations" [76, p. 37]. Aggregating complex data at different scales and granularity, learning dashboards are adopted at individual, group, course, institutional, and even national levels [89] to provide real-time feedback and assist administrators', educators', and learners' decision-making. Institutional use of learning dashboards is often characterized by identifying at-risk students for whom academic intervention is offered. The Signals project at Purdue University [3], a frequently cited successful early warning system, used a simple dashboard with metaphorical traffic lights to give students timely feedback on their overall course performance, accompanied by tailored messages from instructors. While the system was effective in improving student success, instructors found it difficult to integrate different criteria to evaluate student learning and determine appropriate signals, which may be because a "one size fits all" dashboard cannot fully capture and combine pedagogical intent and students' performance to predict student success [53].

At the micro-level, LA dashboards are developed to reveal to instructors and students otherwise undetectable patterns in process data [88]. Instructors use dashboards to gain insights into student participation and performance in learning activities, level of engagement, group cohesion, and use of supporting tools and resources [2, 16, 28, 62]. Other than presenting performance data, many LA dashboards have been developed to support students' self-regulated learning (SRL) and metacognition [10, 28, 44, 72, 86].

Student-facing dashboards visualize learning data and prompt students to actively manage their learning through awareness, reflection, and adjustment of learning tactics. Two recent review papers presented the state of the art of research in student-facing dashboards. Bodily and Verbert [7] reviewed student-facing LA reporting systems, discussing functionality, data sources, design, user perceptions, and effects of the systems. Many of these dashboards emphasize comparison with others in the same class. Peer comparisons have produced mixed results, and there is reason to believe they have negative motivational consequences for a significant number of students. Primary data sources of current dashboards include resource use, assessment results, social interactions, and time on tasks. A small number of dashboards have also collected survey and sensor data. Common data visualization types such as bar charts and line charts still dominate dashboard visual presentations. Emphasizing student use of the dashboard as a reporting system, Bodily and Verbert proposed future research should include user needs assessment and ensure dashboards are designed to genuinely serve students as stakeholders.

A review by Jivet et al. [42] offered insights into the conceptual contextualization of student-facing dashboards. The review identified five competence goals of the dashboards: metacognitive, cognitive, behavioral, emotional, and self-regulatory. Using Zimmerman's cyclical model of SRL [99] as the theoretical lens, the authors pointed out that awareness and self-reflection are the focus of most dashboards, but the other two phases of SRL, forethought (including goal-setting and planning) and performance (including self-monitoring of progress), are not supported. Social (i.e., normative) comparison is a commonly used reference frame to compare individual students to their classmates, teammates, and other peers. Notably, ipsative comparison (comparison with one's own past performance) is seldom found in dashboards. Goal achievement reference is frequently incorporated in dashboards but is limited to the learning outcomes expected by instructors, and as a result appeals to performance-oriented learning, which may lead to undesired learning outcomes.

Few [26] discussed three types of dashboards: strategic, analytical, and operational. If student-facing dashboards are operational by allowing students to monitor their key performance, instructor-facing dashboard falls in the category of strategic dashboards which present high-level measures of class performance to support instructor's strategic decision-making. When student interaction data are presented on a dashboard in a concise and actionable format, they can help instructors to make key decisions at class, group, and individual levels. Real-time analytics also allow instructors to adapt teaching and learning activities "on the fly" [75]. In collaborative learning, group activity status and student participation can be visualized for prompt intervention from the instructor [57, 58]. Dashboards can visualize enrolled students as dynamic social networks and evolving learning communities [16], thus allowing instructors to manage and assess collaborative learning [5]. Like student-facing dashboards, instructor-facing dashboards also face challenges. Although dashboards are meant to inform instructors of ways they can intervene to improve learning outcomes, instructors are not often involved in the dashboard design processes and the information presented in dashboards is often misaligned with their instructional goals and practices [70].

Directed by their primary purpose of raising learner awareness and fostering self-reflection, most current dashboards support solo learning but not collaborative learning. Dashboards for collaborative learning merit more attention from researchers because they offer the prospect of strengthening group cohesiveness, enhancing learners' social awareness, and fostering shared regulation of learning, all necessary for effective collaborative learning. The main purposes of this chapter are to (1) critically review research in analytic dashboards supporting collaborative learning, (2) examine opportunities and challenges in using learning dashboards to aid students' construction of shared conceptions and instructors' orchestration of learning across the spectrum of activities on multiple social levels, and (3) propose principles able to guide the design of learning dashboards for collaborative learning. As the data sources for learning analytics are usually from virtual learning environments (VLE), the collaborative learning discussed in this review is restricted to Computer Supported Collaborative Learning (CSCL). We introduce collaborative learning theories as the theoretical foundation for learning dashboards in CSCL, discuss the technologies and analytic dashboards that support collaborative learning, and consider the challenges and opportunities of using dashboards in CSCL. We conclude by integrating the chapter's themes into three high-level principles for guiding the design of dashboards intended to support collaborative learning.

9.2 Collaborative Learning Theories

Grounded in constructivist epistemology, CSCL extends cognitive boundaries from the individual mind to group cognition. There is not, however, a unified theory of CSCL, and the research approaches group learning processes from different theoretical perspectives. We discuss four theoretical premises that have been adopted to guide the design and analysis of collaborative learning activities and can ground an understanding of CSCL dashboards.

9.2.1 Group Cognition (GC)

According to Stahl [83], "group cognition" is the idea that a small group can collaborate "so tightly that the process of building knowledge in the group discourse cannot be attributed to any individual or even reduced to a sequence of contributions from individual minds" (p. 12). Group cognition is not simply the sum of individual cognition nor is it the intersection of individual mental representations, but rather is an emergent quality of individual cognitive processes that transcends individual cognition. While individual members contribute to shared meaning and collaborative knowledge building, central to group cognition is the collective discourse members internalize as individual learning and externalize in their communities as certifiable knowledge [82]. Conversation analysis is a methodology used to examine the episodes of meaning-making and knowledge building in intersubjective interactions. Stahl argues that learning tools for group cognition should focus on community building and providing artifacts that mediate group discourse.

9.2.2 Shared Mental Models (SMMs)

From a socio-cognitive perspective, social interaction leads to individual development through a process that integrates individual mental models, which are personal and unique, with socially shared cognition, which holds the generic knowledge of the world. Shared mental models are "knowledge structures held by members of a team that enable them to form accurate explanations and expectations for the task, and, in turn, coordinate their actions and adapt their behavior to demands of the task and other team members" [12, p. 228]. Shared mental models are the supporting and coordinating mechanisms in collaborative learning [71], which set the foundation for collaboration processes such as setting team goals, assigning roles, monitoring team progress, and interacting in a social context. Model visualization is a method for externalizing and sharing mental models [69].

Two types of SMM can be distinguished: team-related mental models and task-related mental models [60]. Team-related mental models are the shared conceptions of team interactions, including roles and responsibilities, interaction patterns, information flow, communication channels, and the shared knowledge among the team members about one another. Task-related mental models include the shared understanding of the technological environment with which learners interact and the shared task models that describe task procedures, strategies, and contingencies. Successful collaborative learning requires both mental models to come into play. SMM has two key properties: model accuracy and model similarity. Model accuracy describes how accurate the SMM reflects the "true state of the world" [22], and similarity is the degree of convergence of each team members' individual mental models. While both properties are required for good team performance, Edwards et al. [22] found that team mental model accuracy is a stronger predictor of team performance and mediates the relationship between team ability and performance. In complex problem-solving, it is advantageous to establish SMM to guide the team to coordinate and adapt to dynamic problem space [69].

9.2.3 Situational Awareness (SA)

The situational awareness of a collaborating learner is acquired through direct observation of the environment and information provided by other team members [23, 24]. Gutwin et al. [32] discussed four types of situational awareness in collaborative learning: social awareness, task awareness, concept awareness, and workspace awareness. While learners engage in group learning environment, they develop awareness about their social relations with team members, task completion procedures, connection between activities and their existing knowledge, and information about their team members' interactions with the shared workspace. Support can be provided to increase learners' awareness of different aspects of their interaction. Social awareness is often supported by providing the tools and opportunities for learners to communicate and negotiate ideas and information. Task and concept awareness can be supported by instructions, hints or other guidance for learning tasks and problem-solving. Workspace awareness can be supported by informing learners of each other's activities in the shared workspace. Sarter and Woods [73] distinguished between SA and mental models: mental models are the systematic mental representations of specific elements, while SA is the awareness of a continuously changing system that involves various unpredictable and interacting agents and tools.

9.2.4 Socially Shared Regulation of Learning (SSRL)

A new concept that has emerged in the collaborative learning context, socially shared regulation of learning (SSRL), places social context at the center of self-regulated learning [33]. According to Järvelä and Hadwin [38], shared regulation occurs when groups co-construct task perceptions or group goals. Multiple ideas and perspectives are weighed and negotiated through distributed regulation until consensus is met. Two principal shared regulatory activities in SSRL are (a) shared cognitive and metacognitive regulatory strategies, and (b) shared motivational and emotional regulation [64]. In SSRL, regulation strategies are situated and are a result from resolving the tension and ongoing coordination between individual and collective, and the pursuit for a shared ground and consensus is throughout the process from the initial planning to the final evaluation. Collaborative learning environments are characterized by intricate social and cognitive contexts in which learners interact and coordinate with one another, evaluate individual operations against group goals and progress, and achieve and maintain common ground to construct shared conceptions. In order to achieve the group's goals, a regulative mechanism is required at the group level to guide group cognition, social interactions, as well as emotional and motivational tendencies.

9.3 Tools for CSCL

Software tools have been developed from both pedagogical and social perspectives in CSCL to promote participation [21, 36], enhance group awareness of shared strategies [48, 66], encourage socially shared regulation of learning [39, 40, 54], guide collaborative discourse [85], and support complex group task execution [80]. Kreijns et al. [50] pointed out two pitfalls asynchronous distributed learning groups succumb to. One is the assumption that social interaction happens automatically as long as the environment makes it technologically possible; the other is the tendency to restrict interactions to cognitive processes while neglecting socio-emotional processes.

Social presence theory and social translucence theory have both been used to guide the design of virtual learning environments for productive social interaction. Social presence theory [31] deals with learners' awareness of their *social presence* and their sense of community as the foundation of social interaction. In an asynchronous distributed learning environment, participants create social presence by projecting their identities through interaction, negotiation, and collaborative knowledge construction. Social translucence theory [25] defines three characteristics of digital environments that promote coordinated social interaction. First, vital social cues, such as the expectation that one participant will respond to the idea posed by another, are *visible* to users. Second, users are made *aware* of other's actions, activity status, and roles. Finally, users are held socially *accountable* for their actions. Now we turn to three types of tools intended to support social presence, visibility, social awareness, and accountability in collaborative learning environments.

9.3.1 Group Awareness Tools (GATs)

Group awareness is defined as the “consciousness and information of various aspects of the group and its members” [30, p. 327] which plays an essential role in grounding members in collaborative tasks and guiding collaborative activities. Janssen and Bodemer [35] differentiated cognitive group awareness and social group awareness. Cognitive group awareness is awareness of group members’ knowledge and opinions. It is used to coordinate activities in the content space of collaboration such as sharing information and identifying knowledge gaps. Social group awareness is the awareness of group members’ collaborative behavior. It is used to coordinate activities in the relational space of collaboration such as planning, monitoring and evaluating group activities.

CSCL tools that offer information to help members coordinate their relational and cognitive contributions are called group awareness tools [37]. The Participation Tool [36] visualizes students’ contributions to encourage active participation in coordinating, regulating, and planning social interaction (Fig. 9.1). An experimental assessment of the tool found that it encouraged positive collaborative behaviors, such as providing encouraging feedback, and reduced negative behaviors, such as using disrespectful language, but it had no effect on participation equality, awareness of group processes, or group product quality. Buder and Bodemer [9] used an augmented group awareness tool to visualize peer ratings with respect to members’ contributions and the perceived novelty of the contributions. The purpose of the tool was to counter majority influence often found in collaborative learning and encourage awareness and deeper reflection of team members’ contributed content, which can lead to higher quality collaboration. The results pointed to an increased minority influence and higher correctness of group decisions. A limitation of the study is that the researchers used peer ratings to determine information influence patterns, a self-report measure that is only a proxy for actual social influence. Combining the self-reports with unobtrusively gathered data captured by the tool might yield more consistent results.

Phielix et al. [66] combined a peer feedback tool (Radar) and a reflection tool (Reflector) to visualize group assessment of six social and cognitive behavioral traits of the members including influence, friendliness, cooperation, reliability, productivity, and quality of contribution. As shown in Fig. 9.2, Radar visualized the peer assessment of group members by either the group in aggregate (e.g., Group about Chris) or other individual group members (e.g., Group members about Chris). The study results showed group performance was positively influenced by students’ higher awareness of shared interpersonal behavior and higher social and cognitive behavior.

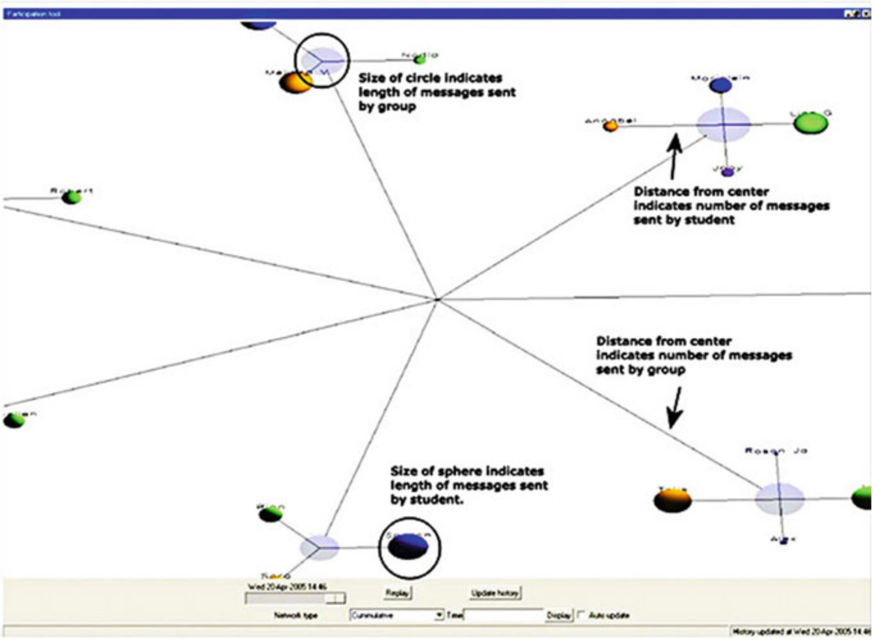


Fig. 9.1 Screenshot of the Participation Tool [36]

9.3.2 *Shared Mirroring Systems*

Soller et al. [81] ordered three types of support for metacognition in collaborative learning from the least to the most external support: mirroring tools, metacognitive tools, and guiding systems. Designed to raise students' awareness of their actions and behaviors in collaborative learning, mirroring tools collect and aggregate data about student interactions and reflect the data back to students. Without attempting to abstract or evaluate learner actions, mirroring systems allow learners to interpret the data, identify meaningful patterns and make remedial decisions themselves. Other similar terms used for the same purpose include "group mirrors" [19] and "shared mirroring display" [98]. Second Messenger (see Fig. 9.3) is a dynamic mirroring tool designed to raise collaborators' awareness of imbalanced participation [21]. The goal was to encourage more equitable participation and improve discussion dynamics and information sharing. The visualizations describe individual participation in relation to other group members, emphasizing extreme differences in participation. A line of equal participation was drawn in the graphs as a reference to an implied ideal. An evaluation of the tool found it led to reduced contributions from overactive participators and unchanged participation level of less active participators.

Jermann and Dillenbourg [41] went a step further to compare the effect of a mirroring tool and a metacognitive tool. The group mirroring tool displayed the

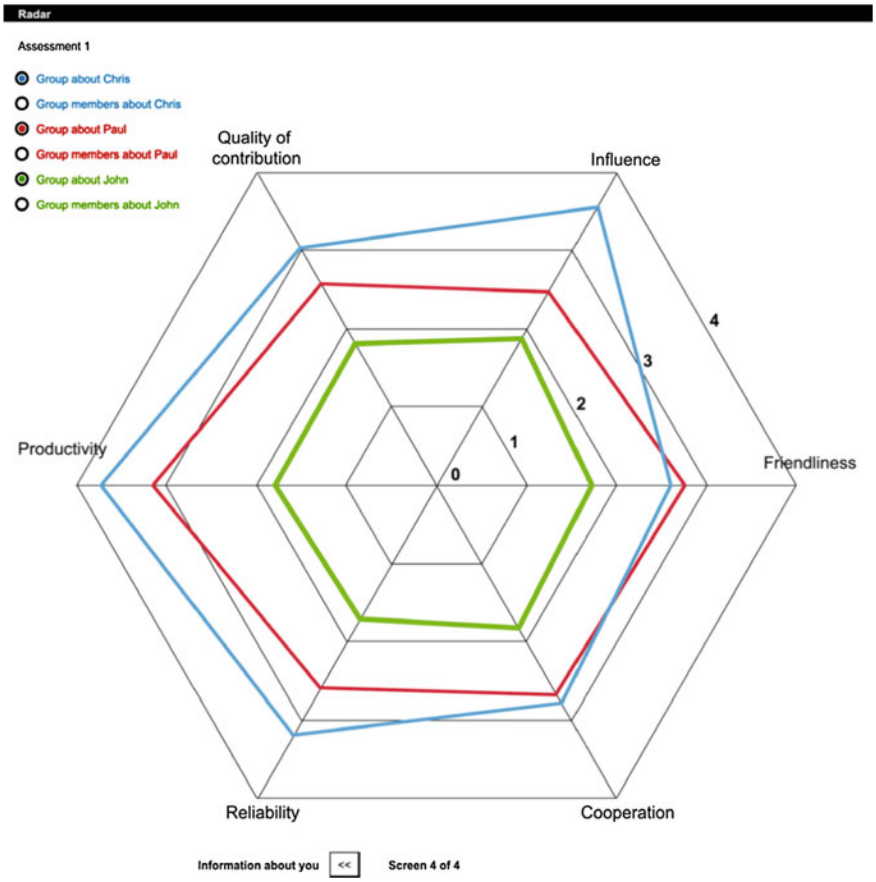


Fig. 9.2 Screenshot of Radar output: Group assessment [66]

length of discussions and the number of problem-solving actions to reflect learners' contributions and actions, and the metacognitive tool visually presented the standards of productive interaction in a dial format to encourage learners to compare and regulate their interactions. The mirroring tool turned out to be ineffective in regulating interactions. The result may be due to collaborators' lack of mental models for collaborative problem-solving, irrelevant information presentation, and inadequate presentation format of the mirroring tool. As Dillenbourg [19] pointed out, the two main features of group mirrors, content of the display and mode of display, largely decide the effectiveness of mirroring tools.

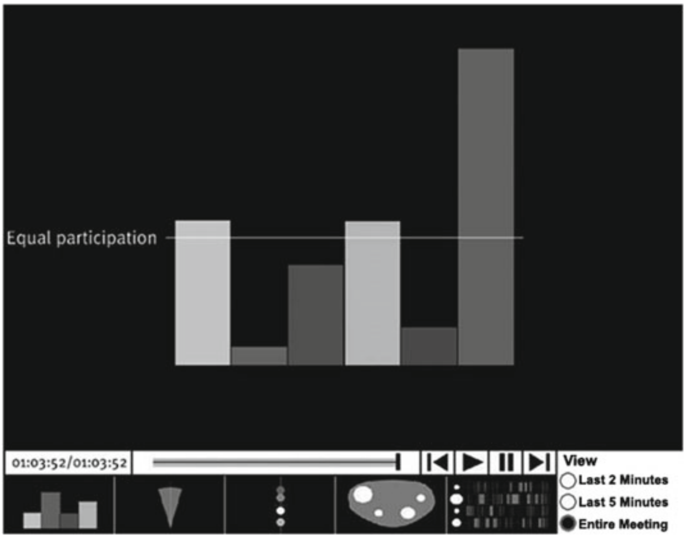


Fig. 9.3 Screenshot of the control panel of Second Messenger [21]

9.3.3 Ambient Displays

Ambient displays are "abstract and aesthetic peripheral displays portraying non-critical information on the periphery of a user's attention" [54, p. 1]. Some key words extracted from the various definitions of ambient information systems reviewed by Pousman and Stasko [67] describe such systems as "minimally attended", "outside a person's primary focus", "without distracting or burdening the user", lightweight, and "extraneous or supplemental to a users' attention priority". Börner et al. [8] reviewed ambient displays for learning and identified various objectives of ambient displays including supporting awareness, monitoring relevant information, maintaining interaction, disseminating information, triggering behavioral change, providing feedback, and supporting collaborative activities. Streng et al. [84] investigated using diagram representation and metaphorical representation in ambient displays to mirror and provide feedback on the quality of group argumentation. The quality of argumentation, measured by whether claims were justified or qualified, was diagrammatically represented by a bar chart and metaphorically represented by illustrations of weather conditions and healthy or unhealthy trees. They found when feedback is presented metaphorically, it has a stronger impact on learner's self-regulation of collaborative processes, as measured by the promptness of learners' actions in response to feedback from members. Charleer et al. [13] created ambient dashboards for display in classrooms to facilitate collaborative learning in "design critique" feedback sessions. Groups providing feedback are mapped on the ambient display according to the quantity and the quality of their feedback as measured through a live "like" voting system. The display promoted balanced feedback participation by motivating under-participators and limiting over-participation. It also helped the instructor to organize and orchestrate the session. Ambient displays tend to be limited by a novelty effect evident when users' interest and attention decreases over time [77]. It also appears likely that when the data representation in an ambient display does not dynamically vary in real time, its impact is greatly reduced.

Group awareness tools, shared mirroring systems, and ambient displays are all designed to raise awareness. They use a range of techniques such as activity tracing, simple data presentation, and non-intrusive group interventions. Group awareness tools are often guided by a predetermined goal to direct learners' awareness to aspects relevant to group cohesion and productivity. Shared mirroring systems require learners to reflect on and interpret the information that they regard as important or meaningful to their learning. Ambient displays deal with peripheral awareness, which allows learners to attend to both their own activities and those of others, as well as the context that frames the activities. A drawback of all these tools is they are not interactive, and evaluations have at most reported changes in patterns of participation. No studies have investigated their effects on learning outcomes. Typically, how learners use data presented to them is not tracked, and consequently it is challenging to evaluate the tools' effects on awareness. Research on promoting group awareness may need to adopt more interactive visualizations and gather data allowing researchers to track participants responses to those visualizations.

9.4 Learning Dashboards for CSCL

Core to CSCL is the process of negotiation and interaction among learners in achieving shared conceptions of group tasks [82]. Analytics can be conducted at both individual and group levels and presented as feedback to facilitate learners' self-regulated or shared regulation of learning [94], increase learners' sense of community and social presence, support awareness and reflection processes, and build a common ground for shared conceptions. Below we examine six learning dashboards used in collaborative learning context. The studies used various methods such as case studies, questionnaires, experiments, observational studies, and qualitative evaluations to assess the usability, usefulness, predictability of performance, visualization types of the dashboards. The purposes of the dashboards are to support group orchestration, foster group awareness, and encourage self-regulated learning and reflective learning.

TrAVis (Tracking Data Analysis and Visualization Tools) [61] visualizes real-time communication activities at different levels (Fig. 9.4). At the most granular levels, the system mirrors individual participation with quantitative information such as the number of messages posted, read, quoted, and replied, the number of threads started, and the frequency of logged in sessions. At the cooperation level, these are presented in a way that allows learners to see how their own activities compare with others in their group. At the collaboration level, the number of messages, threads, files, participants, and forum access are aggregated to illustrate the level of collaboration of

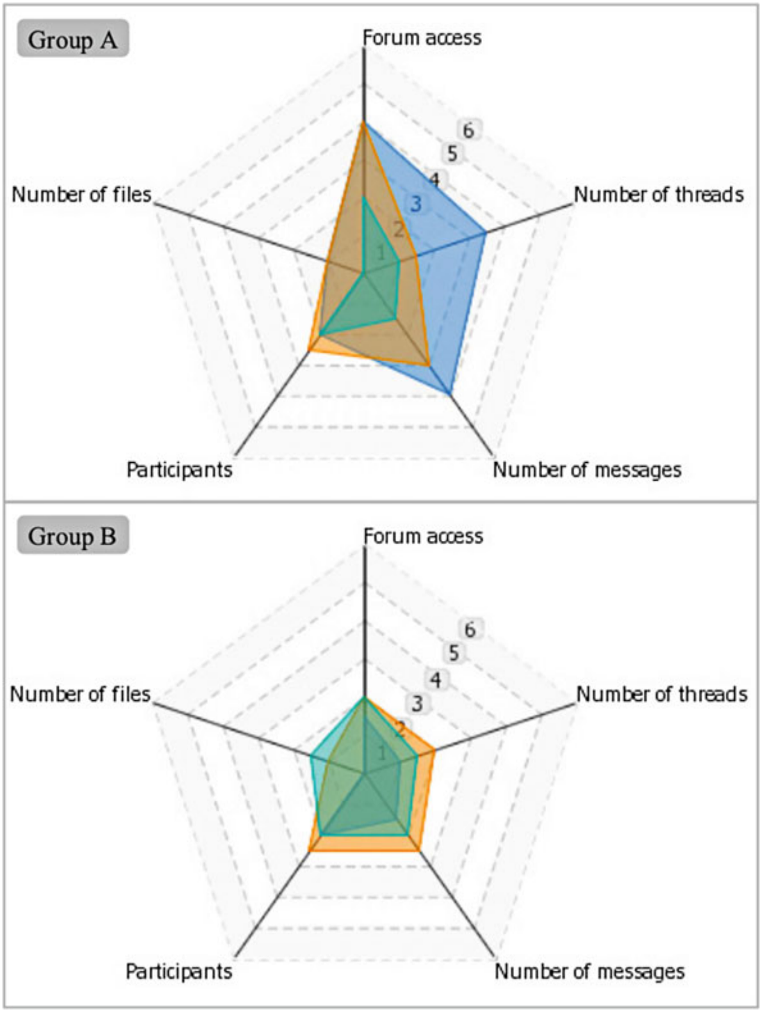


Fig. 9.4 Screenshot of the collaboration-level group view of *TrAVis* [61]

each group. Learners can select different sets of indicators to self-monitor, assess, and reflect on their learning at different levels. In this sense, the dashboard visualizations are interactive and invite learners to explore and interpret the aggregated data. A future implementation, according to the researchers, is an “editor of data indicators”, which would provide more personalized analytics by allowing learners to compose new sets of data indicators based on the existing ones.

Counts of messages posted and replied, files uploaded and downloaded, or frequency of logins can portray students’ general participation and interaction patterns, but without interpretation with reference to effective strategies and behaviors, dis-

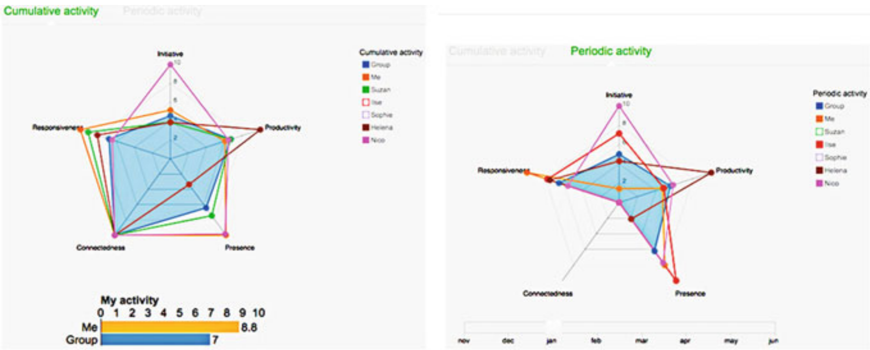


Fig. 9.5 Screenshot of the cumulative and periodic views of five activity indicators [74]

playing these quantitative indicators is likely to have no beneficial impact on collaboration and learning. Research must establish causal links between detectable behavior patterns and intended learning outcomes, and then visualizations can be deployed that show gaps between learners' behaviors in a particular context (phase of learning, type of task, etc.) and practices empirically established as most beneficial in that context. In a word, learning analytics shown to learners and teachers must be *actionable*.

Scheffel et al. [74] developed a group awareness and performance widget using data from Elgg, an open-source social networking engine. The purpose of the dashboard was to raise students' awareness of their own activity relative to that of others in their group and to foster students' reflection on how their activity influences their academic achievement relative to others in their group. A student's activity was profiled as initiative (number of posts initiated), responsiveness (number of comments made on others' posts), presence (number of pages the student viewed), connectedness (number of contacts with other students), and productivity (the student's contributions versus page views). As shown in Fig. 9.5, the five indicators were visualized for students in a five-axis radar chart in both periodic and cumulative view to give formative and summative feedback.

The researchers found positive correlations between students' indicator scores and their final grades as measured by tutor-assigned scores for a group research report, the group collaboration process, and individual performance. The study is a useful model showing how evidence can be used to select dashboard indicators, a practice often missing from the design of current learning dashboards. Only by establishing an evidence-based link between dashboard indicators and their intended benefits can learning dashboards truly serve instructors and students.

Upton and Kay [90] developed Narcissus, the visualization shown in Fig. 9.6, to mirror collaborative coding on an open-source web-based project management system (Trac). Narcissus showed each member's contribution to the group project relative to the group plans. The level of activity was measured daily on a one-to-four scale and visualized with correspondent color intensity. An aggregate summary of

Fig. 9.6 Screenshot of Narcissus group view [90]

each group member's overall activity was also provided. Learners could navigate the visualization to view detailed activities such as scripts added, wiki page updates, or ticket activities that contributed to group progress. Presenting only a single indicator, Narcissus compensated by showing fine details of learners' activities. To process information of high granularity, however, learners must deal with greater cognitive load. A disadvantage of such visualizations is that users may not be able to grasp the most important information at a glance. Rather than presenting a mass of detailed data, a learning dashboard may be more helpful if it selects and aggregates data to show variables most relevant to the learning process.

Martinez-Maldonado et al. [57, 58] designed an instructor-driven dashboard, *Collaid* (Collaborative Learning Aid), to assist instructors in orchestrating collaborative learning in a face-to-face interactive tabletop environment. Using microphone data and speech recognition to capture learners' discussions and their physical actions on the tabletop while they collaboratively construct concept maps, the dashboard visualizes the amount and symmetry of student participation, collaborative interactions, progress towards group goals, and collaboration at both class and group levels. Collaid modeled collaboration as a mathematical combination of the number of active participants in verbal discussions, amount of speech, number of touches to

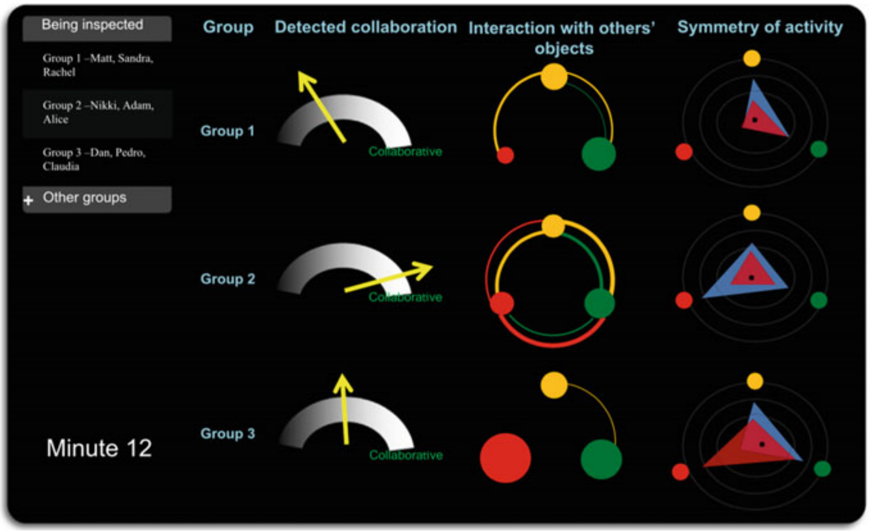


Fig. 9.7 Screenshot of Collaid showing an overview of three groups. Group 1: a group with a free-rider (Red); Group 2: a collaborative group; Group 3: a group in which students work independently [56]

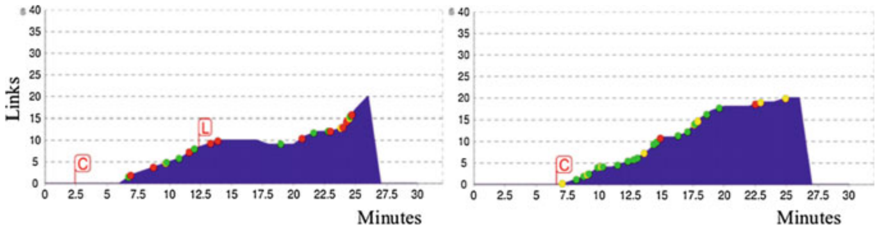


Fig. 9.8 Screenshot of Collaid evolution of the group map. Left: A group with a dominant participator (red) and an infrequent participator (yellow). Right: A group with an infrequent participator (red) [57, 58]

the tabletop, and symmetry of activity. The visualization of students' behavior over time was designed to help the instructor to orchestrate the class through two key processes: state awareness and workflow manipulation [20]. The various visualization types combined with a timeline allow the instructor to zoom into different aspects of learning and view the evolution of group interaction and group product (Figs. 9.7, 9.8, 9.9 and 9.10).

What is missing are the performance criteria and contextual references for the interaction patterns that would explain why students are not interacting with each other but are engaged in solo learning, why interactions are active at one point but not at another, and why there is a sudden drop or increase of collaborative activity. Both Narcissus and Collaid demonstrate how timelines are useful for showing

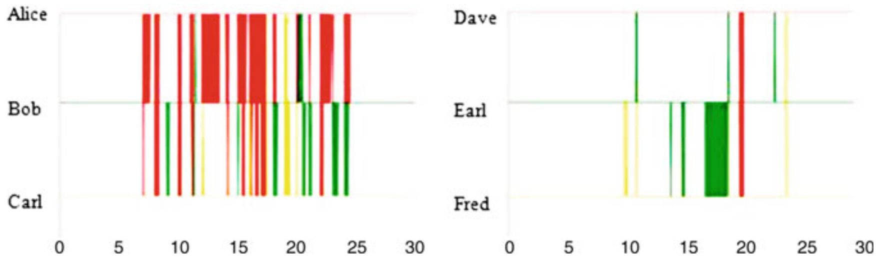


Fig. 9.9 Screenshot of Collaid timeline of interaction. Each vertical line on the horizontal timeline represents an interaction with another learner's objects. Left: A group with a dominant learner (Red). Right: group members that worked independently with very few interactions [57, 58]

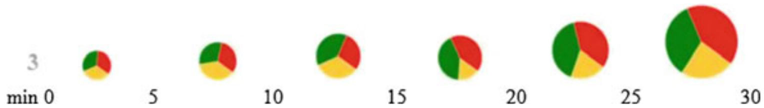


Fig. 9.10 Screenshot of Collaid contribution chart that shows how relative contributions by members of a three-student group vary over time [57, 58]

changes that occur in collaborative processes. Ideally, dashboard timelines would be augmented to show the collaborative and cognitive phases such as planning, analyzing, or evaluating. The key is, again, to provide actionable information to guide instructors' interventions at the right time.

Tarmazdi et al. [87] developed a teamwork dashboard, shown in Fig. 9.11, to visualize collaborative software development. The dashboard focused on role distribution and learner emotions as measured by sentiment analysis. Using natural language processing, team roles were classified according to the seven core components of teamwork proposed by Dickinson and McIntryre [18]: team leadership, team orientation, monitoring, coordination, communication, feedback, and backup behavior. A lexicon-based sentiment analysis method was used to identify eight fundamental emotions expressed in learners' texts: anger, trust, surprise, sadness, joy, fear, disgust, and anticipation. Instructors were shown an overview of all teams' activities and could choose to closely examine a single team over a selected time span. In the assignment planning stage, instructors could use the dashboard to observe team orientation and coordination behavior. The evolution of learner roles and emotions could be monitored as work on a learning task progressed. Instructors could also access online activity and intervene to urge team members to participate more or help them productively regulate their emotions. The evolution of roles and emotions could be viewed together to reveal the transitions between stages of collaboration. Combining the display of team activities and emotions was a significant innovation in helping instructors understand the quality of each team's social interdependence as changes in emotional states can indicate conflicts, productive or harmful interactions, and other events affecting team cohesion. The sentiment chart could be enhanced by linking the analysis of the emotional states with particular tasks or assignments. This

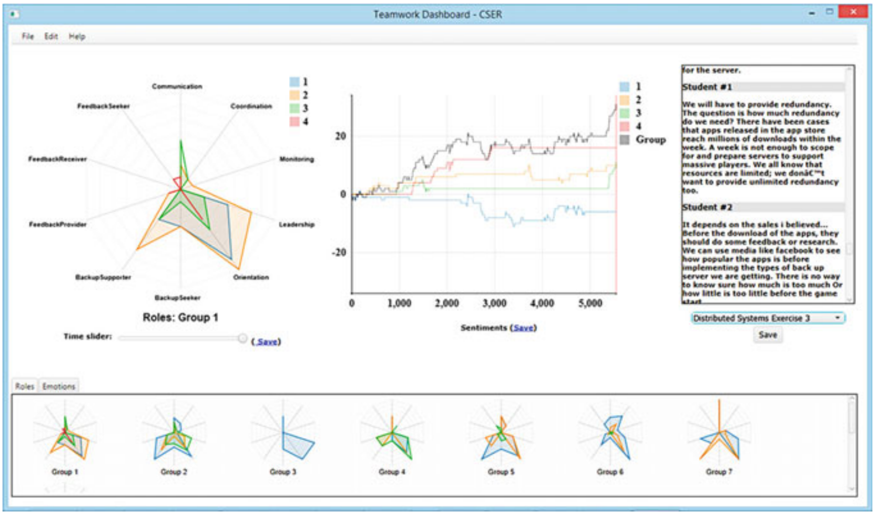


Fig. 9.11 Screenshot of the teamwork dashboard [87]

would provide contextual information that would help instructors design or select learning tasks to promote smoother collaboration. We would also suggest further analysis of the teamwork indicators to provide more explicit guidance to the collaborative process. For example, the dashboard might identify unfilled roles and group members who could shift from their current activities to take them on.

Learner participation, contribution, and interaction in CSCL are the fundamental processes learning dashboards record. The processes are complex, multifaceted, and entwined with personal, emotional, social, and environmental factors. Simply presenting available quantitative data without relating them to strategic decision making by students or instructors is unlikely to enhance collaborative learning. Among the learning dashboards we have reviewed, only Scheffel et al. [74] provided evidence for the selection of indicators relevant to the instructional design. We found radar charts are the visualization most frequently adopted to display multivariate data for collaborative learning dashboards. Compared with competing visualizations, radar charts have greater aesthetic appeal and can show a wide range of indicators more compactly. Nevertheless, they have shortcomings which we discuss in the following section.

9.5 How Can Collaborative Learning Dashboards Be Improved?

Computer-supported collaborative learning is among the most intensively studied pedagogical methods in the learning sciences [82], and is widely recognized as an approach that offers benefits at multiple levels of education. Despite its strengths, however, CSCL has not always proven effective. Phenomena such as the free-rider effect [46], the sucker effect [45], and the social loafing effect [51] are known to harm group motivation, cohesion, and performance. Lack of group awareness and sense of community can lead to apathy and unproductive interaction. Poor task coordination and inadequately shared conceptions of group process can hinder productivity. Because they are non-interactive, group awareness tools, mirroring tools, and ambient displays are limited in their ability to address these issues. Learning dashboards, on the other hand, are powerful data analysis and reporting tools with potential to raise learner awareness, help students to build shared mental models, and improve socially shared regulation of learning. Dashboards can also inform instructors of students' interaction and progress, and help instructors to guide group goals and activities, as well as deal appropriately with individual students' social-emotional responses. For education researchers, learning dashboards can offer insights into processes of collaborative learning and shine a light inside the "black box" of collaborative interaction.

Marzouk et al. [59] observed that many learning analytics have been created simply because data and analysis technologies were readily available. In some dashboards used in CSCL environments there is also a tendency to display log data that are within convenient reach without fully considering their utility in meeting users' needs. Like reviewers of dashboards designed for other contexts, we found several features in collaborative learning dashboards that might have been excluded or rendered differently if a more principled and goal-driven design process had been adopted. To conclude this chapter, we propose three broad principles for designing collaborative learning dashboards so that they better serve the needs of learners and instructors. We regard the three principles as general yet pragmatic heuristics that draw together the chapter's themes within a design framework.

9.5.1 Principle 1: Adopt Iterative, User-Centred Design

The dashboard designs we reviewed showed little concern for the moment-to-moment functional needs of learners. To ensure each component of the dashboard assists in the process of collaborative learning, we recommend an iterative design method in which components are kept, improved or rejected depending on learner responses over extended series of trials. This approach is exemplified by design-based research, "a systematic but flexible methodology aimed to improve educational practices through iterative analysis, design, development, and implementation, based on collaboration among researchers and practitioners in real-world settings, and leading to contextually-sensitive design principles and theories" [92, p. 6]. Because they uniquely focus on the problem of bringing designs into fine alignment with learner needs, iterative, user-centred methods such as design-based research may be crucial for unlocking the potential of collaborative dashboards.

Kirschner [47] proposed a six-stage procedure for a user-centered instructional design research of CSCL environments: 1. Observe what learners actually do before designing and developing the tool. 2. Determine what can be done to support learners. 3. Determine the constraints and the conventions in the environment. 4. Determine how learners perceive and experience the support provided. 5. Determine how learners actually use the support. 6. Use the lessons learned to revise theoretical understanding of how learning occurs in the situation. We would add that (a) the design of a dashboard should make clear to learners how the tool can be used in the performance of learning activities and (b) the design should support learners' agency by offering them choices in how they can respond to information provided by the tool [96, 93].

9.5.2 Principle 2: Navigate the Theoretical Space

Adopting a highly inductive, iterative design method does not negate the value of a priori, evidenced-based theory. Indeed, without input from learning theories, dashboard designs may easily revert to visualizing data that are readily available rather than data that are pedagogically relevant and actionable. In a complex learning environment such as CSCL, the guidance offered by theory in collecting, analyzing, and interpreting data is especially important. Figure 9.12 shows how the collaborative learning theories discussed earlier in this chapter can be forged into a common framework with one dimension ranging between cognition and metacognition and a second dimension ranging between individual and sociocultural concepts of learning.

Group cognition is built from the cognitive conception of individual learning, emphasizing acquisition of knowledge and cognitive skills, and the sociocultural conception of learning as a process of collective knowledge construction, emphasizing context, interaction, and situatedness. Greeno [29] and Akkerman et al. [1] suggested one can start with theories of individual cognition and analyze situations as contexts for cognitive processes, *or* start with the theory of social interactions and analyze the structures of knowledge produced by the interactions. We propose that, depending on the instructional purpose, the design of collaborative learning dashboards can selectively combine elements of these analytical strategies. Dashboards can be designed to both increase individual learners' situational awareness by tracing interaction and communication, *and* build shared mental models by focusing on team processes such as coordination of task and team related activities. Working in the other dimension, designs can be similarly guided by the instructional purpose to facilitate both self-regulated and socially shared regulation of learning. The idea is to find an analytical path through the theoretical space that optimizes group cognition for a particular instructional goal and learning activity.

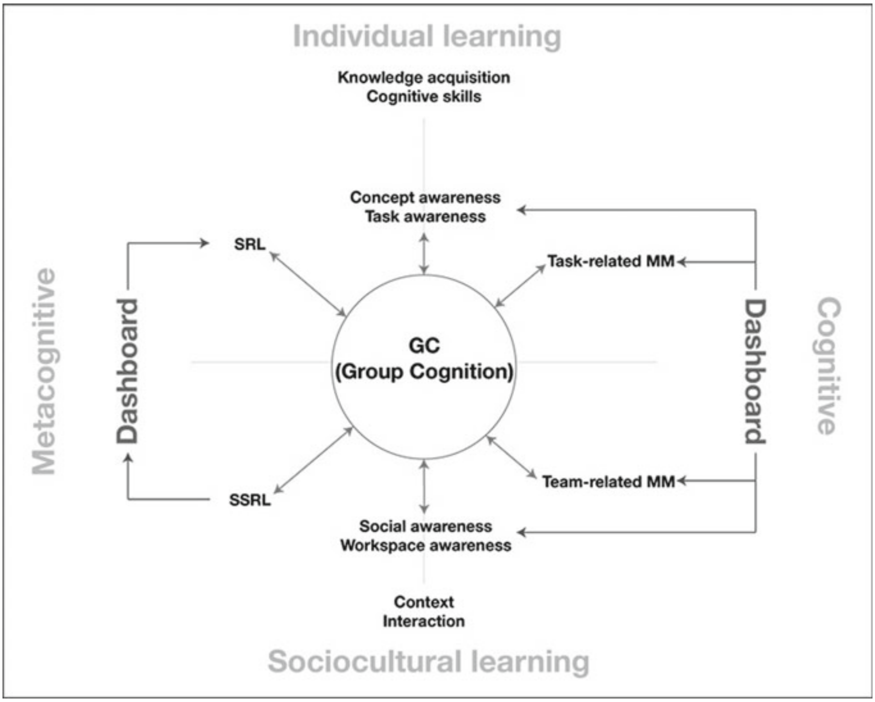


Fig. 9.12 A theoretical framework for learning dashboards in CSCL

9.5.3 Principle 3: Visualize to Support Decision-Making

Learning dashboards should be tools that provide actionable information for users. The purpose of visualization is not to show the current status of the learning activities or performance, but to allow instructors or students to interact with data in ways that help them make informed decisions about their teaching or learning. Modern visualization technology provides abundant options for representing data, and it is easy to inappropriately select and apply these in a particular pedagogical context. CSCL is capable of producing copious multivariate data, which, as we have seen, are often visualized using radar charts. Designers should carefully assess whether the visualizations they select meet the needs of users [14]. For example, both bar and radar charts can be used to compare values of variables sharing a common scale, but it is far more difficult to compare the lengths of spokes in a radar chart than bars in a bar chart. Likewise, although bar charts are more suitable than line charts for comparing arbitrarily ordered measurements, line charts are more suitable for showing variation across sampled points in time. Designers should strive to assess the sub-second cognitive requirements created by the decision-making context and provide learners with visualizations that optimally support those requirements. A concise recapitulation of this principle, and indeed this entire chapter, is the idea that collaborative learning dashboards should be designed not to simply show a group's interactive behavior, but rather to inform and motivate future decisions.

References

1. Akkerman, S., Van den Bossche, P., Admiraal, W., Gijselaers, W., Segers, M., Simons, R.J., Kirschner, P.: Reconsidering group cognition: From conceptual confusion to a boundary area between cognitive and socio-cultural perspectives? Educ. Res. Rev. **2**(1), 39–63 (2007)
2. Ali, L., Hatala, M., Gašević, D., Jovanović, J.: A qualitative evaluation of evolution of a learning analytics tool. Comput. Educ. **58**(1), 470–489 (2012)
3. Arnold, K.E., Pistilli, M.D.: Course signals at Purdue: using learning analytics to increase student success. In: Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, pp. 267–270. ACM, New York, NY (2012). https://doi.org/10.1145/2330601.2330666
4. Baker, R.S.J.d., Corbett, A.T., Aleven, V.: More accurate student modeling through contextual estimation of slip and guess probabilities in Bayesian knowledge tracing. In: Proceedings of the 9th International Conference on Intelligent Tutoring Systems, pp. 406–415. Springer, Berlin, Heidelberg (2008)
5. Barr, J., Gunawardena, A.: Classroom salon: a tool for social collaboration. In: Proceedings of the 43rd ACM technical symposium on Computer Science Education, pp. 197–202. ACM, New York, NY (2012)
6. Blikstein, P.: Using learning analytics to assess students' behavior in open-ended programming tasks. In: Proceedings of the First International Conference on Learning Analytics and Knowledge, pp. 110–116. Association for Computing Machinery, New York, NY (2011)
7. Bodily, R., Verbert, K.: Trends and issues in student-facing learning analytics reporting systems research. In Proceedings of the 7th International Conference on Learning Analytics and Knowledge, pp. 309–318. ACM, New York, NY (2017)
8. Börner, D., Kalz, M., Specht, M.: Beyond the channel: a literature review on ambient displays for learning. Comput. Educ. **60**(1), 426–435 (2013)
9. Buder, J., Bodemer, D.: Supporting controversial CSCL discussions with augmented group awareness tools. Int. J. Comput. Support. Collab. Learn. **3**(2), 123–139 (2008)
10. Bull, S., Ginon, B., Boscolo, C., Johnson, M.: Introduction of learning visualisations and metacognitive support in a persuadable open learner model. In: Proceedings of the Sixth International Learning Analytics & Knowledge Conference (LAK'16), pp. 30–39. ACM, New York, NY (2016)
11. Campbell, J.P., Oblinger, D.G.: Academic Analytics. EDUCAUSE White Paper (2007). http://www.educause.edu/ir/library/pdf/PUB6101.pdf
12. Cannon-Bowers, J.A., Salas, E., Converse, S.: Shared mental models in expert team decision making. In: Castellan, N.J. (ed.). Individual and Group Decision Making, pp. 221–245. Lawrence Erlbaum Associates (1993)
13. Charleer, S., Klerkx, J., Duval, E., Laet, T.D., Verbert, K.: Towards balanced discussions in the classroom using ambient information visualisations. Int. J. Technol. Enhanc. Learn. **9**(2–3), 227–253 (2017)
14. Chen, C.H., Härdle, W.K., Unwin, A.: Handbook of Data Visualization. Springer Handbooks of Computational Statistics. Springer, Berlin, Heidelberg (2008)
15. Dawson, S.: 'Seeing' the learning community: an exploration of the development of a resource for monitoring online student networking. Br. J. Educ. Technol. **41**(5), 736–752 (2010)

16. Dawson, S., Bakharia, A., Heathcote, E.: SNAPP: Realising the affordances of real-time SNA within networked learning environments. In: Dirckinck-Holmfeld, L., Hodgson, V., Jones, C., de Laat, M., McConnell, D., Ryberg, T. (eds.) Proceedings of the 7th International Conference on Networked Learning, pp. 125–133. University of Lancaster, Lancaster, UK (2010)
17. Diana, N., Eagle, M., Stamper, J.C., Grover, S., Bienkowski, M.A., Basu, S.: An instructor dashboard for real-time analytics in interactive programming assignments. In: Proceedings of the Seventh International Learning Analytics & Knowledge Conference. LAK '17, pp. 272–279. ACM, New York, NY (2017)
18. Dickinson, T.L., McIntyre, R.M.: A conceptual framework for teamwork measurement. In: Brannick, M.T., Salas, E., Prince, C. (eds.) Team Performance and Measurement: Theory, Methods, and Applications, pp. 19–43. Lawrence Erlbaum Associates, Mahwah, NJ (1997)
19. Dillenbourg, P.: Designing biases that augment socio-cognitive interactions. In: Bromme, R., Hesse, F.W., Spada, H. (eds.) Barriers and Biases in Computer-Mediated Knowledge Communication, pp. 243–264. Springer, Boston, MA (2005)
20. Dillenbourg, P., Zufferey, G., Alavi, H., Jermann, P., Do-Lenh, S., Bonnard, Q.: Classroom orchestration: the third circle of usability. In: Proceedings of the International Conference on Computer Supported Collaborative Learning 2011 (CSCL 2011), pp. 510–517. HK, China (2011)
21. DiMicco, J.M., Hollenbach, K.J., Pandolfo, A., Bender, W.: The impact of increased awareness while face-to-face. Hum. Comput. Interact. **22**(1), 47–96 (2007)
22. Edwards, B.D., Day, E.A., Arthur, W., Bell, S.T.: Relationships among team ability composition, team mental models, and team performance. J. Appl. Psychol. **91**, 727–736 (2006)
23. Endsley, M.R.: Toward a theory of situation awareness. Hum. Factors **37**(1), 32–64 (1995)
24. Endsley, M.R.: Communication and situation awareness in the aviation system. Paper presented at Aviation Communication: A Multi-Cultural Forum, Prescott, AZ (1997)
25. Erickson, T., Kellogg, W.A.: Social translucence: An approach to designing systems that support social processes. ACM Trans. Comput. Hum. Interact. (TOCHI) **7**(1), 59–83 (2000)
26. Few, S.: Information Dashboard Design: The Effective Visual Communication of Data. O'Reilly Media Inc., Sebastopol, CA (2006)
27. Gašević, D., Dawson, S., Siemens, G.: Let's not forget: learning analytics are about learning. TechTrends **59**(1), 64–71 (2015)
28. Govaerts, S., Verbert, K., Duval, E., Pardo, A.: The student activity meter for awareness and self-reflection. CHI'12 Extended Abstracts on Human Factors in Computing Systems, pp. 869–884. ACM, New York, NY (2012)
29. Greeno, J.G.: The situativity of knowing, learning and research. Am. Psychol. **53**, 5–26 (1998)
30. Gross, T., Stary, C., Totter, A.: User-centered awareness in computer-supported cooperative work-systems: structured embedding of findings from social sciences. Int. J. Hum. Comput. Interact. **18**(3), 323–360 (2005)
31. Gunawardena, C.N.: Social presence theory and implications for interaction and collaborative learning in computer conferences. Int. J. Educ. Telecommun. **1**(2), 147–166 (1995)
32. Gutwin, C., Stark, G., Greenberg, S.: Support for workspace awareness in educational groupware. In: The First International Conference on Computer Support for Collaborative Learning, pp. 147–156. L. Erlbaum Associates Inc. (1995)
33. Hadwin, A., Oshige, M.: Self-Regulation, coregulation, and socially shared regulation: exploring perspectives of social in self-regulated learning theory. Teach. Coll. Rec. **113**(2), 240–264 (2011)
34. Ifenthaler, D., Widanapathirana, C.: Development and validation of a learning analytics framework: Two case studies using support vector machines. Technol. Knowl. Learn. **19**, 221–240 (2014)
35. Janssen, J., Bodemer, D.: Coordinated computer-supported collaborative learning: awareness and awareness tools. Educ. Psychol. **48**(1), 40–55 (2013)
36. Janssen, J., Erkens, G., Kanselaar, G., Jaspers, J.: Visualization of participation: does it contribute to successful computer-supported collaborative learning? Comput. Educ. **49**(4), 1037–1065 (2007)

37. Janssen, J., Erkens, G., Kirschner, P.A.: Group awareness tools: it's what you do with it that matters. Comput. Hum. Behav. **27**(3), 1046–1058 (2011)
38. Järvelä, S., Hadwin, A.F.: New frontiers: regulating learning in CSCL. Educ. Psychol. **48**(1), 25–39 (2013)
39. Järvelä, S., Kirschner, P.A., Panadero, E., Malmberg, J., Phielix, C., Jaspers, J., Järvenoja, H.: Enhancing socially shared regulation in collaborative learning groups: designing for CSCL regulation tools. Educ. Tech. Res. Develop. **63**(1), 125–142 (2015)
40. Järvelä, S., Kirschner, P.A., Hadwin, A., Järvenoja, H., Malmberg, J., Miller, M., Laru, J.: Socially shared regulation of learning in CSCL: understanding and prompting individual- and group-level shared regulatory activities. Inter. J. Computer-Supported Collab. Lea. **11**(3), 263–280 (2016)
41. Jermann, P., Dillenbourg, P.: Group mirrors to support interaction regulation in collaborative problem solving. Comput. Educ. **51**(1), 279–296 (2008)
42. Jivet, I., Scheffel, M., Drachsler, H., Specht, M.: Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. In: Proceedings of the 12th European Conference on Technology-Enhanced Learning, pp. 82–96. Springer, Cham (2017)
43. Kardan, S., Conati, C.: A framework for capturing distinguishing user interaction behaviors in novel interfaces. In: Pechenizkiy, M., Calders, T., Conati, C., Ventura, S., Romero, C., Stamper, J. (eds.) Proceedings of the 4th International Conference on Educational Data Mining, pp. 159–168. Eindhoven, the Netherlands (2011)
44. Kerly, A., Ellis, R., Bull, S.: (2007) CALMsystem: a conversational agent for learner modelling. In: Ellis, R., Allen, T., Petridis, M. (eds.) Applications and Innovations in Intelligent Systems XV: Proceedings of AI-2007, 27th SGAI International Conference on Innovative Techniques and Applications of Artificial Intelligence, pp. 89–102. Springer, Berlin, Heidelberg
45. Kerr, N.L.: Motivation losses in small groups: a social dilemma analysis. Personal. Soc. Psychol. **45**, 819–828 (1983)
46. Kerr, N.L., Bruun, S.E.: Dispensability of member effort and group motivation losses: free rider effects. J. Personal. Soc. Psychol. **44**, 78–94 (1983)
47. Kirschner, P.A.: Can we support CSCL? Educational, social and technological affordances for learning. In: Kirschner, P. (ed.) Three Worlds of CSCL: Can We Support CSCL, pp. 7–47. OUNL, Heerlen (2002)
48. Kirschner, P.A., Kreijns, K.: Designing sociable CSCL environments: applying interaction design principles. In Dillenbourg, P., Strijbos, J.W., Kirschner, P.A., Martens, R.L. (eds.) Computer-Supported Collaborative Learning, vol. 3, pp. 241–263 (2004)
49. Kock, M., Paramythis, A.: Activity sequence modelling and dynamic clustering for personalized e-learning. User Model. User Adapt. Interact. **21**(1–2), 51–97 (2011)
50. Kreijns, K., Kirschner, P.A., Jochems, W.: Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: a review of the research. Comput. Hum. Behav. **19**(3), 335–353 (2003)
51. Latané, B., Williams, K., Harkins, S.: Many hands make light the work: the causes and consequences of social loafing. J. Personal. Soc. Psychol. **37**, 822–832 (1979)
52. Lockyer, L., Heathcote, E., Dawson, S.: Informing pedagogical action: aligning learning analytics with learning design. Am. Behav. Sci. **57**(10), 1439–1459 (2013)
53. Macfadyen, L.P., Dawson, S.: Mining LMS data to develop an "early warning system" for educators: a proof of concept. Comput. Educ. **54**(2), 588–599 (2010)
54. Mankoff, J., Dey, A.K., Hsieh, G., Kientz, J., Lederer, S., Ames, M.: Heuristic evaluation of ambient displays. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 169–176. ACM, New York, NY (2003)
55. Martin, B., Mitrovic, A., Koedinger, K., Mathan, S.: Evaluating and improving adaptive educational systems with learning curves. User Model. User Adapt. Interact. **21**(3), 249–283 (2011)
56. Martinez-Maldonado, R., Yacef, K., Kay, J.: TSCL: a conceptual model to inform understanding of collaborative learning processes at interactive tabletops. Int. J. Hum. Comput. Stud. **83**, 62–82 (2015)

57. Martinez-Maldonado, R., Kay, J., Yacef, K., Schwendimann, B.: An interactive teacher's dashboard for monitoring groups in a multi-tabletop learning environment. In: Cerri et al. (eds.) Proceedings of the 11th International Conference on Intelligent Tutoring, pp. 482–492. Springer, Berlin, Heidelberg (2012)
58. Martinez-Maldonado, R.M., Kay, J., Yacef, K., Schwendimann, B.: An interactive teacher's dashboard for monitoring groups in a multi-tabletop learning environment. In: International Conference on Intelligent Tutoring Systems, pp. 482–492. Springer, Berlin, Heidelberg (2012)
59. Marzouk, Z., Rakovic, M., Liaqat, A., Vytasek, J., Samadi, D., Stewart-Alonso, J., Ram, I., Woloshen, S., Winne, P.H., Nesbit, J.C.: What if learning analytics were based on learning science? Australasian J. Educ. Tech. **32**(6), 1–18 (2016)
60. Mathieu, J.E., Heffner, T.S., Goodwin, G.F., Salas, E., Cannon-Bowers, J.A.: The influence of shared mental models on team process and performance. J. Appl. Psychol. **85**(2), 273 (2000)
61. May, M., George, S., Prévôt, P.: TrAVis to enhance students' self-monitoring in online learning supported by computer-mediated communication tools. Comput. Inf. Syst. Ind. Manag. Appl. **3**, 623–634 (2011)
62. Mazza, R., Milani, C.: Gismo: a graphical interactive student monitoring tool for course management systems. In: International Conference on Technology Enhanced Learning, pp. 1–8, Milan (2004)
63. Miller, M., Hadwin, A.: Scripting and awareness tools for regulating collaborative learning: changing the landscape of support in CSCL. Comp. Human Behav. **52**, 573–588 (2015)
64. Panadero, E., Järvelä, S.: Socially shared regulation of learning: a review. Eur. Psychol. **20**, 190–203 (2015)
65. Pardo, A., Jovanovic, J., Dawson, S., Gašević, D., Mirriahi, N.: Using learning analytics to scale the provision of personalised feedback. Br. J. Educ. Technol. (2017)
66. Phielix, C., Prins, F.J., Kirschner, P.A., Erkens, G., Jaspers, J.: Group awareness of social and cognitive performance in a CSCL environment: effects of a peer feedback and reflection tool. Comput. Hum. Behav. **27**(3), 1087–1102 (2011)
67. Pousman, Z., Stasko, J.: A taxonomy of ambient information systems: Four patterns of design. In: Proceedings of the Working Conference on Advanced Visual Interfaces, pp. 67–74. ACM, New York, NY (2006)
68. Premlatha, K.R., Dharani, B., Geetha, T.V.: Dynamic learner profiling and automatic learner classification for adaptive e-learning environment. Interact. Learn. Environ. **24**(6), 1054–1075 (2016)
69. Redlich, B., Siemon, D., Lattemann, C., Robra-Bissantz, S.: Shared mental models in creative virtual teamwork. In: Proceedings of the 50th Hawaii International Conference on System Sciences. Kaua'i, USA (2017)
70. Rienties, B., Toetenel, L.: The impact of 151 learning designs on student satisfaction and performance: social learning (analytics) matters. In: Proceedings of the Sixth International Conference on Learning Analytics & Knowledge, pp. 339–343. ACM, New York, NY (2016)
71. Salas, E., Sims, D., Burke, C.: Is there a 'Big Five' in teamwork? Small Group Res. **36**, 555–599 (2005)
72. Santos, J.L., Govaerts, S., Verbert, K., Duval, E.: Goal-oriented visualizations of activity tracking: a case study with engineering students. 2nd International Conference on Learning Analytics and Knowledge, pp. 143–152. ACM, New York, NY (2012)
73. Sarter, N.B., Woods, D.D.: Situation awareness: a critical but ill-defined phenomenon. Int. J. Aviat. Psychol. **1**(1), 45–57 (1991)
74. Scheffel, M., Drachsler, H., De Kraker, J., Kreijns, K., Slootmaker, A., Specht, M.: Widget, widget on the wall, am I performing well at all? IEEE Trans. Learn. Technol. **10**(1), 42–52 (2017)
75. Schmitz, M., van Limbeek, E., Greller, W., Sloep, P., Drachsler, H.: Opportunities and challenges in using learning analytics in learning design. In: Lavoué, É., Drachsler, H., Verbert, K., Broisin, J., Pérez-Sanagustín, M. (eds.) Data Driven Approaches in Digital Education. EC-TEL 2017. Lecture Notes in Computer Science, vol. 10474. Springer, Cham (2017)

76. Schwendimann, B.A., Rodriguez-Triana, M.J., Vozniuk, A., Prieto, L.P., Boroujeni, M.S., Holzer, A., Gillet, D., Dillenboug, P.: Perceiving learning at a glance: a systematic literature review of learning dashboard research. IEEE Trans. Learn. Technol. **10**(1), 30–41 (2017)
77. Shen, X., Moere, A. V., Eades, P., Hong, S.: The long-term evaluation of Fisherman in a partial-attention environment. In: Proceedings of the 2008 Conference on Beyond Time and Errors: Novel Evaluation Methods for Information Visualization, pp. 1–6. ACM, New York, NY (2008)
78. Shum, S.B., Crick, R.D.: Learning dispositions and transferable competencies: pedagogy, modelling and learning analytics. In: Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, pp. 92–101. ACM, New York, NY (2012)
79. Siemens, G.: Learning analytics: the emergence of a discipline. Am. Behav. Sci. **57**(10), 1380–1400 (2013)
80. Slof, B., Erkens, G., Kirschner, P.A., Jaspers, J.: Design and effects of a representational scripting tool on group performance. Educ. Technol. Res. Dev. **58**, 589–608 (2010)
81. Soller, A., Martínez, A., Jermann, P., Muehlenbrock, M.: From mirroring to guiding: a review of state of the art technology for supporting collaborative learning. Int. J. Artif. Intell. Educ. **15**(4), 261–290 (2005)
82. Stahl, G.: Group Cognition: Computer Support for Building Collaborative Knowledge. MIT Press, Cambridge, MA (2006)
83. Stahl, G.: Theories of cognition in collaborative learning. In: Hmelo-Silver, C., Chinn, C., Chan, C., O'Donnell, A. (eds.) The International Handbook of Collaborative Learning, pp. 74–90. Routledge, New York, NY (2013)
84. Streng, S., Stegmann, K., Hussmann, H., Fischer, F.: Metaphor or diagram? Comparing different representations for group mirrors. In: Proceedings of the 21st Annual Conference of the Australian Computer-Human Interaction Special Interest Group: Design: Open 24/7, pp. 249–256. ACM, New York, NY (2009)
85. Suthers, D., Hundhausen, C., Girardeau, L.: Comparing the roles of representations in face-to-face and online computer supported collaborative learning. Comput. Educ. **41**, 335–351 (2003)
86. Tan, J.P.L., Koh, E., Jonathan, C.R., Yang, S.: Learner dashboards a double-edged sword? Students' sense-making of a collaborative critical reading and learning analytics environment for fostering 21st century literacies. J. Learn. Anal. **4**(1), 117–140 (2017)
87. Tarmazdi, H., Vivian, R., Szabo, C., Falkner, K., Falkner, N.: Using learning analytics to visualise computer science teamwork. In: Proceedings of the 2015 ACM Conference on Innovation and Technology in Computer Science Education, pp. 165–170. ACM, New York, NY (2015)
88. Teasley, S.D.: Student facing dashboards: one size fits all? Technol. Knowl. Learn. **22**(3), 377–384 (2017)
89. United States Education Dashboard (n.d.): https://dashboard.ed.gov/
90. Upton, K., Kay, J.: Narcissus: group and individual models to support small group work. In: International Conference on User Modeling, Adaptation, and Personalization, pp. 54–65. Springer, Berlin, Heidelberg (2009)
91. Verbert, K., Drachsler, H., Manouselis, N., Wolpers, M., Vuorikari, R., Duval, E.: Dataset-driven research for improving recommender systems for learning. In: Proceedings of the 1st International Conference on Learning Analytics and Knowledge, pp. 44–53. ACM, New York, NY (2011)
92. Wang, F., Hannafin, M.J.: Design-based research and technology-enhanced learning environments. Educ. Technol. Res. Dev. **53**(4), 5–23 (2005)
93. Wise, A.F., Vytasek, J.M., Hausknecht, S., Zhao, Y.: Developing learning analytics design knowledge in the "middle space": the student tuning model and align design framework for learning analytics use. Online Learn. **20**(2), 155–182 (2016)
94. Wise, A.F., Azevedo, R., Stegmann, K., Malmberg, J., Rosé, C.P., Fischer, F.: CSCL and learning analytics: opportunities to support social interaction, self-regulation and socially shared regulation. In: Proceedings of Computer Supported Collaborative Learning (CSCL) Conference 2015, pp. 607–614. Gothenburg, Sweden (2015)

95. Wise, A.F., Zhao, Y., Hausknecht, S.N.: 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, pp. 48–56. ACM, New York, NY (2013)
96. Wise, A.F.: Designing pedagogical interventions to support student use of learning analytics. In: Proceedings of the Fourth International Conference on Learning Analytics and Knowledge, pp. 203–211. ACM, New York, NY (2014)
97. Wolf, G.: Know thyself: tracking every facet of life, from sleep to mood to pain, 24/7/365. Wired Magazine (2009). https://www.wired.com/2009/06/lbnp-knowthyself/
98. Yusoff, N.M., Salim, S.S.: A systematic review of shared visualisation to achieve common ground. J. Vis. Lang. Comput. **28**, 83–99 (2015)
99. Zimmerman, B.J.: Attainment of self-regulation: A social cognitive perspective. In: Boekaerts, M., Pintrich, P.R., Zeidner, M. (eds.) Handbook of Self-Regulation, pp. 13–39. Academic Press, San Diego, CA (2000)

Part IV
Learning Analytics as Tools to Support Learners and Educators in Synchronous and Asynchronous e-Learning

Chapter 10
Learning Analytics in Distance and Mobile Learning for Designing Personalised Software

Katerina Kabassi and Efthimios Alepis

Abstract Distance Learning, in its synchronous and asynchronous form, has gained an increasing interest over the last decades, both because of the realization of the "digital era" and also due to the reachability and accessibility it offered to human education. Lately, mobile learning has also been gaining a lot of interest due to the widespread popularity of Smartphones. In order to improve human educational interaction with Personal Computers and Smartphones, collecting learning analytics data and utilizing them is considered as a valuable requirement. Distance and mobile learning analytics may improve and assist the entire learning process by providing personalized software solutions. This paper focuses on the collection and the combination of the learning analytics data offered by different modalities in Personal Computers and modern Smartphones. For this combination two different Multi-Criteria Decision making theories are used, namely the Analytical Hierarchy Process and the Simple Additive Weighting model.

Keywords Learning analytics · Distance learning · Mobile learning · Multi-criteria analysis

10.1 Introduction

Distance learning is not a new phenomenon. Colleges and universities are forging ahead to provide learning at a distance, and many institutions are making substantial investments in new technologies for teaching [1]. Open and distance learning has grown because of its perceived advantages [2]. Therefore, recently there has been an explosive growth in online distance learning that is "rapidly transforming post-secondary education" [3].

K. Kabassi (✉)
Ionian University, Zakynthos, Greece
e-mail: kkabassi@Ionio.gr

E. Alepis
University of Piraeus, Piraeus, Greece
e-mail: talepis@unipi.gr

M. Virvou et al. (eds.), *Machine Learning Paradigms*, Intelligent Systems Reference Library 158, https://doi.org/10.1007/978-3-030-13743-4_10

Phipps and Merisotis [1] reviewed some studies and concluded that, regardless of the technology used, distance learning courses compare favorably with classroom-based instruction and enjoy high student satisfaction. However, they also found that a gap that required further investigation and information was that most research did not take the differences among students into account.

Another subset of e-learning that is usually considered as a union to distance learning is mobile learning. Mobile learning has both benefits and drawbacks when compared to more "classic" educational software solutions that are offered through personal computers, as it is covered in the next sections of this chapter.

In 2016, according to [4], worldwide mobile device shipments represented 81% of total computer device shipments, while adding tablets as the "ultramobile" market further increases this percentage. As Gartner analysts in [5] state, as Smartphones, laptops, tablets and other consumer devices have multiplied, the consumer space has largely converted to a mobile-first world. In the same press release it is also forecasted that more than 50% of global network users will use a tablet or a Smartphone device first for all their on-line activities. As expected, 2016 has been the year when mobile web usage overtook desktop web usage for the first time in history [6].

Over the last years of Smartphone development, modern mobile learning software industry needed more fine-grained adaptive user models for learning analytics purposes, since a large amount of complex data were handled, such as those extracted from the embedded sensors, providing high levels of context awareness. Most importantly, mobile devices are being constantly used in most peoples' everyday life and improving the experience of users who are using them may further improve their accompanying services. As a result, learners e.g. who were inexperienced with computers, as well as children and elderly are nowadays Smartphone users who may use mobile applications for the same purposes, such as for their education.

For a system to provide individualized support, it should use information about the learning process of the users. These learning analytics are further used by the system to adapt its support. The collection of information may be done by different modes in PCs and Smartphones. However, the information collected by a mode may be different from the information collected by another. A way to aggregate this information and provide individualized support is using a Multi Criteria Decision Making (MCDM) theory.

MCDM has evolved rapidly over the last decades [7]. Various MCDM methods are available, such as AHP, Fuzzy AHP, TOPSIS, Fuzzy TOPSIS, Data Envelopment Analysis (DEA), Multi-attribute utility theory and many more. Analytic Hierarchy Process [8] is one of the most popular MCDM theories. The choice of AHP amongst other MCDM theories is because it presents a formal way of quantifying the qualitative criteria of the alternatives and in this way removing subjectivity of the result [9]. Furthermore, the method's ability in making decisions by making a pair wise comparison of uncertain, qualitative and quantitative factors and also its ability to model expert opinion [10] is another important reason for its selection against other alternatives.

However, a main problem of AHP is that the complexity rises with the increase of alternatives. A way to resolve this problem is by combining AHP with another theory that manages to process and sort several alternatives without increasing the complexity disproportionately, such as Simple Additive Weighting [11].

The main body of the paper is organised as follows: Sects. 10.2 and 10.3 provide an introduction in Distance and Mobile Learning. Section 10.4 provides more information on personalized software with emphasis on mobile software. In Sect. 10.5, the procedure of data collection is described using PCs and Mobile devices as well as the different corresponding modalities. The information collected is combined together using multi-criteria decision making. This procedure is described in Sect. 10.6. Finally, in the last section we give the conclusions drawn from this work and the contributions of the paper.

10.2 Distance Learning

Open and distance learning has grown within a more general expansion of education [2]. Indeed, the increasing popularity of the Internet and the WWW has affected computer assisted learning which is now turning into Web-based learning since there are many advantages that the Web may offer to education. Distance education via the Internet can provide colleges and universities with a low-cost, flexible option to expand into global markets [12].

The change from traditional classroom education to online distance education affects every aspect of educational practices [13, 14]. However, the design of different types of learning environments can depend on the learning objective, target audience, access (physical, virtual and/or both), and type of content [15].

Gunawardena and McIsaac [16] summarize Distance Education (DE) as one in which the teacher and learner are separated from each other and involve in a two-way interaction using technology to mediate the necessary communication. In the e-learning environment, instructors can no longer directly observe students' learning dynamic through patrol classroom, and students can no longer get face-to-face communication with instructors and other students about learning tasks [17].

E-learning platforms take advantage of technologies that enable students to learn and seek out knowledge at their own learning pace, giving educators the ability to create 'online courses, virtual seminars, and practical training' [18]. Indeed, courses, programs and learning objects, which are available in OLEs, can either be self-paces, self-directed or instructor-lead [15]. For this reason, on-line systems may employ different strategies for learning or adaptation to improve learning. A systematic literature review on strategies on self-regulated learning using e-learning tools is made by Garcia et al. [19]. However, what seems more important is that the system should have the ability to adapt to the learners' individual characteristics, such as preferences, knowledge, skills etc.

10.3 Mobile Learning and Mobile Learning Analytics

During the last decade, both learners and educational institutions have realized the importance of mobile learning mobile software. Some important assets of mobile learning applications include platform and hardware independence and also the actual benefit offered to students of learning at any time and at any place, away from the necessity of the context of a real classroom. In many cases this is translated at learning at home or some other site, supervised remotely, synchronously or asynchronously, by human educators. In these cases the interaction is achieved between humans and computers through computer assisted learning or e-learning. A thorough investigation in the field of mobile learning can be found in [20], while work in this research field expanded in the area of learners with special needs can be found in [21]. Smartphone technology can provide numerous additional services to most computer-based applications including educational applications. As a result, Smartphone features can be of great assistance to educational procedures since they offer mobility to learners and also to their educators.

Considering that user modelling in mobile learning originates from the systematic observing and corresponding recording of learners through all the available modalities of interaction, we can come to the conclusion that Learning Analytics can be utilized through Smartphones in completely different levels, in new dimensions. Two can be considered as the most important reasons towards this conclusion. Firstly, taking into consideration the number of modalities of human–computer interaction one may easily observe the chaotic difference between personal computers and modern Smartphones. While learners are used to interact with a personal computer or a laptop through a keyboard and a mouse for data input and the computer screen for data output, there are tens of sensors that enable a multimodal interaction between Smartphones and users, to be further analyzed in next section. Secondly, and perhaps even more importantly, we should examine the tight "bond" between users and their Smartphones, in contrast with their PCs. Namely, while learners have a personal computer in a home or office installation, used only when there is actual need to do so, a Smartphone mobile device can be seen as a kind of "wearable" almost always in the learners' context and almost always powered on. In modern times, it is very rare to find people not accompanied by a mobile device, while their interaction with these devices has been very recently been counted in terms of tens per hour.

Combining the two aforementioned reasons, one may easily deduct that smart mobile devices "live" with their users in their daily life, accompanying them anytime, everywhere, while at the same time they possess a surprisingly big number of sensors that can interact with their context. As a result, the available data that can be used for Learning Analytics reasons, easily get stamped as Big Data. Towards this end, the next sections provide a more thorough analysis of the dimensions where modern Smartphones have met Learning Analytics.

The authors of [22] suggest that learning attribute-sharing mobile features and attribute-specific mobile features effectively is significant to user attributes learning. To address these challenges, they propose a unified model, the so-called graphconstrained multi-source multi-task learning model (gMM), in order to infer user attributes.

As it is stated in [23], the increasing popularity of wearable devices in recent years means that a diverse range of physiological and functional user data can now be captured continuously for applications including sports, wellbeing, and healthcare. As a result, this wealth of information requires efficient methods of classification and analysis where deep learning is considered as a promising technique for large-scale data analytics.

The research work of [24] includes an overview and also a brief tutorial on deep learning in mobile big data analytics and further discusses a scalable learning framework over Apache Spark. More specifically, its authors execute distributed deep learning as an iterative MapReduce computing on many Spark workers, where each Spark worker learns a partial deep model on a partition of the overall mobile, and a master deep model is then built by averaging the parameters of all partial models.

In [25] the role of mobile learning analytics in self-regulated learning is investigated. Towards this end, its authors explore the effects of tracking and monitoring time devoted to learn with a mobile tool, on self-regulated learning, experimenting with graduate students from three different online courses, using their own mobile devices to track how much time they devoted to learn over a period of four months.

10.4 Personalised Learning Software

Personalization in Smartphone educational software interfaces and more generally mobile learning analytics is a promising field of research that gathers interest in an increasing pace. This is clearly stated in [26], where the challenge of how to provide learners with personalized services anywhere and anytime, without requiring the user to bootstrap a user model from scratch every time is described.

Avouris and Yiannoutsou [27] provide a very interesting review on smartphone location-based games for learning. They introduce the theoretical and empirical considerations of Smartphone location-based games, and then discuss an analytical framework of their main characteristics through typical examples. Their paper focuses on the narrative structure of Smartphone location-based games, the interaction modes that they afford, their use of physical space as prop for action, the way this is linked to virtual space and the possible learning impact such game activities have.

In the work of [28], the factors during design of personalized smartphone applications in cultural heritage environments are investigated. This paper presents a formal description of these factors which allows both for a systematic survey of existing practice, and for supporting the design process of Smartphone cultural heritage applications in the future.

Another aspect of Smartphone personalization in software applications is described in [29]. Smartphone personalization through user modeling is applied in order to provide remote health monitoring together with behavior change support features and persuasion strategies.

The authors of [30] examine another educational domain, namely the cultural heritage domain and propose a framework on how to monitor visitor behavior on the go, in order to determine personality traits. As the authors state, this resultant knowledge can be then further used along with context to give tailored advice, while methods of monitoring visitor behavior, converting that to traits and to personality types are also described. This paper also discusses about different dimensions of how to give tailored advice based on user personality.

After a thorough investigation in the research field of personalization in mobile learning we have come up with the conclusion that although there is massive research work in the domains of mobile learning and software personalization over the last decade, there are only minor efforts published regarding their intersection to date. The rise of research efforts in the field of mobile learning analytics provides a clear indication that personalization in mobile learning and in distance learning will be increasing in the years to come.

In [31] the domain of mobile learning context for people with special needs is investigated, as a big challenge for digital media in education. It is sated that the usage of mobile technology is growing, and that it affects other technologies by bringing in new innovation and methods. As a result, mobile learning can be seen as a bridge between higher level of abstracted knowledge and practical experiences, which supports the personalization in a learning process.

The literature review of [32] deals with the personalization issue in mobile learning, and more specifically on how agents can be used to support solving this issue. As the authors claim, the main objective of this study is to review recent and up to date studies on personalization in mobile learning and the use of agent technology, towards solving this issue by deploying agents more effectively to support personalization in mobile learning.

Badidi [33] describes a proposed cloud-based framework for delivering adaptive mobile learning services, while the paper also explains the benefits and requirements of cloud-based solutions for educational organizations, and the components of the proposed framework together with the process of integrating learning objects imported from third-party providers with in-house learning objects of the educational organization.

Finally, in [34] the authors conducted a study on the added value of a gaming context and intelligent adaptation for a mobile learning application. Their main results indicated that the students in the experimental condition (Mobile English Learning-enhanced) outperformed the children from the control group (Mobile English Learning-original), although the former group did not spend more time with the learning material than the latter, and that the students in the experimental group valued Mobile English Learning-enhanced more than the children from the control group valued Mobile English Learning-original.

10.5 Data Collection

Collecting data from multiple sources regarding learners and their environment is evidently a one-way path in order to serve learning analytics, both for adaptation and for recommendation purposes. In this regard, since smart devices that accompany learners in their everyday life consist of numerous sensors and modalities of interaction, a large amount of data can be recorded and further processed. Correspondingly, all the available information about learners can be divided in two major subsets, one of the information that comes implicitly from learners and one that comes explicitly from them. Explicit learner information to a large extend derives from information submitted by them to a software mobile system, in forms such as dialogs, required information and questions targeted to learners. Implicit learner data may be collected from a very wide variety of sources, including sensors, additional modalities of interaction and context awareness software mechanisms. Implicit data may also be collected by software third party service entities, which usually communicate with mobile devices through internet. In most cases, Smartphones provide an initial criterion, communicated with the third parties, such as location, or date-time, and correspondingly receive a response of useful data, such as weather information about a specific location, or even public transport schedules. In this regard, both explicit and implicit learner information could be used for learning analytics and profiling purposes, nevertheless, not always being confident about the learners' anonymity and privacy rights. As it will be further analyzed and discussed, according to the GDPR [35], learners should always both have full knowledge and control about their personal data that are being recorded and also should at any time be able to revoke the software mobile systems' access to their personal records.

As it becomes quite evident, both finding and recording explicit data is not only more straightforward as an approach, but also requires less effort by a software mobile system in terms of mining data and revoking stored data processes. Explicit information given by learners is in a sense "expected", since it is mostly either a mobile system initiated process, i.e. requested by the mobile system, or a learner initiated process, i.e. data submitted by the learner, on learner demand. In this sense, explicit data acquisition is also more easily transformed into a structured data model, such as a relational data base, with basic functions such as selecting, updating, inserting, or deleting incorporated data.

On the other hand, implicit learner data seem more complicated both to collect and also to retrieve, process and even erase. As a data model, implicit data coming from a variety of different sources and sensors, seem chaotic. As a result, other means of data base management mobile systems had to be recruited, such as NoSQL star database schemas, with their corresponding software, mostly cloud as a service, infrastructure. Reasonably, we may argue that the amount of data that can emerge from an implicit data collection model, i.e. working silently on the background and monitoring the learners' lives and environment, is plausibly times of magnitude larger than the more "conventional" explicit data model. Thus, while discussing about crowd-sensing and crowd-sourcing data, by Smartphones, the discussion is arguably leaded to big data.

Big data as a research field is both large, of great significance and interest, and also evolving in great speeds. And of course is accompanied with a number of challenges, such as sufficient storage mechanisms, data filtering and real time processing. As a result, these challenges also appear in implicit learner data modelling. In general, future centralized learning analytics through crowd-sourcing are expected to confront both resource and also processing complexity issues.

Preserving privacy, in distance and mobile learning is also a challenge for learning analytics. As it can be easily inferred, even the attributes that remain in an anonymized dataset may constitute quasi-identifiers. Quasi-identifiers consist of attributes that may facilitate indirect re-identification of respondents, learners, through external data sources [36]. As an example, we may consider the cases of geolocation mobile systems, which are very popular over the last decade. Collecting a large amount of location coordinates, even when they are not accompanied by an explicit learner id, a sophisticated software module may still find patterns, such as specific geographic areas with an extraordinary number of records, implying in many cases learners' homes and classrooms. These pattern observations, further processed with timestamp data, may subsequently lead to quite "safe" assumptions for distinguishing between learners' home places and classrooms. In the same example, even subsequent location coordinates, processed with their corresponding bearing values, speed and accuracy of measurements, could reveal learners' routes on maps, further compromising their anonymity and personal data. Concluding, while working on providing learners with more adapting and helping software, in order to better serve their needs, software architects in learning analytics should carefully investigate whether their approaches may compromise learners' privacy.

In this section we present the most common data collection mechanisms, realized as hardware sensors which can be considered as modalities of interaction between learners, computerized and mobile devices and their environment. Additionally, significant software engineering attempts that take advantage of sensors' capabilities are also covered. This section also presents future trends regarding new coming Smartphone modalities of interaction, as well as ways to use them in order to improve Learning Analytics through context awareness. Finally, in this section, related work regarding data collection through personal computers and Smartphones is also included.

10.5.1 Modalities of Interaction in PCs

As it is stated in [37], a modality of interaction is the classification of a single independent channel of sensory input/output between a computer and a human. In the same paper it is stated that a system is designated unimodal if it has only one modality implemented, and multimodal if it has more than one. Since 2001 the authors of [38] have suggested that multiple modalities can be used in combination to provide complementary methods that may be redundant but convey information more effectively. Towards this direction, a number of papers have been published in the past, that combine data from multiple modalities, either for more "common" tasks such as user recommendations [39, 40], or for even more complex reasoning mechanisms, such recognizing human affect [41]. The modalities of interaction in question can be realized in two "forms", namely human–computer modalities and computer–human modalities. These two forms regard the direction of data flowing between human and computer.

Analyzing the modalities of interaction, taking into account the aforementioned definition and applying it strictly into human–computer interaction, we deduce that the independent channels of both input and output are basically unidirectional, while only a limited set of them may behave as bidirectional channels too. A unidirectional channel of interaction is a modality that accepts, and is used only for, either input, or output of data. In human–computer interaction, such channels, which are the most common, include the computer's keyboard and mouse, the screen, the microphone, the speakers and the camera. Bidirectional channels of interaction are mostly represented by modern PC touchscreens, where this modality can be used both for receiving visual data and also for passing touch data to the computer.

Table 10.1 illustrates these channels in terms of modalities of interaction, accompanied by information about whether they are used for sending data to a computer, or receiving data from a computer and consequently whether they are unidirectional, or bidirectional. Some more, yet uncommon, modalities are also presented, for research completeness purposes. Nevertheless, these modalities are not thoroughly used yet in "traditional" Learning Analytics systems, since they cannot be found in the majority of personal computers. As a result, such data are being able to cause "inconsistency" issues both to software algorithms and to software implementations. Namely, data coming from a modality, representing a very low percentage of the entire dataset (e.g. <1%), may cause inconveniencies in the way the Learning Analytics algorithms process their data, since in many supervised learning AI approaches, much larger datasets are required as input. Respectively, relational architecture database management systems may suffer from data fragmentation and resource decreasing. In this regard, Learning Analytics software architects design, in essence, their systems taking into consideration the modalities that are present in most of the personal computer installations. As it will be discussed in the next sections, this is the case of the human–Smartphone interaction, where widespread mobile sensors may be utilized by the state of the art Learning Analytics Smartphone applications.

Concluding, while all available channels of communication in HCI are very important for the realization of communication between human and computer, regarding Learning Analytics, the criteria differ. Indeed, humans feel more "comfortable" interacting with computers, the more available modalities they have for their interaction. Nevertheless, Learning Analytics are based on the concept of building a conceptual understanding of the user and consequently requires as much input as possible from the user, namely from input modalities of interaction, i.e. human–computer modalities. In this regard, while a conventional PC screen may serve as a great way to enhance user experience through improved user interfaces, nevertheless cannot contribute in the "quest" for data coming from the users. On the contrary, a touch screen is capable of providing Learning Analytics software with a wealth of user data, vary-

Table 10.1 Modalities of interaction in Human–Computer communication

Modalities in HCI	Input to PC	Output from PC
Common modalities		
Keyboard	Yes	No
Mouse	Yes	No
Microphone	Yes	No
Speaker	No	Yes
Camera	Yes	No
Conventional screen	No	No
Touch screen	Yes	Yes
Touchpad	Yes	No
Uncommon modalities		
Drawing pad	Yes	No
Haptic devices	Yes	Yes
Connectivity modalities		
Bluetooth	Yes	Yes
Wi-Fi	Yes	Yes
Common peripherals		
Printer	No	Yes
Scanner	Yes	No
CD/DVD ROM	Yes	Yes
USB Stick/Drive	Yes	Yes

ing from filled form data, i.e. what do users type, to more complex biometric user data, i.e. how and when users touch the screen.

10.5.2 Modalities of Interaction in Smartphones

In [42], the authors explore how human interact with modern Smartphone devices, while the paper concludes by presenting a framework for capturing all the available information from Smartphone sensors in order to be further processed and analyzed.

A mobile learning system that incorporates Smartphone sensors is found in [43]. This system's authors propose a portable and convenient learning assisted system by using Android Smartphone with wireless sensors. The resulting system senses and collects the data of learning behaviors with a Smartphone as the processing unit.

The authors of [44] report on the development of a new, versatile, and cost-effective clinical tool for mobile voice monitoring that acquires the high-bandwidth signal from an accelerometer sensor placed on the neck skin above the collarbone.

Table 10.2 Modalities of interaction in Human–Smartphone communication

Modalities in Smartphones	Incoming data	Outgoing data
Accelerometer	Yes	No
Barometer	Yes, environmental atmospheric pressure	No
Bluetooth	Yes	Yes
Camera	Yes	No
Flashlight	No	Yes
GPS	Yes	No
Gyroscope	Yes	No
Keyboard buttons	Yes	No
Heart rate sensor	Yes	No
Lightsensor	Yes	No
Magnetometer	Yes	No
Microphone	Yes	No
Touchscreen	Yes, through touch	Yes
Touch pressure sensor	Yes	No
Proximity sensor	Yes	No
Speaker	No	Yes
Step detector	Yes	No
Thermometer	Yes	No
Vibrator	No	Yes
NFC	Yes. Requires touch with other device	Yes. Requires touch with other device
Connected wearables	Yes	Yes

Prudencio et al. [45] propose a novel set of features for distinguishing five physical activities using only sensors embedded in the Smartphone by introducing features that are normalized using the orientation sensor.

The authors of [46] present a prototype on an Android Smartphone that can sample the related sensors during the user's movement and collect the sensor data for further processing on personal computers, while the work of [47] analyzes the challenges in unassisted orientation and way-finding, especially in unexplored and potentially dangerous environments for visually impaired users.

Table 10.2 illustrates a surprising number of reported modalities of interaction through Smartphones, in the wider sense of sensors, namely all the available hardware and or software means that enable the communication between a Smartphone and its context. A Smartphone's context usually includes but is not limited to the Smartphone's corresponding users, the smartphone's physical environment and also other IoT devices, such as smart watches and devices in smart houses. The entire context of the Smartphone is considered as of high importance for Learning Analytics, since in most cases is also the learner's context. In this regards, our research systematically recorded more than twenty modalities of interaction on Smartphones. For each one of the available modalities, corresponding fields of interest are also reported. Namely, the modalities capability in sending and receiving data in general and also whether a modality is capable of receiving data from the users. Additionally, since as already mentioned the users' geolocation plays a very important role nowadays, our report also includes an indication whether a modality is capable of directly, or indirectly locating the user. After a thorough research in the related scientific literature, we come to the conclusion that this kind of information on Smartphone modalities of interaction for the purposes of Learning Analytics has not been reported yet. In this regard, this section's findings can be utilized both for Learning Analytics purposes and also for other software architecture needs, such as human–Smartphone interaction and user experience (UX).

10.6 Multi-criteria Analysis

A way to combine the different modes of evidence collected by the different modalities is using a Multi-Criteria Decision Making theory. In view of the above, we use Analytic Hierarchy Process (AHP) [8] in combination with Simple Additive Weighting (SAW) [11], to combine the most common modalities in HCI or Smartphone that allow input data. AHP can be used to implement all the stages of a decision making process until having the alternatives shorted. However, the complexity rises with the increase of alternatives; therefore, it is better to combine AHP with another theory that manages to process and sort several alternatives without increasing the complexity disproportionately. Such a theory is the Simple Additive Weighting (SAW) [11]. The SAW method is one of the simplest but nevertheless good decision making methods. This is because SAW provides a formal way for connecting criteria in order to make a decision. However, it does not have a good way for calculating the weights of the criteria. Therefore, the combination of AHP with SAW seems rather effective.

The implementation of the steps of AHP and SAW are presented in the subsections below.

10.6.1 Combining Modalities of Interaction in HCI

In order to apply AHP, the following steps should be implemented:

1. **Developing a goal hierarchy**
    a. **Forming the overall goal**: The overall goal is to combine the learning analytics by different modes

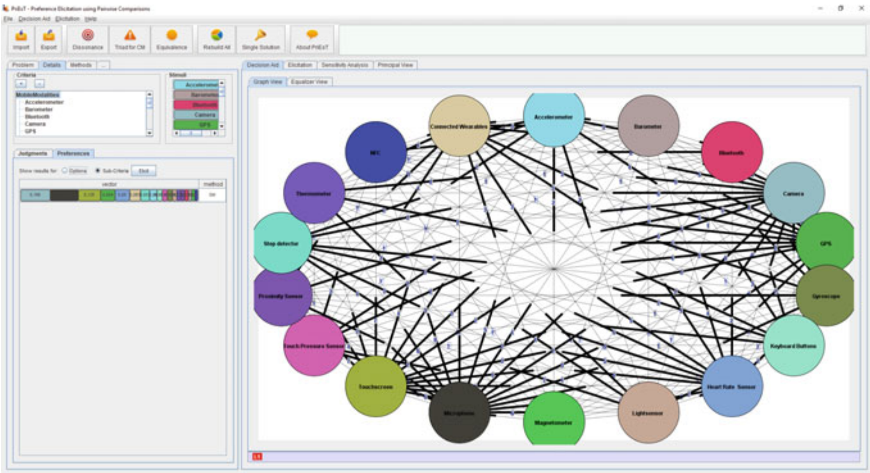


Fig. 10.1 The PriEst interface

b. **Forming the set of modalities**: The most common modalities in HCI that allow input data are selected. As one can observe in Table 10.1, these modes are: keyboard, mouse, microphone, camera, touch screen, touchpad.

2. **Form the set of evaluators**: The set of evaluators consists of 3 Software Engineers, 3 Educators, 3 HCI experts and 1 Mobile Software Engineer.
3. **Setting up a pair-wise comparison matrix of modalities**: In this step a comparison is implemented among the modalities of the same level.
4. **Calculating weights of modalities**: After making pair-wise comparisons, estimations are made that result in the final set of weights of the modalities. In this step, the principal eigenvalue and the corresponding normalised right eigenvector of the comparison matrix give the relative importance of the various modalities being compared. The elements of the normalised eigenvector are the weights of modalities. In terms of simplicity, we have use the ‘Priority Estimation Tool’ (PriEst) [48] (Fig. 10.1), an open-source decision-making software that implements the Analytic Hierarchy Process (AHP) method, for making the calculations of AHP. As a result, w_i are calculated with $i = 1 \ldots 7$ being the 7 modalities.

$$w_{1-keyboard} = 0.149$$

$$w_{2-mouse} = 0.092$$

$$w_{3-microphone} = 0.241$$

$$w_{4-camera} = 0.412$$

$$w_{5-touchscreen} = 0.064$$

$$w_{6-touchpad} = 0.042$$

Then the SAW model is applied

1. **Calculating the values of each modality is calculated**: In this step, the value of each proposal for each modality is calculated.
2. **Calculate Weighted Ratings**: The weighted value is calculated as: $v_{ij} = w_i \cdot r_{ij}$, where w_i is the weight and r_{ij} is the value of the ith modality for the evaluated learning proposal.
3. **Calculate Sum of Weighted Rating**: Finally, the function C is used to calculate a crisp value for each alternative proposal X_j combining the analytics collected by different modalities and the following formula is used:

$$C(X_j) = \sum_{i=1}^{n} w_i x_{ij}$$

The proposal combining all different HCI modalities that maximizes function C is selected by the system to be proposed to the user in order to provide individualized support.

10.6.2 Combining Modalities of Interaction in Smartphones

Similarly to the above described combination of modalities in HCI, the modalities of Smartphones are combined.

1. **Developing a goal hierarchy**
   a. **Forming the overall goal**: The overall goal is to combine the learning analytics by different modes
   b. **Forming the set of modalities**: The most common modalities in Smartphones that allow input data are selected. As one can observe in Table 10.1, these modes are: Accelerometer, Barometer, Bluetooth, Camera, GPS, Gyroscope, Keyboard Buttons, Heart Rate Sensor, Lightsensor, Magnetometer, Microphone, Touchscreen, Touch Pressure Sensor, Proximity Sensor, Step detector, Thermometer, NFC, Connected Wearables.
2. **Form the set of evaluators**: The same set of evaluators is used.
3. **Setting up a pair-wise comparison matrix of modalities**: In this step a comparison is implemented among the modalities of the same level.
4. **Calculating weights of modalities**: After making pair-wise comparisons, estimations are made that result in the final set of weights of the modalities. As a result, w_i are calculated with $i = 1 \ldots 18$ being the 18 modalities

$$w_{1-Accelerometer} = 0.04$$

$$w_{2-Barometer} = 0.019$$

$$w_{3-Bluetooth} = 0.021$$

$$w_{4-Camera} = 0.169$$

$$w_{5-GPS} = 0.084$$

$$w_{6-Gyroscope} = 0.027$$

$$w_{7-KeyboardButtons} = 0.031$$

$$w_{8-HeartRateSensor} = 0.08$$

$$w_{9-Lightsensor} = 0.025$$

$$w_{10-Magnetometer} = 0.018$$

$$w_{11-Microphone} = 0.157$$

$$w_{12-Touchsreen} = 0.126$$

$$w_{13-TouchPressureSensor} = 0.03$$

$$w_{14-\Pr oximitySensor} = 0.022$$

$$w_{15-StepDetector} = 0.052$$

$$w_{16-Thermometer} = 0.023$$

$$w_{17-NFC} = 0.015$$

$$w_{18-ConnectedWearables} = 0.063$$

Then the SAW model is applied

1. **Calculating the values of each modality is calculated**: In this step, the value of each proposal for each modality is calculated.
2. **Calculate Weighted Ratings**: The weighted value is calculated as: $v_{ij} = w_i \cdot r_{ij}$, where w_i is the weight and r_{ij} is the value of the ith modality for the evaluated learning proposal.
3. **Calculate Sum of Weighted Rating**: Finally, the function M is used to calculated a crisp value for each alternative proposal X_j combining the analytics collected by different modalities and the following formula is used:

$$M(X_j) = \sum_{i=1}^{n} w_i x_{ij}$$

10.7 Conclusions

Distance Learning is gaining a lot of interest and people follow learning programs interacting with different means such as PCs and Smartphones. All these means of interaction use different modalities to collect information about the users and provide individualized support. In most cases of learning contexts, the modalities that collect information in HCI are keyboard, mouse, microphone, camera, touch screen and touchpad. The Smartphone on the other hand has increased number modalities that collect information about the user; these are Accelerometer, Barometer, Bluetooth, Camera, GPS, Gyroscope, Keyboard Buttons, Heart Rate Sensor, Light-sensor, Magnetometer, Microphone, Touchscreen, Touch Pressure Sensor, Proximity Sensor, Step detector, Thermometer, NFC and Connected Wearables. Interestingly, the Smartphones can built a more “fine-grained” learner model, using implicit user data, since they are almost always powered-on and functioning and additionally they always accompany their owners.

The information collected by the different modalities can be further combined to extract more accurate and plausible conclusions. In this paper, the combination of the different modes is achieved through the use of MCDM. More specifically, two MCDM theories are incorporated, namely AHP and SAW, to combine the modes in HCI or Smartphone–user interaction. AHP has the ability to model expert opinion and, therefore, was considered ideal for calculating weights of importance of the different modes in an experiment where expert users were asked to make pair-wise comparisons of the different modes.

The most important modality in HCI is found to be the Camera as it has the highest weight of all modalities. Camera is considered to collect the greatest number of information about the user. Other important modalities in HCI that also consider collecting much valuable information and their weight was calculated quite high are microphone and keyboard. Similarly to HCI, the most important modality in

Smartphone interaction is also the mobile Camera, Other modalities that are also considered as very important are the microphone and the Touchscreen, similarly to the microphone and keyboard of the PC.

The weights of the different modes are used in SAW application to combine evident from different modes. The SAW model is quite simple and very effective in combining different modes and evaluating a great number of alternatives.

References

1. Merisitis, JP., Phipps, RA.: What's the Difference?: Outcomes of Distance Vs. Traditional Classroom-Based Learning, Change: The Magazine of Higher Learning **31**(3), 12–14 (1999). https://doi.org/10.1080/00091389909602686
2. Peraton, H.: Open and Distance Learning in the Developing World. Routledge, Taylor & Francis Group, London and New York (2007)
3. Moller, L., Foshay, W., Huett, J.: The evolution of distance education: implications for instructional design on the potential of the Web. TechTrends **52**(4), 66–70 (2008)
4. Gartner: Gartner says by 2018, more than 50 percent of users will use a tablet or smartphone first for all online activities. http://www.gartner.com/newsroom/id/2939217 (2014)
5. Gartner: Gartner forecasts at worldwide device shipments until 2018. http://www.gartner.com/newsroom/id/3560517 (2017)
6. The Telegraph: Mobile web usage overtakes desktop for first time. http://www.telegraph.co.uk/technology/2016/11/01/mobile-web-usage-overtakes-desktop-for-first-time/ (2016)
7. Zopounidis, C.: Knowledge-based multi-criteria decision support. Eur. J. Oper. Res. **195**, 827–828 (2009)
8. Saaty, T.: The Analytic Hierarchy Process. McGraw-Hill, New York, NY (1980)
9. Tiwari, N.:. Using the Analytic Hierarchy Process (AHP) to identify Performance Scenarios for Enterprise Application. Comput. Meas. Group, Measure It **4**(3) (2006)
10. Mulubrhan, F., Akmar Mokhtar, A., Muhammad, M.: Comparative analysis between fuzzy and traditional analytical hierarchy process. In: MATEC Web of Conferences 13 (2014)
11. Hwang, C.L., Yoon, K.: Multiple Attribute Decision Making: Methods and Applications. Lecture Notes in Economics and Mathematical Systems, vol. 186. Springer, Berlin, Heidelberg, New York (1981)
12. Casey, D.: A journey to legitimacy: the historical development of distance education through technology. TechTrends **52**(2), 45–51 (2008)
13. Hong, J.C., Tai, K.H., Hwang, M.Y., Kuo, Y.C., Chen, J.S.: Internet cognitive failure relevant to users' satisfaction with content and interface design to reflect continuance intention to use a government e-learning system. Comput. Hum. Behav. **66**, 353–362 (2017)
14. Al-Gahtani, S.S.: Empirical investigation of e-learning acceptance and assimilation: a structural equation model. Appl. Comput. Inf. **12**(1), 27–50 (2016)
15. Moore, J.L., Dickson-Deane, C., Galyen, K.: e-Learning, online learning, and distance learning environments: are they the same? Internet High. Educ. **14**, 129–135 (2010)
16. Gunawardena, C.N., McIsaac, M.S.: Distance education. In: Jonassen, D.H. (ed.), Handbook of Research for Educational Communications and Technology, 2nd edn., pp. 355–395. Lawrence Erlbaum Associates, Inc., Publishers, Mahwah, New Jersey (2004)
17. Luo, N., Zhang, M., Qi, D.: Effects of different interactions on students' sense of community in e-learning environment. Comput. Educ. **115**(2017), 153–160 (2017)
18. Feldmann, B.: Two decades of e-learning in distance teaching from web 1.0 to web 2.0 at the University of Hagen. In: Learning Technology for Education Challenges, Communication in Computer and Information Science, vol. 446, pp. 163–172 (2014)

19. Garcia, R., Falkner, K., Vivian, R.: Systematic literature review: self-regulated learning strategies using e-learning tools for computer science. Comput. Educ. **123**, 150–163 (2018)
20. Alepis, E., Virvou, M.: Object-Oriented User Interfaces for Personalized Mobile Learning. Intelligent Systems Reference Library, vol. 64. Springer, Berlin (2014)
21. Virvou, M., Alepis, E.: User modeling in mobile learning environments for learners with special needs. In: Tsihrintzis, G., Virvou, M., Jain, L. (eds.): Multimedia Services in Intelligent Environments. Smart Innovation, Systems and Technologies, vol. 25. Springer, Heidelberg (2013)
22. Nie, L., Zhang, L., Wang, M., Hong, R., Farseev, A., Chua, T.-S.: Learning user attributes via mobile social multimedia analytics. ACM Trans. Intell. Syst. Technol. **8**(3), Article 36 (2017)
23. Ravì, D., Wong, C., Lo, B., Yang, G.Z.: A deep learning approach to on-node sensor data analytics for mobile or wearable devices. IEEE J. Biomed. Heal. Inform. **21**(1), 56–64 (2017)
24. Alsheikh, M.A., Niyato, D., Lin, S., Tan, H.P., Han, Z.: Mobile big data analytics using deep learning and apache spark. IEEE Netw. **30**(3), 22–29 (2016)
25. Tabuenca, B., Kalz, M., Drachsler, H., Specht, M.: Time will tell: the role of mobile learning analytics in self-regulated learning. Comput. Educ. **89**, 53–74 (2015)
26. Kuik, T., Mumblat, Y., Dim, E.: Enabling mobile user modeling: infrastructure for personalization in ubiquitous computing. In: 2nd ACM International Conference on Mobile Software Engineering and Systems, MOBILESoft 2015, Florence, Italy, pp. 48–51, 16–17 May 2015
27. Avouris, N.M., Yiannoutsou, N.: A review of mobile location-based games for learning across physical and virtual spaces. J. UCS **18**(15), 2120–2142 (2012)
28. Fidas, C.A., Avouris, N.M.: Personalization of mobile applications in cultural heritage environments. In: 6th International Conference on Information, Intelligence, Systems and Applications, IISA 2015, Corfu, Greece, pp. 1–6, 6–8 July 2015
29. Kirci, P., Unal, P.: Personalization of mobile health applications for remote health monitoring. In: Proceedings of the International Workshop on Personalization in Persuasive Technology Co-located with the 11th International Conference on Persuasive Technology (PT 2016), Salzburg, Austria, April, pp. 120–125, 5 Apr 2016
30. Wecker, A.J., Kuik, T., Stock, O.: Dynamic personalization based on mobile behavior: From personality to personalization: a blueprint. In: Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct, MobileHCI '16, ACM, New York, NY, USA, pp. 978–983(2016)
31. Zare, S.: Personalization in mobile learning for people with special needs. In: Stephanidis, C. (eds.) Universal Access in Human-Computer Interaction. Applications and Services. UAHCI 2011. Lecture Notes in Computer Science, vol. 6768. Springer, Berlin, Heidelberg (2011)
32. Qoussini, A.E.M., Jusoh, Y.Y.B.: A review on personalization and agents technology in mobile learning. In: 2014 International Conference on Intelligent Environments, Shanghai, pp. 260–264 (2014)
33. Badidi, E.: A Cloud-based framework for personalized mobile learning provisioning using learning objects metadata adaptation. In: Proceedings of the 8th International Conference on Computer Supported Education, CSEDU, vol. 1, pp. 368–375 (2016). ISBN 978-989-758-179-3
34. Sandberg, J., Maris, M., Hoogendoorn, P.: The added value of a gaming context and intelligent adaptation for a mobile learning application for vocabulary learning. Comput. Educ. **76**(2014), 119–130 (2014)
35. Politou, E., Alepis, E., Patsakis, C.: Forgetting personal data and revoking consent under the GDPR: challenges and proposed solutions. J. Cybersecur. 1–20 (2018)
36. Casino, F., Domingo-Ferrer, J., Patsakis, C., Puig, D., Solanas, A.: A k-anonymous approach to privacy preserving collaborative filtering. J. Comput. Syst. Sci. **81**(6), 1000–1011 (2015)
37. Karray, F., Alemzadeh, M., Saleh, J.A., Arab, M.N.: Human-computer interaction: overview on state of the art. Int. J. Smart Sens. Intell. Syst. **1**(1) (2008)
38. Palanque, P., Paterno, F.: Interactive Systems. Design, Specification, and Verification. Springer Science & Business Media, p. 43 (2001). ISBN 9783540416630

39. Zahálka, J., Rudinac, S., Worring, M.: Interactive multimodal learning for venue recommendation. IEEE Trans. Multimed. **17**(12), 2235–2244 (2015)
40. Shin, H., Lee, M., Kim, E.Y.: Personalized digital TV content recommendation with integration of user behavior profiling and multimodal content rating. IEEE Trans. Consum. Electron. **55**(3), 1417–1423 (2009)
41. Virvou, M., Tsihrintzis, G.A., Alepis, E., Stathopoulou, I.O., Kabassi, K.: Emotion recognition: empirical studies towards the combination of audio-lingual and visual-facial modalities through multi-attribute decision making. Int. J. Artif. Intell. Tools **21**(02) (2012)
42. Alepis, E., Virvou, M., Drakoulis, S.: Human smartphone interaction: Exploring smartphone senses. In: IISA 2014, The 5th International Conference on Information, Intelligence, Systems and Applications, Chania, pp. 44–48 (2014)
43. Tsai, T.-C., Peng, C.-T.: A Smartphone assisted learning system with wireless sensors. In: Communications in Computer and Information Science, CCIS, vol. 216, Issue PART 3, pp. 557–561 (2011)
44. Mehta, D.D., Zañartu, M., Feng, S.W., Cheyne, H.A.I., Hillman, R.E.: Mobile voice health monitoring using a wearable accelerometer sensor and a smartphone platform. IEEE Trans. Biomed. Eng. **59**(12 PART2), pp. 3090–3096, Article number 6257444 (2012)
45. Prudêncio, J., Aguiar, A., Lucani, D.: Physical Activity Recognition from Smartphone Embedded Sensors. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), LNCS, vol. 7887, pp. 863–872 (2013)
46. Zhang, L., Liu, J., Jiang, H., Guan, Y.: SensTrack: energy-efficient location tracking with smartphone sensors. IEEE Sens. J. **13**(10), 3775–3784, Article number 6563204 (2013)
47. Ahmetovic, D.: Smartphone-assisted mobility in urban environments for visually impaired users through computer vision and sensor fusion. In: Proceedings—IEEE International Conference on Mobile Data Management, vol. 2, pp. 15–18, Article number 6569055 (2013)
48. Sirah, S., Mikhailov, L., Keane, J.A.: PriEsT: an interactive decision support tool to estimate priorities from pair-wise comparsion judgements. Int Trans Oper Res **22**(2), 203–382 (2015)
49. Kabassi, K., Virvou, M.: Combining decision making theories with a cognitive theory for intelligent help: a comparison. IEEE Trans. Hum. Mach. Syst. **45**(2), 176–186 (2015)

Chapter 11
Optimizing Programming Language Learning Through Student Modeling in an Adaptive Web-Based Educational Environment

Konstantina Chrysafiadi, Maria Virvou and Evangelos Sakkopoulos

Abstract This chapter describes ELaCv2, which is the 2nd improved version of ELaC that is described in a previous work [1]. ELaCv2 is a novel integrated adaptive educational environment that provides e-training in programming and the language 'C'. It adapts the learning material and process to the learner's background, knowledge level, needs and ability. The adaptivity is achieved due to the incorporation of a 4-parameter student model that was developed taking into consideration the data and results that have been gathered by the student model of ELaC. The particular student model is responsible for identifying and updating the student's knowledge level and needs each time from the beginning to the end of the learning process, allowing the learner to complete the e-training course at her/his own pace and according to her/his ability. The system can identify, each time and for each individual learner, which domain concepts are partially or completely known, which domain concepts are unknown, which domain concepts have been assimilated and which domain concepts need revision. Thus, the system schedules dynamically the learning material for each individual learner on the fly, minimizing the time that is required for her/his to complete the e-training course, and improving, simultaneously, the learning results.

11.1 Introduction

Nowadays, the use of internet technologies has grown up remarkably. The use of tablets, smartphones, PCs, laptops and other smart devices for accessing online services, like e-shop, e-applications, e-news, e-learning etc., that facilitate the everyday life has been increased. On the other hand, the modern lifestyle requires fast pace,

K. Chrysafiadi (✉) · M. Virvou · E. Sakkopoulos
Software Engineering Lab, Department of Informatics, University of Piraeus,
185 34 Piraeus, Greece
e-mail: kchrysafiadi@unipi.gr

M. Virvou
e-mail: mvirvou@unipi.gr

E. Sakkopoulos
e-mail: sakkopul@unipi.gr

M. Virvou et al. (eds.), *Machine Learning Paradigms*, Intelligent Systems Reference Library 158, https://doi.org/10.1007/978-3-030-13743-4_11

speed and multi-disciplinary knowledge and constant updating of it. Therefore, the need of e-learning is crucial, since everyone can have access to knowledge whenever and wherever s/he desires. However, in order to build an effective e-learning system, adaptivity has to be taken into consideration.

E-learning applications are used from heterogeneous student populations. Therefore, they have to adapt dynamically each time to the specific different needs, knowledge and background of each learner. A solution to this challenge is the technology of student modeling that is used to most educational software applications that aim to be adaptive and personalized. Student modeling is one of the key factors that affect automated tutoring systems in making instructional decisions [2], since a student model enables understanding and identification of students' needs [3].

The data and information that are incorporated into a student model concern the cognitive state of the student, her/his learning needs and particularities, her/his background and knowledge level, her/his progress and the contexts of the learning process. These data can be gathered by tracking the learners during their interactions with online learning environments and activities. They can be used to improve the student model and optimize the learning process providing better adaptivity personalizing the learner experience.

In this chapter, we improve the teaching and learning process of programming building a new version of the student model of an educational environment that has already be implemented. More particular, we take into consideration the data that have been gathered by the student model of ELaC (a web-based adaptive educational environment for e-training in programming on the Language 'C'—Chrysafiadi and Virvou [1], and we improve the student model building a 4-parameter student model. The particular student model is responsible for identifying and updating the student's knowledge level and needs each time from the beginning to the end of the learning process, allowing the learner to complete the e-training course at her/his own pace. Furthermore, it minimizes the time that is required for a learner to complete the e-training course, improving, also, the learning results.

The remainder of this chapter is organized as follows. Section 11.2 presents the related work in student modeling and adaptive educational environments about programming. Section 11.3 describes the student model of the new version of our system. Examples of the operation of the system are given in Sect. 11.4. Section 11.5 presents the system's evaluation. Finally, in Sect. 11.6, conclusions are drawn.

11.2 Related Work

The goal of each web-based educational system is to maximize the effectiveness of learning and introduce the learning and teaching process of real-classroom education to the web. To achieve this, a web-based educational system has to be flexible and able to adjust the instructional process to each individual student's needs and learning characteristics. In particular, an adaptive educational system has to identify the student's learning characteristics, needs, preferences, background, knowledge level and misconceptions, in order to react accordingly offering personalization. A solution to the above problem is the technology of Intelligent Tutoring Systems (ITSs), and more specifically its module that is called 'student model'. According to Millán et al. [4] student model is "the key to individualized knowledge-based instruction". So, when creating an adaptive web- based educational application, we have to focus on the student model, which is a core component in any intelligent or adaptive tutoring system that represents many of the student features such as knowledge and individual traits [5].

Computer programming is a challenging knowledge domain for building an adaptive educational application due to the fact that there are many different programming languages and the population of programming language learners are very heterogeneous. Programming language learners have a variety of different backgrounds and learning characteristics and, also, they can vary from novice programmers to more experienced programmers who know programming languages other than that being taught. In literature, there are many adaptive tutoring systems for programming languages like ELM-ART [6], JavaGuide [7], and Protus [8] have implemented a student model that identifies the student's needs and dynamically adapts the educational process to meet them. However, they do not take into account how either the prior knowledge of programming or the knowledge level of a programming concept, structure or methodology of a learner can affect her/his performance and learning process of other related domain concept of programming. The above are taken into consideration from ELaC an innovative integrated e-learning environment for computer programming and the language 'C' [1]. ELaC incorporates a student model responsible for identifying and updating the student's knowledge level, taking the different pace of learning of each individual learner into account. In particular, ELaC takes into consideration the previous experience on computer programming that a learner may has and the programming languages that she/he already knows. ELaC recognizes when a new domain concept is completely unknown to the learner, or when it is partly known due to the learner having previous related knowledge. Furthermore, it recognizes when a previously known domain concept has been completely or partly forgotten by the learner. Thus, it models either the possible increase or decrease of the learner's knowledge. However, ELaC considers all the learners as novices at the first interaction with the system.

Consequently, in this chapter we describe ELaCv2 (a 2nd version of ELaC), which includes an improved 4-parameter student model. The particular student model is responsible for identifying and updating the student's knowledge level and needs each time from the beginning to the end of the learning process, allowing the learner to complete the e-training course at her/his own pace. The development of the new version of the system was based on the data that have been gathered by the student model of ELaC. The new version of student model has as a result to minimize the time that is required for a learner to complete the e-training course, improving, simultaneously, the learning results.

11.3 Description of the Student Model

11.3.1 Analyzing Data That Have Been Gathered by the Implementation of ELaC

ELaC is a fully implemented and evaluated novel integrated environment for personalized e-training in programming on the Language 'C' [1]. ELaC incorporates a student model responsible for identifying and updating the student's knowledge level, taking the different pace of learning of each individual learner into account. ELaC's student model retains either static information about each student, or dynamic information about them. Static information includes the learner's previous experience on computer programming and the programming languages that she/he already knows, and is gathered at the first interaction of the learner with the system (during her/his registration process to the educational system). Dynamic information includes the learner's errors, misconceptions and knowledge level for each domain concept of the learning material. Dynamic information is inferred by the system each time that the learner interacts with the system. In each learning session, ELaC recognizes the learner's knowledge level and the changes that occur in the state of a domain concept; it then updates the student's overall knowledge level according to the knowledge dependencies between the learning material's domain concepts and the learner's progress. Thus, the system recognizes, in each interaction of the learner with it, which new domain when a new domain concepts are known, partly known or completely unknown to the learner, as well as which domain concepts have been assimilated and which of them need revision.

The implementation and evaluation of ELaC in a postgraduate program in the field of informatics at the University of Piraeus, Piraeus, Greece, has provided the following data:

- There are some domain concepts of the learning material (Fig. 11.1) that are, usually, known to the learners that have previous knowledge on programming. The system infers if a learner knows a domain concept if s/he has not read the particular domain concept and s/he does no more than 20% of errors to the exercises that concern the particular domain concept. In particular, domain concepts that concerns methodologies of programming like calculating of sum and average, counting or finding maximum or minimum. In Table 11.1, the particular domain concepts along with the corresponding percentages of the learner's that already knew them due to their previous knowledge on programming. We notice that the percentage of learners that knew already the domain concepts C3.1, C6.2 and C6.3 is not very high. Therefore, due to the fact that the possibility of a learner to have previous knowledge on these concepts is fifty-to-fifty approximately, the system can infer if a learner knows the particular concepts. So, it is more safe for the effectiveness of the learning result to ask the learners, at their first interaction with the system, about their possible previous knowledge on these concepts.

1. Basics	$C_{1.1.}$ Constants & variables	5. Iteration Structure Unknown n° of Loops	$C_{5.1.}$ While statement
	$C_{1.2.}$ Assignment statement		$C_{5.2.}$ Calculating sum in a while loop
	$C_{1.3.}$ Arithmetic operators		$C_{5.3.}$ Counting in a while loop
	$C_{1.4.}$ Comparative operators		$C_{5.4.}$ Calculating avgr in a while loop
	$C_{1.5.}$ Logical operators		$C_{5.5.}$ Calculating max/min in a while loop
	$C_{1.6.}$ Mathematical functions		$C_{5.6.}$ Do...while statement
	$C_{1.7.}$ Input-output statements		
2. Sequence structure	$C_{2.1.}$ A simple program structure	6. Arrays	$C_{6.1}$ One-dimensional arrays
			$C_{6.2.}$ Searching
3.Conditional Structures	$C_{3.1.}$ If statement		$C_{6.3.}$ Sorting
	$C_{3.2.}$ If...else if $C_{3.2.1}$ Methodology of finding max/min		$C_{6.4.}$ Two-dimensional arrays
	$C_{3.3.}$ Nested if		$C_{6.5.}$ Processing per row
			$C_{6.6.}$ Processing per column
4.Iteration Structure Concrete n° of Loops	$C_{4.1.}$ For statement		$C_{6.7.}$ Processing of diagonals
	$C_{4.2.}$ Calculating sum in a for loop	7.Sub-programming	$C_{7.1.}$ Functions
	$C_{4.3.}$ Counting in a for loop		
	$C_{4.4.}$ Calculating avgr in a for loop		
	$C_{4.5.}$ Calculating max/min in a for loop		

Fig. 11.1 The learning material

Table 11.1 Previous knowledge of domain concepts

Domain concept	Percentage of learners that knew already the corresponding concept (%)
C3.1 Methodology of finding max/min among 3 numbers or more	62
C3.3 Nested If	86
C4.2 Calculating sum in a for loop	92
C4.3 Counting in a for loop	85
C4.4. Calculate average in a for loop	90
C4.5 Calculating max/min in a for loop	92
C5.2 Calculating sum in a while loop	93
C5.3 Counting in a while loop	85
C5.4 Calculating average in a while loop	83
C5.5 Calculating max/min in a while loop	91
C6.2 Searching algorithm	53
C6.3 Sorting algorithm	46
C6.5 Processing per row (2-dimensional array)	88
C6.6 Processing per column (2-dimensional array)	79
C6.7 Processing per diagonal (2-dimensional array)	84

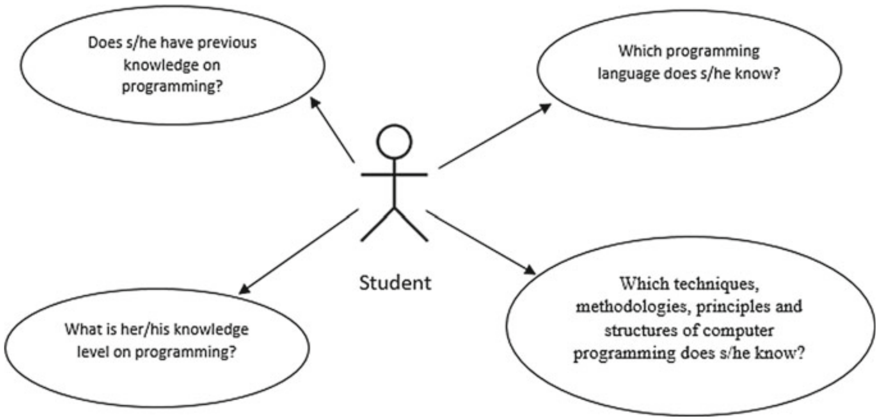


Fig. 11.2 The 4-parameter student model

- There are some domain concepts, in which learners make much more logical errors that syntax errors. Syntax errors are recognized if they belong in one of the following categories: anagrammatism of commands' names, omission of the definition of data, using invalid command names etc. Logical errors are usually errors of design and occur in case of misconceptions of the program and of the semantics and operation of the commands. These domain concepts are presented in Table 11.2.

11.3.2 The Improved Student Model of ELaCv2

Taking into account the results of the above data analysis, we have improved the student model of ELaC constructing a four-parameter student model (Fig. 11.2). The four parameters of the particular student model are described below:

- **Prior knowledge of programming (PrK)**: This takes the value true or false, depending on whether the learner already knows the principles and structures of computer programming or knows another programming language.
- **Known programming language (KPL)**: This considers the programming languages that the learner already knows. In our system these are restricted to Basic, Pascal, and Java, considered adequate for the research scope of this work. KPL takes the value "none" if a learner knows no a programming language, or a value equal to the number of languages known from the set {Basic, Pascal, Java}.
- **A 2-dimension array KNW_LEVEL [2] [31]** (Fig. 11.4): It is used to represent the learner's knowledge level of each domain concept of the learning material. In the cells of the first row of the particular array, the system inserts one value of the set DescrKL = {'Un', 'InK', 'K', 'L'}. More specific, 'Un' declares 'Unknown', 'InK' declares 'Insufficiently Known', 'K' declares 'Known', and 'L' declares

Table 11.2 Percentage of syntax and logical error per domain concept

Domain concept	Percentages	
	Syntax errors (%)	Logical errors (%)
C1.1	91.57	8.43
C1.2	83.33	16.67
C1.3	91.86	8.14
C1.4	76.92	23.08
C1.5	2.8	97.2
C1.6	100	0
C1.7	5.26	94.74
C2.1	33.33	66.67
C3.1	70.78	29.22
C3.2	73.86	26.14
C3.2.1	14.33	85.67
C3.3: Nested If	83.27	16.73
C4.1	13.38	86.62
C4.2 Calculating sum in a for loop	0	100
C4.3 Counting in a for loop	0	100
C4.4. Calculate average in a for loop	0	100
C4.5 Calculating max/min in a for loop	0	100
C5.1	10	90
C5.2 Calculating sum in a while loop	0	100
C5.3 Counting in a while loop	0	100
C5.4 Calculating average in a while loop	0	100
C5.5 Calculating max/min in a while loop	0	100

(continued)

Table 11.2 (continued)

Domain concept	Percentages	
	Syntax errors (%)	Logical errors (%)
C5.6	7.78	92.22
C6.1	27	73
C6.2 Searching algorithm	7.63	92.37
C6.3 Sorting algorithm	8.24	91.76
C6.4	32.17	67.83
C6.5 Processing per row (2-dimensional array)	6.32	93.68
C6.6 Processing per column (2-dimensional array)	6.17	93.83
C6.7 Processing per diagonal (2-dimensional array)	5.49	94.51
C7.1	38.46	61.54

'Learned'. This value of the cell KNW_LEVEL [1] [j], where j ϵ [1, 31], represents the description of the learner's knowledge level on the domain concept that corresponds to the column j. Figure 11.3 presents the correspondence between the columns of the array KNW_Level[][] and the domain concepts of the learning material. For example, if KNW_LEVEL [1] [5] = {'K'}, then it means that the domain concept "C1.5: Logical operators" is 'Known' to the learner. In the cells of the second row of KNW_Level[2][j], where j ϵ [1, 31] the system inserts a value between [0,100] that declares the degree in which the corresponding domain concept is 'Unknown', 'Insufficiently Known', 'Known', or 'Learned'. For example, if KNW_LEVEL [1] [18] = {'L'} and KNW_LEVEL [2] [18] = {'40'}, then it means that the domain concept "C5.1: While statement" is 40% 'Learned' to the learner (the rest 60% is 'Known'). There is the limitation that the different descriptions of knowledge level of a domain concept can be only of adjacent values (that is that the knowledge level of a domain concept can be only 'Un', 'InK', 'K', or 'L', or it can be simultaneously 'Un'and 'InK', or 'InK' and 'K',or 'K' and 'L' at different degrees).

- **Knowledge level (KL)**: This considers the learner's knowledge level and takes one of the following eight values.

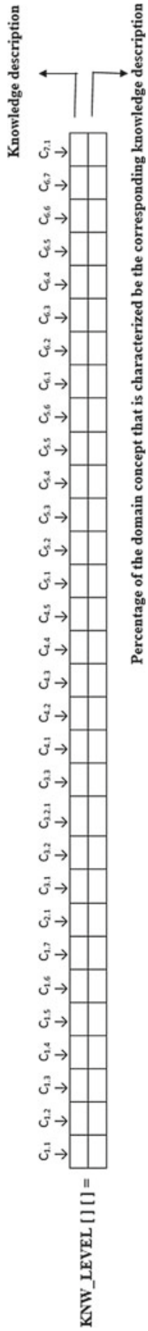


Fig. 11.3 KNW_LEVEL [2] [31] array

– Level 1: Novice learners.
– Level 2: S/he knows basics of ‘C’, as well as the sequence structure of programming.
– Level 3: S/he knows basics of ‘C’, the sequence structure, and the structures of choice.
– Level 4: S/he knows the basics of ‘C’, the sequence structure, the structures of choice, and the iteration structure with concrete number of loops.
– Level 5: S/he knows basics of ‘C’, the sequence structure, the structures of choice, and the iteration structures with concrete or unknown number of loops.
– Level 6: S/he knows basics of ‘C’, the programming language C, the sequence structure, the structures of choice, the iteration structures, and one-dimensional arrays.
– Level 7: S/he knows basics of ‘C’, the programming language C, the sequence structure, the structures of choice, the iteration structures, and arrays.
– Level 8: Expert learners.

11.4 Description of the Operation of the Student Model

At the first interaction with the system, the array KNW_Level is initialized according to the following rules:

I. If PrK = false (that is, the learner has no prior knowledge on programming), then

KNW_Level [] [] =	‘Un’	‘Un’	‘Un’	…	‘Un’
	100	100	100	…	100

II. If PrK = true (that is, the learner already knows the principles and structures of programming or knows another programming language), then

KNW_Level [ ] [ ] =	$C_{1,1}$	…	$C_{1,2}$	$C_{3,2,1}$	$C_{3,3}$	$C_{4,1}$	$C_{4,2}$	$C_{4,3}$	$C_{4,4}$	$C_{4,5}$	$C_{5,1}$	$C_{5,1}$	$C_{5,2}$
	‘Un’	…	‘Un’	x_1	‘K’	‘Un’	‘K’	‘K’	‘K’	‘K’	‘Un’	‘K’	‘K’
	100	…	100	100	100	100	100	100	100	100	100	100	100

KNW_Level [ ] [ ] =	$C_{5,3}$	$C_{5,4}$	$C_{5,5}$	$C_{5,6}$	$C_{6,1}$	$C_{6,2}$	$C_{6,3}$	$C_{6,4}$	$C_{6,5}$	$C_{6,6}$	$C_{6,7}$	$C_{7,1}$
	‘K’	‘K’	‘K’	‘Un’	‘Un’	x_2	x_3	‘Un’	‘K’	‘K’	‘K’	‘Un’
	100	100	100	100	100	100	100	100	100	100	100	100

where x_i, i = 1, 2, 3, is defined by the answer that the learner gives, during her/his first interaction with the system to the following questions:

(a) Do you know the methodology of how to find the maximum or the minimum among 3 numbers or more?

If answer = YES, then x_1 = ‘K’
If answer = NO or ‘I am not sure’, then x_1 = ‘Un’

(b) Do you know the algorithm of searching through an array?

If answer = YES, then x_2 = ‘K’
If answer = NO or ‘I am not sure’, then x_2 = ‘Un’

(c) Do you know the bubble sort algorithm?

If answer = YES, then x_3 = 'K'
If answer = NO or 'I am not sure', then x_3 = 'Un'

At the next interactions with the system, the array KNW_Level is updating according to the learner's performance on the system's test that is asked to be completed each time the learner finishes the study of a section of the knowledge domain. In particular, according to the learner's performance, the values of the [i, j], i = 1 or 2 and j ϵ [1, 31], cells that corresponds to the domain concepts j of the section that is studied by the learner (according to her/his knowledge level that is represented by the value of the parameter KL), are updating. If the learner passes the test, then the value of the cells KNW_Level[1][j], will become 'K' or 'L' (according to her/his grade on the test's exercises that concern the corresponding domain concepts j) and the value of the cells KNW_Level[2][j], will become 100 if KNW_Level[1][j] = 'K' (it indicates that the domain concept j is 100% 'Known') or they can take a value x ≤ 100 if KNW_Level[1][j] = 'L' (it indicates that the domain concept j is x% 'Learned' and (100 − x)% 'Known'). If the learner fails in the test, then the value of the cells KNW_Level[1][j], will become 'Un', 'InK' or 'K' (according to her/his grade on the test's exercises that concern the corresponding domain concepts j) and the value of the cells KNW_Level[2][j], will become less than 100 if KNW_Level[1][j] = 'K' (it indicates that a part of the domain concept j is 'Known' and the other part is 'Insufficiently Known) or they can take a value x ϵ [0, 100] if KNW_Level[1][j] = 'Un' or 'InK' (if KNW_Level[1][j] = 'Un', then it indicates that the domain concept j is x% 'Unknown' and (100 − x)% 'Insufficiently Known', otherwise if KNW_Level[1][j] = 'InK', then it indicates that the domain concept j is x% 'Insufficiently Known" and (100 − x)% 'Known').

Due to the fact that there are dependencies among the domain concepts of the learning material, the changes (increase or decrease) that occur in the knowledge level of a specific domain concept affects the knowledge level of the related domain concepts (either following or preceding concepts). For example, if a learner excels at "calculating sum in 'for' loop," then she/he is inferred to have a high knowledge level at "calculating sum in 'while' loop," too. However, if she/he has misconceptions of how to calculate an average in a "while" loop, then she/he will also have poor knowledge of counting and calculating a sum in a "while" loop. Figure 11.4 depicts the related domain concepts of the concept "counting in a 'for' loop". The changes in the knowledge level of the particular domain concept affect the knowledge level of the concept "calculating sum in a 'for' loop" at 42%, the knowledge level of the concept "calculating sum in a 'while' loop" at 42%, the knowledge level of the concept "counting in a 'while' loop" at 100%, and the knowledge level of the concept "calculating average in a 'while' loop" at 41%. These dependencies are determined by domain knowledge experts. So, the value of KNW_Level[i][j] can affect and determine, also, the value of KNW_Level[1][k], where j and k are two related domain concepts. Therefore, the system can identify that a new domain concept is completely unknown or partly known or completely known to the learner, due to the fact that the learner having previous related knowledge. Furthermore, it recognizes when a

Fig. 11.4 Knowledge dependencies for the concept "Counting in a 'for' loop"

$C_{4.3}$: "Counting in a 'for' loop"	
$C_{4.2}$	42
$C_{5.2}$	42
$C_{5.3}$	100
$C_{5.4}$	41

previously known domain concept has been completely or partly forgotten by the learner. Thus, the system models either the possible increase or decrease of the learner's knowledge and delivers to the learner the appropriate each time learning material to study, advising her/him to revise a domain concept or pointing out that s/he does not need to study a new domain concept. The values of the array KNW_Level[][], determine, each time, the value of the parameter KL. If the learner progresses and the knowledge level of the domain concepts is improved (a domain concept is considered to be learned when it is characterized as 100% 'K' or 'L' at any degree), then the value of KL is increased. Otherwise, she/he remains at the same knowledge level (the value of KL remains the same) or is returned to a previous knowledge level (the value of KL is reduced), if the learner's poor performance affects the knowledge level of other related domain concepts from a previous section. The calculation of how the related domain concepts' knowledge level changes is based on a fuzzy model that has been presented in Chrysafiadi and Virvou [9] and its description is out of the scope of this chapter.

11.4.1 Examples of Operation

This section provides representative examples of the system's operation.

1st example:

John is a novice learner of programming. He has no previous knowledge of computer programming. Consequently, at his first interaction with the system, his student model is initializing as follows:

- PrK = False
- KPL = 'none'
- KNW_Level [ ] [ ] =

$C_{1.1}$	$C_{1.2}$	…	$C_{7.1}$
'Un'	'Un'	…	'Un'
100	100	…	100

- KL = 'Level 1'

Therefore, the content of Sections 1 and 2 content is delivered to the learner. At the next interactions with the system, John is studying the domain concepts of sections 1 and 2, and he is succeeding to the corresponding test. So, the KNW_Level array is becoming

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{1.5}$	$C_{1.6}$	$C_{1.7}$	$C_{2.1}$	$C_{3.1}$	$C_{3.2}$	…	$C_{7.1}$
KNW_Level [ ] [ ] =	'L'	'L'	'L'	'L'	'K'	'K'	'L'	'L'	'Un'	'Un'	…	'Un'
	20	63	80	92	100	100	78	83	100	100	…	100

and KL = 'Level 2'.

Therefore, the content of Section 3 is delivered to the learner. At the next interactions with the system, John is studying all the domain concepts of sections 3, and he is succeeding to the corresponding test, but he is doing errors concerning the domain concept "C1.6: mathematical functions". Consequently, the system is advising him to revise the particular domain concept. So, the KNW_Level array is becoming

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{1.5}$	$C_{1.6}$	$C_{1.7}$	$C_{2.1}$	$C_{3.1}$	$C_{3.2}$	$C_{3.2.1}$	$C_{3.3}$	$C_{4.1}$	…	$C_{7.1}$
KNW_Level [ ] [ ] =	'L'	'L'	'L'	'L'	'K'	'InK'	'L'	'L'	'L'	'L'	'K'	'K'	'Un'	…	'Un'
	20	63	80	92	100	27	78	83	60	20	100	100	100	…	100

and the value of KL is being reduced to 1. However, due to the fact that John's performance on all the domain concepts of section 3 is good, after his successful revision of the domain concept he is transited to the section 4. Now, the KNW_Level array is becoming

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{1.5}$	$C_{1.6}$	$C_{1.7}$	$C_{2.1}$	$C_{3.1}$	$C_{3.2}$	$C_{3.2.1}$	$C_{3.3}$	$C_{4.1}$	…	$C_{7.1}$
KNW_Level [ ] [ ] =	'L'	'L'	'L'	'L'	'K'	'L'	'L'	'L'	'L'	'L'	'K'	'K'	'Un'	…	'Un'
	20	63	80	92	100	68	78	83	60	20	100	100	100	…	100

and KL = 'Level 3.' Then, John is studying the domain concepts of section 4, and he is not succeeding to all the corresponding test. Now, he KNW_Level array is becoming

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{1.5}$	$C_{1.6}$	$C_{1.7}$	$C_{2.1}$	$C_{3.1}$	$C_{3.2}$	$C_{3.2.1}$	$C_{3.3}$	$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	$C_{4.4}$	$C_{4.5}$	$C_{5.1}$	$C_{5.1}$	$C_{5.2}$	$C_{5.3}$	$C_{5.4}$	$C_{5.5}$	$C_{5.6}$	$C_{6.1}$	…	$C_{7.1}$
KNW_Level [ ] [ ] =	'L'	'L'	'L'	'L'	'K'	'L'	'L'	'L'	'L'	'L'	'K'	'K'	'K'	'K'	'K'	'K'	'InK'	'Un'	'K'	'K'	'K'	'K'	'InK'	'Un'	'Un'	…	'Un'
	20	63	80	92	100	68	78	83	60	20	100	100	100	80	72	70	20	100	100	80	72	38	20	100	100	…	100

and the value of KL is remaining 3. However, we notice that John's performance on some of the domain concepts of the next section 5 are getting better. This is happening due to the knowledge dependencies that exist among the domain concepts of section 4 and section 5.

2nd example:

Kate is a learner that have previous knowledge of computer programming. Particularly, she knows the programming language 'Java'. Due to the fact that she knows already a programming language, the system asks her some questions about her previous knowledge. Her answers are:

(a) Do you know the methodology of how to find the maximum or the minimum among 3 numbers or more? Answer = YES

(b) Do you know the algorithm of searching through an array? Answer = YES
(c) Do you know the bubble sort algorithm? Answer = NO

Consequently, at Kate's first interaction with the system, her student model is initializing as follows:

- PrK = True
- KPL = 'Java'
- KNW_Level [ ] [ ] =

$C_{1.1}$	…	$C_{3.2}$	$C_{3.2.1}$	$C_{3.3}$	$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	$C_{4.4}$	$C_{4.5}$	$C_{5.1}$	$C_{5.1}$	$C_{5.2}$	$C_{5.3}$	$C_{5.4}$	$C_{5.5}$	$C_{5.6}$	$C_{6.1}$	$C_{6.2}$	$C_{6.3}$	$C_{6.4}$	$C_{6.5}$	$C_{6.6}$	$C_{6.7}$	$C_{7.1}$
'Un'	…	'Un'	'K'	'K'	'Un'	'K'	'K'	'K'	'K'	'Un'	'K'	'K'	'K'	'K'	'K'	'Un'	'Un'	'K'	'Un'	'Un'	'K'	'K'	'K'	'Un'
100	…	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

- KL = 'Level 1'

Therefore, the content of Sections 1 and 2 content is delivered to the learner, but there are some domain concepts of the learning material (like C3.3 and C5.2) that are considered to be known to Kate. At the next interactions with the system, Kate is studying the domain concepts of sections 1 and 2, and she is succeeding to the corresponding test. So, the KNW_Level array is becoming

KNW_Level [ ] [ ] =

$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{1.5}$	$C_{1.6}$	$C_{1.7}$	$C_{2.1}$	$C_{3.1}$	$C_{3.2}$	$C_{3.2.1}$	$C_{3.3}$	$C_{4.1}$	$C_{4.2}$	…	$C_{4.5}$	$C_{5.1}$	$C_{5.1}$	…	$C_{5.5}$	$C_{5.6}$	$C_{6.1}$	$C_{6.2}$	$C_{6.3}$	$C_{6.4}$	$C_{6.5}$	$C_{6.6}$	$C_{6.7}$	$C_{7.1}$
'L'	'L'	'L'	'L'	'L'	'K'	'L'	'L'	'Un'	'Un'	'K'	'K'	'Un'	'K'	…	'K'	'Un'	'K'	…	'K'	'Un'	'Un'	'K'	'Un'	'Un'	'K'	'K'	'K'	'Un'
100	100	92	87	96	100	89	95	100	100	100	100	100	100	…	100	100	100	…	100	100	100	100	100	100	100	100	100	100

and KL = 'Level 2'. However, only the domain concepts C3.1 and C3.2 are delivered to Kate, since the domain concepts C3.2.1 and C3.3 are considered to be known to Kate. Similarly, at the next interactions with the system, Kate is studying the domain concepts of sections 3, and she is succeeding to the corresponding test. So, the KNW_Level array, now, is becoming

KNW_Level [ ] [ ] =

$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{1.5}$	$C_{1.6}$	$C_{1.7}$	$C_{2.1}$	$C_{3.1}$	$C_{3.2}$	$C_{3.2.1}$	$C_{3.3}$	$C_{4.1}$	$C_{4.2}$	…	$C_{4.5}$	$C_{5.1}$	$C_{5.1}$	…	$C_{5.5}$	$C_{5.6}$	$C_{6.1}$	$C_{6.2}$	$C_{6.3}$	$C_{6.4}$	$C_{6.5}$	$C_{6.6}$	$C_{6.7}$	$C_{7.1}$
'L'	'L'	'L'	'L'	'L'	'K'	'L'	'L'	'L'	'L'	'L'	'L'	'Un'	'K'	…	'K'	'Un'	'K'	…	'K'	'Un'	'Un'	'K'	'Un'	'Un'	'K'	'K'	'K'	'Un'
100	100	92	87	96	100	89	95	86	91	64	82	100	100	…	100	100	100	…	100	100	100	100	100	100	100	100	100	100

and KL = 'Level 4'. However, only the domain concept C4.1 is delivered to Kate, since the rest domain concepts of the section 4 (C4.2, C4.3, C4.4 and C4.5) are considered to be known to Kate. Furthermore, during her learning process, Kate has improved her performance on the domain concepts C3.2.1 and C3.3, which were considered to be known to her by the system, from 100% 'Known' to 64% 'Learned' and 82% 'Learned' correspondingly.

11.5 Evaluation-Results

It is crucial to evaluate whether the improved student model of ELaCv2 optimizes the adaptivity and the programming language leaning. For this purpose, an experiment was conducted. In particular, two groups of learners were used to compare their performance and the mean number of times that they needed to read (or revise) each domain concept of the learning material during the process of learning programming

Table 11.3 Results of the evaluation concerning the learners' performance

	Group	N	Mean	Std. deviation	Std. error mean
Final_grade_S1_S2	1	30	91.3440	7.26382	1.32619
	2	30	94.8913	5.09713	0.93060
Final_grade_S3	1	30	91.0997	6.70402	1.22398
	2	30	94.6787	4.63780	0.84674
Final_grade_S4	1	30	91.2333	4.94803	0.90338
	2	30	93.9667	4.22932	0.77216
Final_grade_S5	1	30	90.6830	4.83306	0.88239
	2	30	93.5230	4.29768	0.78465
Final_grade_S6	1	30	90.1947	4.27359	0.78025
	2	30	92.9460	4.69928	0.85797
Final_grade_S7	1	30	91.2500	6.89546	1.25893
	2	30	94.9833	5.07951	0.92739

through the developed e-learning system. More specifically, group A includes learners that used ELaC (1st version without the initialization of student model and with less examples and diagrams in domain concepts of the learning material that concerns mostly logical programming errors) for learning programming and group B includes learners that used ELaCv2 (2nd version) for learning programming. Both groups were consisted of 30 learners of a post-graduate program in the field of informatics at the University of Piraeus. They used the systems over a three-month period. The results of the experiment are depicted in Table 11.3 (performance of learners) and Table 11.4 (times that a learner needed to read a domain concept in order to learn it). We notice that the performance (grade in a final test, with maximum grade of excellence the 100) for group B is better than group A for all the sections (S1 to S7) of the learning material. Similarly, we notice that the learners of group B needed to read less times each domain concept on average, for all the sections (S1 to S7) of the learning material, in order to learn it than the learners of group A.

However, how can we be sure that the different averages scores are not occurred by chance or due to differences on the education, knowledge level and abilities of the learners of the two groups? To ensure this we choose the statistical method of 'Independent-sample T-test', which used to test whether the different average scores of two groups, represents a real difference between the two populations, or just a chance difference in our samples [10, 11]. It uses the Levene's test for equality of variances to determine the 'sig.' value that indicates how likely we could have gotten the results by chance. If it is greater than 0.05 means that the variability in two groups is about the same. As we notice, this value is greater than 0.05 for all the variables (Tables 11.5 and 11.6). Then, we focus on the value of 'sig. (2-tailed)', which will tell us if the two means are statistically different or if the difference is likely due to chance. This value has to be less than 0.05. In our results, we notice that the particular value is

Table 11.4 Results of the evaluation concerning the number of times that a learner need to read a concept until to learn it

	Group	N	Mean	Std. deviation	Std. error mean
read_tirnes_S1_S2	1	30	1.8470	0.61485	0.11226
	2	30	1.3387	0.39327	0.07180
read_times_S3	1	30	1.4313	0.55184	0.10075
	2	30	1.0483	0.35956	0.06565
read_times_S4	1	30	0.8823	0.40306	0.07359
	2	30	0.5690	0.30716	0.05608
read_tirnes_S5	1	30	0.7723	0.36353	0.06637
	2	30	0.5480	0.30154	0.05505
read_times_S6	1	30	1.1323	0.20108	0.03671
	2	30	0.9753	0.17322	0.03163
read_times_S7	1	30	1.7333	0.99908	0.18241
	2	30	1.2860	0.59915	0.10939

less than 0.05 for all the variables (Tables 11.5 and 11.6). Therefore, the means of the experiment's results are statistically significant and they are not a result of chance. Consequently, the changes that we have done in the student model of ELaC, lead to a more adaptive system that optimizes the learning of programming, since the learners have a better performance reading each domain concept less times (Tables 11.5 and 11.6).

11.6 Conclusion

In this chapter, an improved 4-parameter student model of an adaptive web-based tutoring system that teaching the programming and the programming language 'C' has been presented. The data for creating the improved version of the student model were gathered from a prior first implementation of the system, which was called ELaC. The student model of ELaC does not include initialization processes and considers that all domain concepts of the learning material are completely unknown for all the learners at their first interaction with the system. We have analyzed the data that have been stored in the student model of ELaC and we developed an improved version of the system that includes a student model, which try to identify the needs, background and the prior knowledge of the learners even before their interaction with the system in order to offer a better adaptive learning experience. The evaluation of the developed student model is positive and encouraged. They have showed that the new student model offers better learning results to the learners, reducing simultaneously the time that a learner needs to complete the e-training course.

Table 11.5 Levene's test for equality of variances for learners' grades

		Levene's test for equality of variances		t-test for equality of means					95% confidence interval of the difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
Final_grade_S1_S2	Equal variances assumed	3.512	0.066	−2.190	58	0.033	−3.54733	1.62012	−6.79036	−0.30431
	Equal variances not assumed			−2.190	51.986	0.033	−3.54733	1.62012	−6.79836	−0.29630
Final_grade_S3	Equal variances assumed	3.321	0.074	−2.405	58	0.019	−3.57900	1.48832	−6.55820	−0.59980
	Equal variances not assumed			−2.405	51.585	0.020	−3.57900	1.48832	−6.56611	−0.59189
Final_grade_S4	Equal variances assumed	1.525	0.222	−2.300	58	0.025	−2.73333	1.18842	−5.11221	−0.35446
	Equal variances not assumed			−2.300	56.628	0.025	−2.73333	1.18842	−5.11344	−0.35323
Final_grade_S5	Equal variances assumed	0.005	0.946	−2.405	58	0.019	−2.84000	1.18080	−5.20362	−0.47638
	Equal variances not assumed			−2.405	57.219	0.019	−2.84000	1.18080	−5.20431	−0.47569
Final_grade_S6	Equal variances assumed	1.485	0.228	−2.372	58	0.021	−2.75133	1.15970	−5.07272	−0.42995
	Equal variances not assumed			−2.372	57.485	0.021	−2.75133	1.15970	−5.07316	−0.42951
Final_grade_S7	Equal variances assumed	1.852	0.179	−2.388	58	0.020	−3.73333	1.56364	−6.86329	−0.60337
	Equal variances not assumed			−2.388	53.314	0.021	−3.73333	1.56364	−6.86916	−0.59751

Table 11.6 Levene's test for equality of variances for times of reading

		Levene's test for equality of variances					t-test for equality of means		95% confidence interval of the difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	Lower	Upper
read_times_S1_S2	Equal variances assumed	3.650	0.061	3.440	58	0.001	0.45833	0.13325	0.19160	0.72507
	Equal variances not assumed			3.440	49.326	0.001	0.45833	0.13325	0.19059	0.72607
read_times_S3	Equal variances assumed	3.362	0.072	3.185	58	0.002	0.38300	0.12025	0.14229	0.62371
	Equal variances not assumed			3.185	49.863	0.002	0.38300	0.12025	0.14145	0.62455
read_times_S4	Equal variances assumed	1.750	0.191	3.387	58	0.001	0.31333	0.09252	0.12813	0.49854
	Equal variances not assumed			3.387	54.188	0.001	0.31333	0.09252	0.12785	0.49881
read_times_S5	Equal variances assumed	3.386	0.071	2.601	58	0.012	0.22433	0.08623	0.05172	0.39695
	Equal variances not assumed			2.601	56.084	0.012	0.22433	0.08623	0.05159	0.39707
read_times_S6	Equal variances assumed	1.289	0.261	3.240	58	0.002	0.15700	0.04846	0.06001	0.25399
	Equal variances not assumed			3.240	56.756	0.002	0.15700	0.04846	0.05996	0.25404
read_times_S7	Equal variances assumed	3.510	0.066	2.103	58	0.040	0.44733	0.21269	0.02158	0.87308
	Equal variances not assumed			2.103	47.470	0.041	0.44733	0.21269	0.01956	0.87510

In the future, the gathered data of the presented student model can be used and analyzed further for error diagnosis. Furthermore, the presented student model can be incorporated into educational tutoring systems that teach other domain knowledge rather than programming, like mathematics, physics and foreign languages in order to provide a personalized learning experience to learners.

References

1. Chrysafiadi, K., Virvou, M.: Dynamically personalized e-training in computer programming and the language C. IEEE Trans. Educ. **56**(4), 385–392 (2013)
2. Li, N., Cohen, W.W., Koedinger, K.R., Matsuda, N.: A machine learning approach for automatic student model discovery. In: Proceedings of Conference on Educational Data Mining (EDM 2011), pp. 31–40. Eindhoven, the Netherlands (2011)
3. Sucar, L.E., Noguez, J.: Student modeling. In: Pourret, O., Naom, P., Marcot, B. (eds.) Bayesian Networks: A Practical Guide to Applications, pp. 173–185. Wiley, West Sussex (2008)
4. Millan, E., Loboda, T., Pιrez-de-la-Cruz, J.L.: Bayesian networks for student model engineering. Comput. Educ. **55**(4), 1663–1683 (2010)
5. Brusilovsky, P., Millan, E.: User models for adaptive hypermedia and adaptive educational systems. In: Brusilovsky, P., Kobsa, A., Neidl, W. (eds.) The Adaptive Web: Methods and Strategies of Web Personalization, pp. 3–53. Springer, Berlin (2007)
6. Weber, G., Brusilovsky, P.: ELM-ART: an adaptive versatile system for web-based instruction. Int. J. Artif. Intell. Educ. **12**(4), 351–384 (2001)
7. Hsiao, I.-H., Sosnovsky, S., Brusilovsky, P.: Guiding students to the right questions: adaptive navigation support in an E-learning system for Java programming. J. Comput. Assist. Learn. **26**(4), 270–283 (2010)
8. Klašnja-Milićevića, A., Vesina, B., Ivanovićb, M., Budimac, Z.: E-learning personalization based on hybrid recommendation strategy and learning style identification. Comput. Educ. **56**(3), 885–899 (2011)
9. Chrysafiadi, K., Virvou, M.: Fuzzy Logic for adaptive instruction in an e-learning environment for computer programming. IEEE Trans. Fuzzy Syst. **23**(1), 164–177 (2014)
10. Carver, R., Nash, J.G.: Doing Data Analysis with SPSS. Cengage Learning Inc, United States (2009)
11. Norusis, M.J.: SPSS 17 0 Statistical Procedures Companion. Pearson Education, United States (2009)