# Uma Arquitetura Computacional para Autoria e Personalização de Objetos de Aprendizagem em Ambientes Educacionais Ubíquos

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*À minha família, especialmente meus irmãos Eduardo e Daniel.*

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*“Look up at the stars and not down at your feet. Try to make sense of what you see, and wonder about what makes the universe exist. Be curious.”*

*(Stephen Hawking)*

# Resumo

Os computadores se tornaram ferramentas cotidianas na sala de aula contemporânea. *Laptops*, *tablets*, *smartphones*, lousas eletrônicas e outros dispositivos computacionais são constantemente utilizados para apoiar tanto os professores no processo de ensino quanto os estudantes no processo de aprendizagem. Em ambos os casos, elas podem acessar o conteúdo educacional em qualquer lugar e a qualquer hora. Com isso, Ambientes Educacionais Ubíquos (AEUs) – ou salas de aula enriquecidas com tecnologia – são criados para combinar os ambientes de aprendizagem reais e virtuais para produzir artefatos de estudo mais ricos. No entanto, uma enorme quantidade de Objetos de Aprendizagem (OAs) é produzida, muitas vezes de forma desestruturada, o que torna sua recuperação e apresentação um desafio para esse tipo de sistema computacional, especialmente porque a apresentação deve acontecer de forma clara e organizada e, ainda, considerando as necessidades de cada estudante. Neste trabalho, o conceito de Hipermídia Educacional Adaptativa – do inglês, *Adaptive Educational Hypermedia (AEH)* – que surgiu para lidar com a questão da personalização de conteúdo educacional em ambientes Web, é explorado em conjunto com o conceito de AEUs para geração e disponibilização personalizada de OAs aos estudantes. Para tratar tais questões, propõe-se uma arquitetura computacional baseada em conceitos de AEUs e Sistemas Tutores Inteligentes (STI) capaz de estruturar OAs automaticamente capturados em sala de aula e seus metadados por meio de uma abordagem colaborativa, e oferecer recursos de personalização e recomendação de conteúdo a estudantes. Neste trabalho, o termo *arquitetura* está relacionado com uma infraestrutura computacional que utiliza dados de diferentes naturezas, como interações sociais e colaborativas, restrições contextuais dos dispositivos de acesso e preferências e características pessoais. Tal arquitetura é composta de módulos especializados que foram integrados a uma plataforma de captura multimídia real, chamada Classroom eXperience (CX), utilizada como uma ferramenta complementar de ensino. Experimentos nesse ambiente foram conduzidos com estudantes de cursos da Faculdade de Computação da Universidade Federal de Uberlândia para avaliar diferentes partes da arquitetura. Resultados apontaram a viabilidade da criação de OAs e metadados em AEUs. Além disso, diferenças estatisticamente significativas foram encontradas no desempenho dos estudantes durante o período de personalização de conteúdo baseada em estilos de aprendizagem. Ainda, os recursos sociais e colaborativos foram os que mais despertaram atenção dos estudantes. Finalmente, um repositório de OAs com metadados no formato IEEE Learning Object Metadata (IEEE-LOM) gerados pela plataforma CX foi criado para a comunidade de pesquisa em Informática na Educação.

**Palavras-chave:** Aprendizado Enriquecido por Tecnologia. Hipermídia Educacional Adaptativa. Objetos de Aprendizagem. Ambientes Educacionais Ubíquos.

# A Computational Architecture for Learning Objects Authoring and Personalization in Ubiquitous Learning Environments

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2017

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The undersigned hereby certify they have read and recommend to the PPGCO for acceptance the dissertation entitled **"A Computational Architecture for Learning Objects Authoring and Personalization in Ubiquitous Learning Environments"** submitted by **"Rafael Dias Araújo"** as part of the requirements for obtaining the **DSc degree in Computer Science**.

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# Abstract

Computers have become everyday tools in the contemporary classroom. Laptops, tablets, smartphones, interactive whiteboards, and other electronic devices are constantly used to support both instructors, while teaching, and students in the learning process. In both cases, they can access educational content and activities anywhere and anytime they wish. In this way, Ubiquitous Learning Environments (ULEs) – or Technology Rich Classrooms – are created to combine real and virtual learning environments in order to produce richer study artifacts. However, it produces a huge volume of Learning Objects (LOs), often unstructured, which makes retrieving and presenting such content a challenge for this type of computing system, especially because it should happen in a clear and organized way and considering users' needs. In this work, we explore the concept of Adaptive Educational Hypermedia (AEH) which have appeared to deal with the issue of educational content personalization in Web environments together with ULEs for generating and providing personalized LOs to students. Thereby, this research proposal tackles this issue by designing a computational architecture grounded on ULEs and Intelligent Tutoring Systems (ITSs) concepts, capable of structuring LOs captured in classrooms and their metadata through a collaborative approach, and offering content personalization and recommendation features to students. In this work, the term *architecture* is related to a computational infrastructure which takes into account a mix of data of different natures, such as social and collaborative interactions, devices' contextual constraints, and personal preferences and traits. Such architecture is composed of specialized modules which have been integrated to a real multimedia capture platform, named Classroom eXperience (CX), currently used as a complementary learning tool. Experiments using this environment have been conducted in the context of courses offered by the Faculty of Computing at the Federal University of Uberlândia to evaluate different parts of the architecture. Results pointed out to the feasibility of the LOs authoring approach in ULEs. In addition, statistically significant differences were found in students' performance while experiencing the content personalization based on learning styles. Also, social and collaborative resources were the ones that most attracted students' attention. Finally, a LO repository with metadata in the IEEE Learning Object Metadata (IEEE-LOM) format generated by the CX platform was created to be available to the research community in Informatics in Education.

**Keywords:** Technology Rich Classrooms. Adaptive Educational Hypermedia. Learning Objects. Ubiquitous Learning Environments.

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# Acronyms list

**AH** Adaptive Hypermedia

**AEH** Adaptive Educational Hypermedia

**API** Application Programming Interface

**AULA** Adaptive and Ubiquitous Learning Architecture

**C&A** Capture and Access

**CLEO** Customized Learning Experience Online

**COA** Computer Organization and Architecture

**CX** Classroom eXperience

**DAO** Data Access Object

**FSLSM** Felder-Silverman Learning Styles Model

**HCI** Human-Computer Interaction

**HTML** HyperText Markup Language

**HTTP** HyperText Transfer Protocol

**iDTV** interactive Digital TV

**ILS** Index of Learning Styles

**ITS** Intelligent Tutoring System ITSs

**JSON** JavaScript Object Notation

**LMS** Learning Management System

**LO** Learning Object LOs

**IEEE-LOM** IEEE Learning Object Metadata

**LORI** Learning Object Review Instrument

**LS** Learning Style

**MathL** Mathematical Logic

**NCL** Nested Context Language

**RFID** Radio-Frequency IDentification

**SCORM** Sharable Content Object Reference Model

**SE** Software Engineering

**SM** Student Model

**UbiComp** Ubiquitous Computing

**ULE** Ubiquitous Learning Environment ULEs

**URL** Uniform Resource Locator

**XML** eXtensible Markup Language

# Contents

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Rafael Dias Araújo

# Chapter 1

# Introduction

Computational and technological devices have been widely spread and used in many knowledge fields. As we move towards such scenario, we get closer to the Ubiquitous Computing (UbiComp) vision (WEISER, 1991; WEISER, 1993), in which the presence of computers becomes less visible and eventually they blend into our everyday lives. Particularly, approaches that assist the teaching and learning process are on the rise.

Computers are every time more integrated into classrooms. Notebooks, tablets, smartphones, interactive whiteboards and other electronic devices are being used to support both instructors, while teaching, and students to better absorb what is taught. Particularly in schools and universities, students can access educational content and activities anywhere and anytime they wish. In this way, Ubiquitous Learning Environments (ULEs) are created to combine real and virtual learning environments in order to produce richer study artifacts (ZHAO; OKAMOTO, 2011). Classrooms equipped with electronic whiteboards, microphones and cameras produce artifacts that can reconstruct the captured experiences for later use and review, preventing users from losing any important point while making notes, for example.

However, a large volume of digital content is generated in different formats and must be retrieved and presented in a clear way, mainly to comply with the user's needs, which becomes a challenge for information retrieval systems. Thus, such content may be useless if appropriate means for reaching and visualizing it are not provided to users. Content recommendation and personalization, as well as device constraints and user context, can all play an important role here. For example, audio content should be avoided if headphones are not available on the student's device when in a public library.

Adaptive Hypermedia (AH) has emerged as a solution to the problem of Web content personalization (BRUSILOVSKY, 2001), avoiding the "one-size-fits-all" approach. Particularly in the educational field, Adaptive Educational Hypermedia (AEH) comes to meet each student needs, adapting the content to his/her objectives, knowledge level, personal interests, preferences, and learning styles.

Furthermore, social and collaborative mechanisms made available to students may help in content retrieval and personalization as well as enriching the content in order to create a more complete material. Increasingly, the integration of social and traditional technologies has shown many benefits on fostering students learning (BRUSILOVSKY et al., 2016; SOBAIH et al., 2016; LEE; BRUSILOVSKY, 2014; BRUSILOVSKY, 2012).

Another important point to be considered in the content personalization is the fact that people behave differently and learn in a different pace from each other. Therefore, individual differences should be taken into account while tailoring the content for each student. Recently, several studies have deemed cognitive aspects, such as cognitive traits and learning styles (TRUONG, 2015).

It is not clear what kind of differences makes students maximize their learning. However, studies in the literature point out to a better learning experience when considering cognitive aspects. For example, students may prefer to receive different types of content depending on their context or previous experiences. Previous studies indicate that teaching organized according to learning styles has positive impacts on learning outcomes (ALSHAMMARI; ANANE; HENDLEY, 2015; EL-BISHOUTY et al., 2014; AKBULUT; CARDAK, 2012; MAMPADI et al., 2011; BROWN et al., 2009).

In general, literature research shows that a considerable amount of effort has been put on some of the desirable requirements mentioned above. However, they have not been explored all together in a single and cohesive computational architecture. In this way, this research proposal aims at exploring contextual, cognitive, social, and collaborative aspects in online learning environments in order to offer adaptive learning features to students in ULEs. The term *architecture*, in this work, is not limited to software only. It is used in a broader sense, meaning a computational infrastructure to support the modern teaching/learning process. According to Laan (2013), “architecture is the philosophy that underlies any system. It defines the purpose, intent, and structure of a system”.

## 1.1 Motivation

Students usually tend to spend a significant portion of their time taking notes – when they actually do – in classroom with the hope of having trustworthy and sufficient information for future revisions. As a result, they may lose important details for their learning. Therefore, recording lessons for later retrieval associated with the use of multimedia authoring to improve learning through the Internet have become increasingly attractive to schools and universities, aiming at boosting the interactivity between instructors and students.

At the same time, the concept of Learning Object (LO) has emerged to minimize the time and effort spent for developing reusable educational content. LOs are important assets to leverage the restructuring of traditional pedagogical practices, including the use of communication, information and interaction in educational environments (WILEY, 2000). Nevertheless, LO authoring remains a difficult task, both in terms of design and preparation of the content itself, as well as the process of obtaining and filling out their associated metadata, which is needed to organize, classify and effectively further reuse them.

On the one hand, ULEs becomes an intrinsic factory of LOs. However, the volume of digital content generated in different formats tends to increase every single day. Therefore, retrieving such content becomes a boring task that eventually turns into an ineffective procedure.

Thus, we face the challenge of taking advantage of the nature of ubiquitous educational environments to generate structured learning objects and, at the same time, presenting them in an organized way, with intuitive interfaces, to assist students in their learning process and to facilitate the interaction between instructors and students outside the classroom.

## 1.2 Research Questions, Goals and Methodology

Given the motivation, this work was guided by the following research questions:

Q1: Can ULEs provide support for automatic creation of structured LOs?
    Q1.1: Which kind of information can be extracted from those environments in order to classify LOs according to the Felder-Silverman Learning Styles Model (FSLSM)?

Q2: How does content adaptation based on learning styles affect student performance in ULEs?
    Q2.1: Do students notice that the content is being personalized in such environments?

The main goal of this research study is to design and evaluate a computational architecture for adaptive hypermedia applications in ubiquitous learning environments in order to tackle the complex problem of individualized learning. Such architecture should be grounded on ULEs and ITSs concepts and support multimedia content recommendation and personalization by means of specialized modules that combine cognitive, social, collaborative, and contextual aspects.

In this way, some concepts will be studied and analyzed separately so that they can be integrated together as part of the architectural proposal. Thus, the specific goals of this project are:

- ❑ Design of a process to create LOs and their metadata in ULEs, using the IEEE-LOM standard;
- ❑ Design of a cognitive module for handling learning styles according to the FSLSM integrated with both the LO authoring process and the student profile;

- ❏ Implementation of the proposed modules and their integration into the Classroom eXperience platform for validation;

- ❏ Creation of an LO repository freely available for the research community.

To answer the above research questions, this research has taken an experimental and exploratory approach since ubiquitous computing researches are characterized by the need to first perform case studies and qualitative analyses (WEISER, 1993; TRUONG, 2005). Thereby, abstractions and models can be built in order to become part of the final architecture, which has been designed in an iteratively and incrementally manner aiming at getting a robust architecture at the end that takes into account the desired requirements. Functional prototypes have been used to check the feasibility of proposed solutions to contribute towards a more complete infrastructure.

## 1.3 Results and Contributions

As a product of this doctoral project, a well-defined computational architecture was designed for adaptive hypermedia applications that includes contextual, social, collaborative, and cognitive information in order to recommend and personalize educational content in ULEs. In addition, as a way of getting around the problem of generating LOs, we have explored the use of multimedia capture as a paradigm for educational content authoring. Further, an approach for content personalization based on LS was implemented for validating the architecture.

Looking at evaluation aspects, the proposed approach was implemented in a real ULE and used by students of the Faculty of Computing at Federal University of Uberlândia in order to evaluate it through automated registration of activities and usability experiments which results have been published at relevant conferences and journals in the area. Also, we made the LOs created in this environment available to the Brazilian research community in Informatics in Education, at first, since they are created in Portuguese, with plans to later extend such availability.

Finally, other study cases have be carried out in conjunction with the University of Pittsburgh since we have established an international research collaboration with the Personalized Adaptive Web Systems Lab[1], headed by Dr. Peter Brusilovsky.

## 1.4 Outline

This thesis proposal is structured as follows: Chapter 2 presents a literature review pointing out the key concepts important to understand this document as well as some

[1] http://adapt2.sis.pitt.edu/wiki

related work; the details of the proposed approach are introduced in Chapter 3; Chapter 4 presents the conducted experiments along with their results and discussions; then, final considerations are exposed in Chapter 5, including the resulted publications, some limitations and future work.

Chapter 2

# Literature Review

This chapter presents the main background concepts needed to understand the work presented in this document, such as Ubiquitous Learning Environments, Intelligent Tutoring Systems, Adaptive Educational Hypermedia, Learning Objects, Learning Styles, and the Classroom eXperience platform, as well as some related work found in the literature.

## 2.1 Theoretical Background

### 2.1.1 Ubiquitous Learning Environments

Weiser (1991) defined the concept of Ubiquitous Computing (UbiComp) in the late 1980s to describe the increasingly ubiquitous integration of computing devices into people's daily lives, rather than having only a single personal computer. One of its sub-areas is called Capture and Access (C&A) which aims at creating applications that record daily activities for future review in different contexts and domains.

Traditional educational environments have changed in the past years and now they include a variety of electronic devices and make students assume a more active role in the learning process. The use of technology can help instructors and students in the teaching/learning process through the automation of pedagogical tasks that can be accessed in different contexts. It gives rise to the so-called Ubiquitous Learning Environments (ULEs) or Technology Rich Classrooms (SETTLE; DETTORI; DAVIDSON, 2011; HUANG; HU; YANG, 2015). Classrooms equipped with computing devices, such as projectors, electronic whiteboards, microphones and video cameras, can produce multimedia artifacts, in a non-intrusive way, capable of simulating experiences lived in classrooms and have a positive impact on students learning, as suggested by findings from Settle, Dettori and Davidson (2011).

Abowd et al. (1996) proposed a reference architecture to C&A applications to be structured in four phases: pre-production, live recording, post-production, and access. The pre-production phase is responsible for setting the base content of the lecture, such as title, keywords, abstract, some metadata information and the content itself, that will be presented later. The live recording phase occurs when the instructor delivers his/her lecture to the class. At the end of the lecture, the post-production phase takes place. This phase is responsible for synchronizing the captured media streams and generating the documents to be presented to the user. The last phase, access phase, consists of presenting captured content to students. In addition, a fifth phase, called extension, can also be included to allow users to enrich the capture material with supplementary information (PIMENTEL et al., 2001). The flow of these phases is presented by Figure 1.

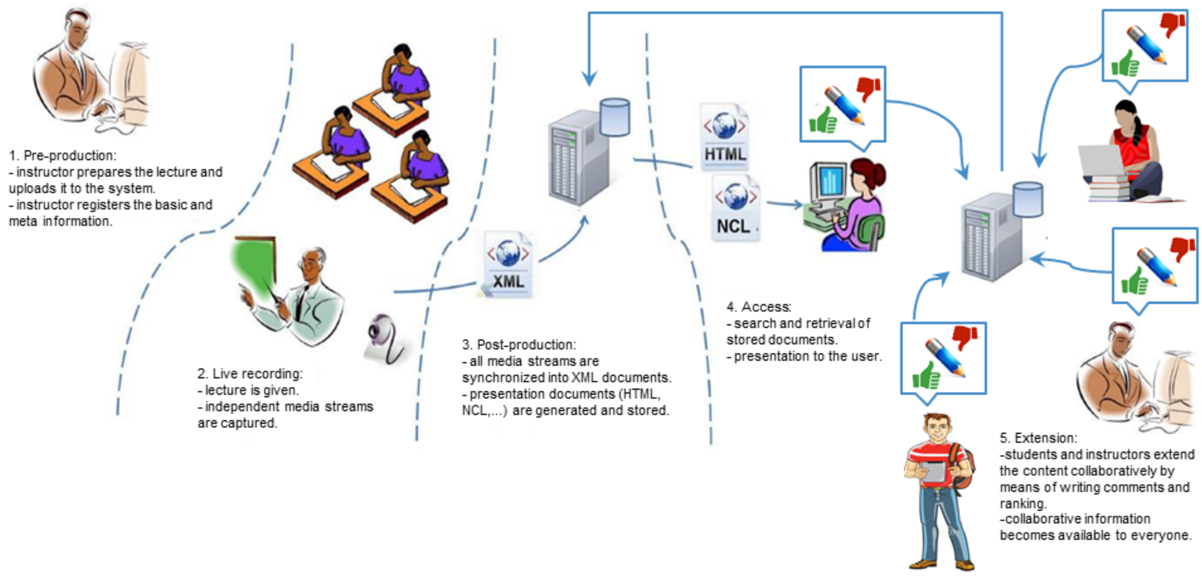



Figure 1 – C&A phases (ARAÚJO et al., 2017).

In general, the main characteristics of such environments can be summarized as follows (OGATA; YANO, 2004):

- Permanency: learning activities are recorded continuously and should not be lost, unless they are explicitly deleted;
- Accessibility: learners can access the content from anywhere they wish;
- Immediacy: any information can be retrieved immediately by learners, so they are provided with content to help them solve problems quickly;
- Interactivity: the environment should provide synchronous or asynchronous communication mechanisms to enable learners to interact with their peers;
- Situation of instructional activities: problems and knowledge required to understand and solve them are presented in their authentic forms in order to enable learners to notice what make particular actions relevant.

Other authors include privacy, API availability, scalability, reuse and extensibility, entities representation, additional instructional content, and context-aware features as additional characteristics for developing learning environments (MARTIN et al., 2011).

### 2.1.2 Intelligent Tutoring Systems

Intelligent Tutoring Systems (ITSs) are specialized software systems developed to provide students with individualized learning activities like a human tutor (ZHIPING et al., 2012). In general, they use artificial intelligence techniques to be able to offer adaptivity, flexibility and personalized learning to students (WOOLF, 2008).

Usually, an ITS implement a general architecture that has four well-defined components that interact with each other to achieve its goal: *(i)* domain model, *(ii)* student model, *(iii)* pedagogical model, and *(iv)* user interface (SLEEMAN; BROWN, 1982; BADARACCO; MARTÍNEZ, 2011).

The Domain Model is responsible for representing how the educational content is structured and the existing relationships among subjects of the domain knowledge. It contains the subjects (also called concepts, or topics) to be learned and how they are related to each other. It can include other pedagogical information, such as importance, difficulty and semantic density of subjects.

The Student Model (SM) represents and stores students' characteristics, such as knowledge, skills, learning preferences, learning experiences, errors and misconceptions. This model should be able to infer what the student knows or does not know about the domain knowledge. In general, cognitive activities performed during the learning process are considered in this component. With this information, it is possible to analyze how different is the learning process of one student to another.

The pedagogical model, also called tutoring module, is responsible to select the best content (or learning activity) at any given time. That is, it must use intelligent mechanisms to guide students in their learning path considering individual needs aiming at maximizing their learning. This model uses information from the SM to determine which content from the Domain model should be presented. According to Brusilovsky, Schwarz and Weber (1996), curriculum sequencing, interactive problem-solving support, and intelligent analysis of student solutions are the traditional intelligent techniques applied in ITSs.

Finally, the educational content is presented through a user interface, which is apart from the other components. It is responsible for managing and tracking interactions between the system and the users, as well as providing a suitable user experience to students.

### 2.1.3 Adaptive Educational Hypermedia

The ability to provide efficient mechanisms to select and present the best content to users is a challenge already known to the area of multimedia educational environments (ZENG; ZUO; LU, 2010; ÖZYURT; ÖZYURT; BAKI, 2013; MAHNANE; LASKRI; TRIGANO, 2013; BALAKRISHNAN; LIEW; POURGHOLAMINEJAD, 2015). In order to avoid the *"one-size-fits-all"* approach, i.e., the same content is presented exactly in the same way to all users, Adaptive Hypermedia (AH) has emerged as a solution to the problem of Web content personalization (BRUSILOVSKY, 1996; BRUSILOVSKY, 2001).

Brusilovsky (1996) defines Adaptive Hypermedia Systems as:

> *"By adaptive hypermedia systems we mean all hypertext and hypermedia systems which reflect some features of the user in the user model and apply this model to adapt various visible aspects of the system to the user".*

The AH approach allows users with different tastes and preferences to receive different content. A typical adaptive hypermedia system considers differences among users, such as preferences, knowledge, goals, and previous experience to offer a personalized content every time they access the system. Particularly in the educational domain, it aims at maximizing students learning and efficiency (SOMYÜREK, 2015; JUVINA; HERDER, 2005; BRUSILOVSKY, 1996).

In the educational context, this approach is called Adaptive Educational Hypermedia (AEH) and provides students with individualized learning content, adapted to their needs in a given context. Basically, AEH systems create connections between the knowledge space – or a concepts network – and the hyperspace of educational content, as shown in Figure 2. To be able to create those connections, the domain knowledge and the educational content must be well-structured. It could be compared to the Domain model of ITSs, defined in the previous section, which comprises a set of small domain knowledge elements. Indexing approaches are created to identify which concepts are presented in each knowledge element and may consider different granularities.

In general, the educational content is produced by specialized authoring tools that provide support for representing the content internally (through metadata fields) as well as for creating the connections between them. However, their design is not always easy to use and requires advanced and expert users to be able to understand and to use such tools properly.

In order to provide adaptivity to students, AEH systems should have a student model, another concept inherited from ITSs. It is responsible for estimating students' knowledge level on each concept to be able to identify what they know and what they do not know to help them to achieve the established educational goals.

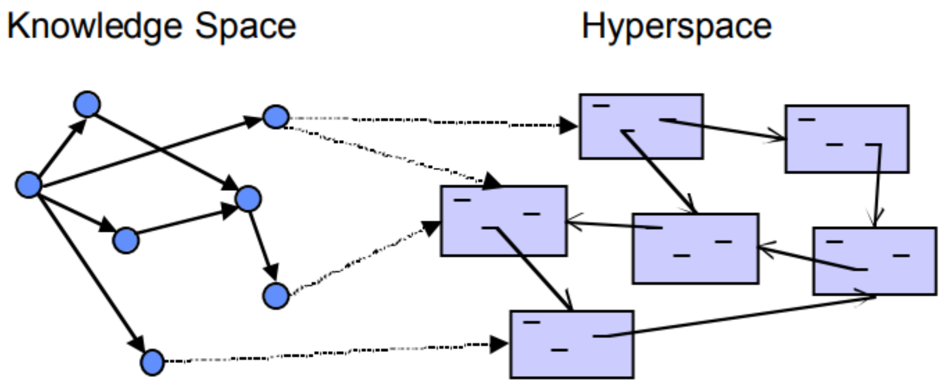



Figure 2 – Typical structure for connecting the knowledge space and the hyperspace in AEH systems (BRUSILOVSKY, 2003).

### 2.1.4 Learning Objects

Web-based learning environments have been used to assist educational activities more and more. Creating materials for such environments requires a lot of effort, which includes creativity, time availability, and knowledge of appropriate technologies. In this way, the concept of Learning Object (LO) has emerged to minimize the time and effort spent for developing reusable educational content.

LOs are important assets to leverage the restructuring of traditional pedagogical practices, including the use of communication, information and interaction in educational environments (WILEY, 2000). According to IEEE, LOs are digital or non-digital entities that can be used in learning contexts (IEEE, 2002). The term reuse is often added to this definition, which makes the use of standards a necessity. In this way, organizations like IEEE, IMS Global Learning Consortium, and ADL (Advanced Distributed Learning), have produced specifications and standards to address this need.

In this work, the IEEE Learning Object Metadata (IEEE-LOM) (IEEE, 2002) standard was chosen to represent metadata of LOs since it has been widely used and represents a major step forward in terms of resource description, discovery, and reusability (VAN ASSCHE et al., 2003). IEEE-LOM support content interoperability among repositories and enables automated content search and retrieval.

The IEEE-LOM is formatted as an XML file and its data elements are structured into nine categories: General, Life Cycle, Meta-Metadata, Technical, Educational, Rights, Relation, Annotation, and Classification. Each data element has a name, a description, a datatype and maximum size, and the order inside its parent node. Some data elements have their own vocabulary as a list of recommended values. In some cases, the element value may contain a list of values rather than a single value.

The Educational category is one of the most important for this work, because it brings educational and pedagogical characteristics of LOs, such as “Learning Resource Type”, “Interactivity Type”, “Interactivity Level”, “Semantic Density”, etc. However, other fields bring important semantic information as well, for instance, the format of the object and its structure. Each field used in this work will be detailed later.

There are also extensions created to add higher semantic meanings to the vocabularies proposed by the IEEE-LOM, as the case of the Customized Learning Experience Online (CLEO) extensions (CLEO, 2003) created by the CLEO Lab, which comprises some commercial content providers such as Cisco Systems, Inc., IBM Corporation, Microsoft Corporation, and Thomson NETg. This work includes the vocabulary of the CLEO extensions for the "Learning Resource Type" field, containing the following values: *additional resource*, *analogy*, *assessment*, *assessment item*, *attractor*, *community*, *definition*, *demonstration*, *example*, *feedback*, *glossary*, *guidance*, *guideline*, *illustration*, *importance*, *introduction*, *non example*, *note*, *objective*, *outline*, *overview*, *practice*, *prerequisite*, *presentation*, *recall*, *reference*, *reinforcement*, *scenario*, and *summary*.

It is important to note that including a new vocabulary does not change the structure of the metadata. It only adds new possible values to the default ones. Thus, the reuse property of the LO is maintained.

### 2.1.5 Personalization of Learning Objects

ULEs are potential producers of LOs. In addition to providing support for the automatic generation of educational materials, they are still capable of automatically or semiautomatically creating metadata that becomes a source of information to support personalization and recommendation processes.

A first level of personalization is associated to UbiComp concepts, mainly related to the context awareness of the designed system. For example, if the internet bandwidth is low, it is not recommended to view the lecture's recorded video. If device screen is too small, then textual information would be preferred over slides.

Combined with this strategy, cognitive information may be used to adapt the content to make it more individualized and improve the learning experience and its gains. For example, there are people who learn easily from examples and when they do practical activities. On the other hand, other people perform better when exposed to more abstract content. Koedinger et al. (2015) explored the use of informational assets, such as text and videos, versus practical activities in their context.

However, there is no easy way to identify people's cognitive profiles. In general, people are required to answer extensive questionnaires that may be misinterpreted. Hence, data-driven approaches to identify individual differences or people's behavior are on the rise. For instance, the Problem-Solving Genome was firstly proposed by Guerra et al. (2014), which the main idea was to find navigation micro-patterns to describe small chunks of repetitive behavior that might define each student individually in the way he/she solves problems.

Kinnebrew, Segedy and Biswas (2017) have developed methods to track and interpret students' open-ended learning and problem-solving behaviors. They combined model-driven metrics with data-driven pattern discovery to analyze the way students work in an open-ended learning environment using data mining and machine learning techniques. Although this work does not aim to propose a new solution in this direction, it should foresee different types of interactions in the proposed architecture to provide support for researches of this nature.

**Learning Styles**

While there are many different approaches for personalization and recommendation of educational content, many of them have deemed cognitive characteristics, such as cognitive traits, cognitive styles, and learning styles (TRUONG, 2015). Studies found in the literature indicate that students learn differently from each other (ESSALMI et al., 2015; GRAF et al., 2014; BRUSILOVSKY, 2001). Teaching strategies that consider the individual differences of students have been studied for a while.

This work will focus on LS once previous studies indicate that teaching organized according to LS has positive impacts on learning outcomes (ALSHAMMARI; ANANE; HENDLEY, 2015; EL-BISHOUTY et al., 2014; YANG; HWANG; YANG, 2013; AKBULUT; CARDAK, 2012; MAMPADI et al., 2011; BROWN et al., 2009). Note that this was the technique chosen for validating our architectural proposal, whose specific module that contemplates such theory can be replaced by other techniques in the future.

An LS model classifies students according to the way they perceive and process information received in educational contexts. Such models can determine how each individual interacts and reacts in a learning environment, reflecting their real preferences. Several theories related to LS have been introduced mainly by Felder and Silverman (1988), Kolb (1984), Dunn et al. (1995), and Honey and Mumford (1992). In this work, we use the Felder-Silverman Learning Styles Model (FSLSM), which is one of the most used models in adaptive learning systems. According to the FSLSM, learning styles represent tendencies rather than fixed characteristics. The model defines eight different LS grouped into four dimensions related to perception, processing, presentation and organization of information during the learning process.

Briefly, each dimension can be described as:

- Processing (Active/Reflective LS): on one side are the students who are proactive. They like practical activities, discussions, experimentation, and working in group. On the other side are the students who like learning through in a passive way, i.e., through introspective observation;

- Perception (Sensing/Intuitive LS): sensing students tend to be practical, methodical and they like to learn from facts, data, and experimentation. They are patient with details and they like to solve problems by standard methods. Intuitive students like abstractions, innovative things and prefer discovering new possibilities and relationships;

- Input (Visual/Verbal LS): this dimension is related to the way students tend to remember better when they receive information. Visual students remember better what they see, either by images, diagrams, charts, films, or demonstrations. On the other hand, verbal students prefer text description or spoken explanations;

- Organization (Sequential/Global LS): sequential students like following a logically structured content, learning in linear steps, while global students tend to learn in large jumps, trying to get the "big picture" of the topic.

Generally, manual instruments are used for assessing students' LS. The Index of Learning Styles (ILS) is a questionnaire composed of 44 questions used to identify the LS of students according to the FSLSM. Each of the four dimensions contains 11 questions with two alternatives each. The output is four values ranging from -11 to +11 that strength a preference for one side of the dimension. Although it is a statistically validated instrument, its manual filling causes displeasure and lack of motivation, which can lead to possible imprecise answers.

Some studies found in the literature have questioned the effectiveness of the use of LS (KIRSCHNER, 2017; AN; CARR, 2017). Generally, the criticisms are related to the classification of learners into only one LS without considering any mixed preferences or, even without considering that such preferences can actually change from one style to another over time. Thus, the models have antagonistic LS and, once students are classified, they remain in only one end of the dimension, without considering uncertainties.

### 2.1.6 Classroom eXperience

This section presents the *Classroom eXperience (CX)*[1] as a primary basis for this experimental and exploratory research and has been an object of study since 2010. CX is a real-world application designed to automatically record lectures in classrooms. It performs capture, storage, access and extension of multimedia content in a classroom instrumented with electronic whiteboard, microphones, cameras and projectors. Specialized software components capture all media streams from each device and, then, integrate and synchronize them, generating hypermedia documents in different presentation formats.

Built as an extension of the iClass platform (PIMENTEL; CATTELAN; BALDOCHI, 2007), CX has its own architecture for content personalization, allowing the customization of captured content presentation according to the preferences and access context of each student (ARAÚJO et al., 2013). CX assists instructors with ubiquitous computing

[1] http://cx.facom.ufu.br

resources without changing the conventional dynamics of the class, while students are assisted with later access to all information presented during the classes.

The general architecture follows a well-structured sequence of activities that occur between the content capture and its subsequent release. These activities are divided into four steps previously discussed in subsection 2.1.1: pre-production, live recording, post-production, and access. In addition, a fifth phase called "extension" is considered in this work. The extension phase is characterized by content enrichment provided by students and instructors while accessing the captured content to create a more complete material (PIMENTEL et al., 2001). In order to synthesize the C&A process embodied in the CX, Figure 3 presents the five mentioned phases. Dotted arrows indicate where LOs and their metadata are created/updated.

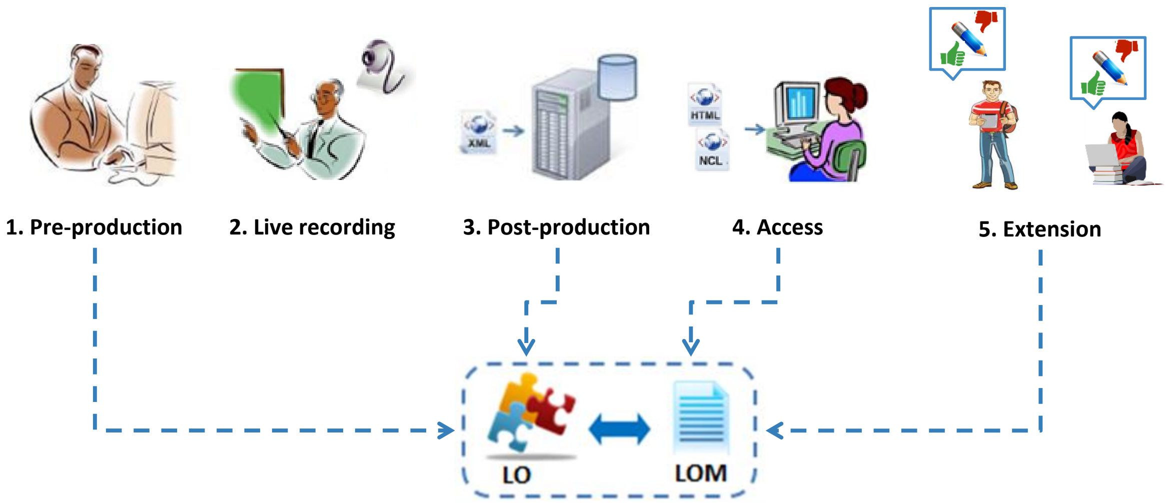



Figure 3 – The five phases of capture and access process in CX.

The pre-production phase is responsible for setting the content that will be captured at classroom. At this stage, the instructor will register any information relevant to the lecture using a Web interface. All lecture information is organized in 3 categories: basic data, additional data (meta information) and the content itself, that will later be presented. The metainformation is classified and organized using extensions based on IEEE-LOM.

The live recording phase occurs when the instructor gives his lecture to the class. At this point, the instructor accesses a Web frontend, selects the desired lecture, which content, previously registered, is loaded in the interactive whiteboard. The specialized capture components then start recording individual media streams (digital ink, audio and video). Figure 4 shows two instrumented classrooms in the Faculty of Computing at Federal University of Uberlândia.

The post-production phase begins immediately after the live recording phase. This phase is responsible for synchronizing captured media streams through XML documents, which contain all interactions between the instructor and the capture system. Then, doc-

Figure 4 – Two instrumented classrooms at UFU.

uments to be presented to the user, such as HTML for Web visualization, and NCL[2] for interactive Digital TV (iDTV) are generated, compressed, and stored through a specialized peer-to-peer layer (ARAÚJO et al., 2012).

The access phase consists in presenting the captured content to interested parties, in this case to students. All multimedia content that was captured during the class is made available to students. This step is based on a user-centered design, in order to encourage the students to visualize the captured contents. Currently, CX uses an approach that takes into account the user's access context, user preferences and, also, the presentation constraints to personalize the captured content. These constraints are related to the environment in which students access the system. For example, if the bandwidth is low, it is not recommended to view the lecture recorded video or, if the device's display has reduced dimensions, then textual information may be preferred instead of lecture slides. Constraints like these can therefore directly influence the presentation experience of the captured content to the user.

The extension phase occurs when the content is already available to students and they wish to enrich what has been recorded with comments and ratings for each LO. Also, the system provides additional content related to the covered topics.

As can be noticed, CX can assume a role of an LO generator, including its metadata. It has already more than 600 lectures created and thousands of LOs. Its ubiquity happens at two different moments: *(i)* when lectures are captured by computational devices inside a classroom and generates LOs; and, *(ii)* when students access this content through a contextualized interface.

[2] http://www.ncl.org.br

## 2.2 Related Work

Wang and Wu (2011) present a context-aware approach using recommendation algorithms to assist students in their learning process. They use Radio-Frequency IDentification (RFID) to provide the context-aware notion and the Sharable Content Object Reference Model (SCORM) as a metadata standard for the their LOs. In short, the recommendation process uses association rules in a mining model to analyze students' preferences according to their learning profile.

Youubi (MONTEIRO; GOMES; NETO, 2016; MONTEIRO et al., 2017) is a ULE designed as a component-oriented architecture and accessible through mobile, web, smartwatch and iDTV platforms. It is a platform that provides support for formal and informal learning by means of contextual, social, and gamification features. Their architecture focuses on recommendations for elementary entities, such as Person, Location, Event, Challenge, and Group. The approach proposed here focuses on personalized and individual content adaptation as well as LOs authoring structured according to the IEEE-LOM standard.

GlobalEdu (BARBOSA et al., 2013) is a ubiquitous learning architecture that explores the concept of LOs, also represented in the IEEE-LOM standard, to explore pedagogical opportunities in a context-aware environment. Their approach matches learners with similar or complementary interest to stimulate their interaction. GlobalEdu also adapts LOs according to students' LS.

An adaptive content delivery framework for u-Learning environments was proposed by Zhao and Okamoto (2011). This framework gets original PowerPoint files and delivers adaptive content based on learners' context, preferences and social networks information. They developed the so called AubiLearn mobile system to evaluate their approach. In total, 20 students participated in the study. Authors claimed that learners may get a better learning experience while using the proposed adaptation content delivery model implemented on the AubiLearn system.

Machado and Oliveira (2013) modeled an ontology with contextual information to recommend places or persons of interest which are close to user's location, as well as indicate study materials and notifications about teacher's or student's appointments. In this case, they do not provide students with adaptive content.

The Generalized Intelligent Framework for Tutoring (GIFT) (SOTTILARE et al., 2012; SOTTILARE et al., 2017) is an adaptive tutoring architecture that includes a myriad of features, such as authoring tools, learner model, sensor processing module, pedagogical module, among others. It is an open-source project, designed as a service-oriented framework for building, delivering, and evaluating intelligent tutoring systems. The GIFT Authoring Tool is based on a visual course building interface that represents a course flow in a timeline of events that the learner will encounter (OSOSKY; SOTTILARE; BRAWNER, 2017). Some differences from this work may be pointed out. As we noticed, GIFT does not consider either refinement nor collaborative content enrichment. According to the authors, the GIFT is compatible with different metadada standards – such as IEEE-LOM, SCORM, and IMS Global Learning Resource Metadata. However, it does not consider the CLEO extensions and does not provide a way to classify LOs according to LS. Although they provide a graphical interface for content sequencing, it is still a manual task performed as many times as the desired number of sequencing.

Vidal et al. (2016) proposed an adaptive hypermedia-based approach for assisting students to accomplish their activities in Accounting courses. Their approach takes into consideration a domain model, representing accounting knowledge, a student model that considers static and dynamic information, and an adaptive model which provides an adaptive navigation mechanism based on student model. The static information of the student model is obtained through a questionnaire about students' professional interests and the dynamic information contains activity-solving performance data. The adaptive model implements a rule-based mechanism that maps student professional interests to an appropriate content structure in the domain model.

An adaptive framework to suggest learning paths that meet students learning objectives was proposed by Onah and Sinclair (2015). When students register in the system, they answer a survey to capture their learning objectives. Based on that, learning paths were created to match students' objectives and LOs concepts. When answering multiple-choice questions, students receive an instant feedback and a recommended content based on their performance.

AdaptWeb® (OLIVEIRA et al., 2003; GASPARINI et al., 2009) is an adaptive system created for distance learning with the purpose of adapting the content, the presentation and the navigation according to students profile. It considers students' course domain, knowledge, preferences and navigational history, technological resources and learning style. The content is organized through a hierarchical structure of concepts with pre-requisite criteria. The navigation can be sequential (considering prerequisites) or free. It also provides a message board and a discussion forum to students.

Social and collaborative features have also been studied as means of improving learning experiences in e-Learning systems (BRUSILOVSKY et al., 2016; SOBAIH et al., 2016; LEE; BRUSILOVSKY, 2014; BRUSILOVSKY, 2012). Edooware (BALAKRISHNAN; LIEW; POURGHOLAMINEJAD, 2015) is a Learning Management System (LMS) that includes social media features such as flexibility in profile management, possibility of sending invitation to external social networks users, document and reference materials sharing, comments, among others, in order to improve the students' learning experience.

Chao et al. (2014) presented an architecture of m-learning content recommendation services. They exploit mobile social interactions to identify similar learners and favorite learning content. In addition, contextual information such as GPS and wireless function is considered.

U-Learning Community (CAYTILES; JEON; KIM, 2011) is a web-based e-learning system that includes a social u-Learning model for wireless sensor networks. They provide students with personalized content according to their social and collaborative interactions as well as the environment context.

The use of cognitive characteristics has attracted attention of researchers in this area. LS adaptivity in e-learning systems have been studied. Graf et al. (2014) proposed an adaptive mechanism that extends LMSs based on the FSLSM. Their mechanism uses two techniques: adaptive annotation, which classifies the LOs as recommended or standard, and adaptive sorting, which is used to determine the sequence of the LOs within a section. For adaptation purposes, 12 different types of LOs are considered: commentaries (or outlines), content objects, quizzes, self-assessment tests, discussion forum, additional reading materials, animations, exercises, examples, real-life applications, conclusions, and assignments. Some differences of our proposal may be pointed out. For example, the LO type must be informed by the instructor, differently from this work in which this information is collaboratively obtained by the system. In addition, the LOs are not generated in a ULE and they do not consider contextual information for personalizing the content.

AMDPC (YANG; HWANG; YANG, 2013) is an adaptive learning system that considers learning styles and cognitive styles. Content is extracted from raw materials and chunks of information for composing personalized learning materials are generated. The presentation layout is adjusted according to students' cognitive styles (Field-Dependent or Field-Independent measures) (WITKIN et al., 1977) and the instructional strategy is based on students learning styles (FSLSM). Both measures are obtained through the application of specialized instruments for each one. Authors claim that the proposed system could improve students learning achievements as well as their belief of learning gains. In addition, they found that students' mental load was significantly decreased.

Mahnane, Laskri and Trigano (2013) proposed an adaptive educational hypermedia system based on learner's thinking and learning styles, called AEHS-TLS. Their system was structured in three basic components: the domain model, the learner model and the adaptation model. The domain model stores, organizes and describes the learning content in 12 types: learning objectives, additional information for the course, examples and analogies, multiple-choice questions, little theoretical activity, little theoretical activity in groups, large theoretical activity, large theoretical activity in groups, little practical application, little practical application in groups, great practical application, and great practical application in groups. The learner model gathers information about students' goals and preferences, thinking and learning style, and knowledge and performance. Lastly, the adaptation model contains a set of rules that specifies how the learners' knowledge and thinking style modify the presentation of the content.

Boticario et al. (2012) have proposed a framework for content recommendation based on standards and interoperable components which are integrated through a service-oriented architecture. This framework is part of the EU4ALL project, founded by a European Consortium composed of 15 institutions from 8 different European countries. They have developed the dotLRN LMS (SANTOS et al., 2007) which provides a set of social and collaborative features such as blogs, discussion forums, chats, and study groups. Their SM stores personal information, preferences, learning styles according to the FSLSM, goals and competencies, progress and indicators about attention, memory and time management. Their work is quite related to the proposed here, however, some differences can be pointed out. First, the framework does not consider hierarchical LOs with different granularity levels. Also, they are not produced in a ubiquitous environment and then classified according to LS dimensions based on their metadata.

In order to summarize the information presented in this chapter, Table 1 presents the main related work indicating their nature (ubiquitous and/or adaptive educational system), which kind of information they take into account – contextual (including access context, contextual preferences, and access constraints), social, and/or cognitive aspects, and whether they provide features for LO enrichment/refinement and some standard metadata format. A filled circle (●) indicates that the work includes the respective attribute, an empty circle (○) indicates that it does not include the respective attribute, and a half-filled circle (◐) means that the attribute is partially considered. A double dash indicates that either the work does not consider the attribute, or it was not mentioned.

Table 1 – Comparison of related work.

| | Nature | | Included information | | | Features | |
|---|---|---|---|---|---|---|---|
| Work | Ubiquitous | Adaptive | Contextual | Social | Cognitive | LO Enrich. | Metadata |
| Wang and Wu (2011) | ● | ○ | ● | ○ | ○ | ○ | SCORM |
| Monteiro, Gomes and Neto (2016), Monteiro et al. (2017) | ● | ○ | ● | ● | ● | ○ | – |
| Barbosa et al. (2013) | ● | ● | ● | ● | ● | ○ | – |
| Zhao and Okamoto (2011) | ● | ● | ● | ● | ● | ○ | LOM |
| Sottilare et al. (2012), Sottilare et al. (2017) | ● | ● | ● | ◐ | ○ | ○ | LOM, SCORM, IMS |
| Vidal et al. (2016) | ○ | ● | ○ | ○ | ○ | ○ | – |
| Oliveira et al. (2003), Gasparini et al. (2009) | ○ | ● | ● | ● | ● | ○ | – |
| Onah and Sinclair (2015) | ○ | ● | ○ | ○ | ○ | ○ | – |
| Chao et al. (2014) | ● | ○ | ● | ● | ○ | ○ | – |
| Caytiles, Jeon and Kim (2011) | ● | ● | ● | ● | ○ | ○ | – |
| Graf et al. (2014) | ○ | ● | ○ | ● | ● | ○ | – |
| Mahnane, Laskri and Trigano (2013) | ○ | ● | ○ | ● | ● | ○ | – |
| Boticario et al. (2012) | ○ | ● | ● | ● | ● | ◐ | LOM, SCORM, IMS, ISO, others |
| This work | ● | ● | ● | ● | ● | ● | LOM+ CLEO |

As can be observed, most studies are focused on some of the key aspects proposed in this research: context-awareness, collaboration/social interactions, and cognitive profile. In addition, the concept of LO along with standard metadata representation is not always explored, nor its enrichment and refinement. Moreover, this research aims at using information produced by ubiquitous learning environments to make the adaptive web-based educational systems richer, which highlights its contribution to the area.

Chapter 3

# AULA: Adaptive and Ubiquitous Learning Architecture

Consider a Ubiquitous Learning Environment (ULE) that records activities in an instrumented classroom with an electronic whiteboard, projectors, microphones and video cameras. In such scenario, various multimedia artifacts are generated in a single capture session. Clearly, those environments have the potential to generate a huge amount of Learning Objects (LOs) that could become useless if students cannot easily find what they need. In this way, a computational architecture for personalizing and recommending educational content in ULEs is presented in this chapter.

First, an overview of the architecture is presented in Section 3.1. Then, the architecture details are described in two perspectives: looking at LOs authoring, in Section 3.2; and, looking at LOs personalization, in Section 3.3, in order to provide support for individual tailoring of educational content. Finally, Section 3.4 provides a discussion about the architectural components.

## 3.1 Architecture Overview

As previously seen, recording lectures for later retrieval, multimedia authoring and improving learning through the Internet have become increasingly used to enhance the interactivity between instructors and students. Also, LOs have been important assets to leverage the restructuring of traditional pedagogical practices, including the use of communication, information and interaction in educational environments. Therefore, the main goal of this research work is to design and evaluate a computational architecture for adaptive hypermedia applications in ubiquitous learning environments that combines cognitive, social and contextual aspects to create and personalize LOs.

The proposed architecture design is grounded in the five phases used in the Classroom eXperience (CX) platform, as shown in Figure 1. First, in the pre-production phase, instructors prepare their lectures before going to the classroom. Then, different computing devices scattered in the environment take charge of recording them during the live recording phase. In the post-production phase, all media streams are synchronized and stored. Once recorded and stored, each lecture becomes available for students to access it in a personalized way. Finally, students and instructors can enrich the original content in the extension phase. Each module may also be related to ITSs concepts and will be discussed as they appear.

The Adaptive and Ubiquitous Learning Architecture (AULA) comprises some specialized modules with distinct roles that will be described further in this chapter. Each individual involved in the teaching/learning process plays a key role at these phases and they are responsible for creating the learning experience together. The architecture provides support for contextual, collaborative, social, and cognitive features. Figure 5 shows its overview.

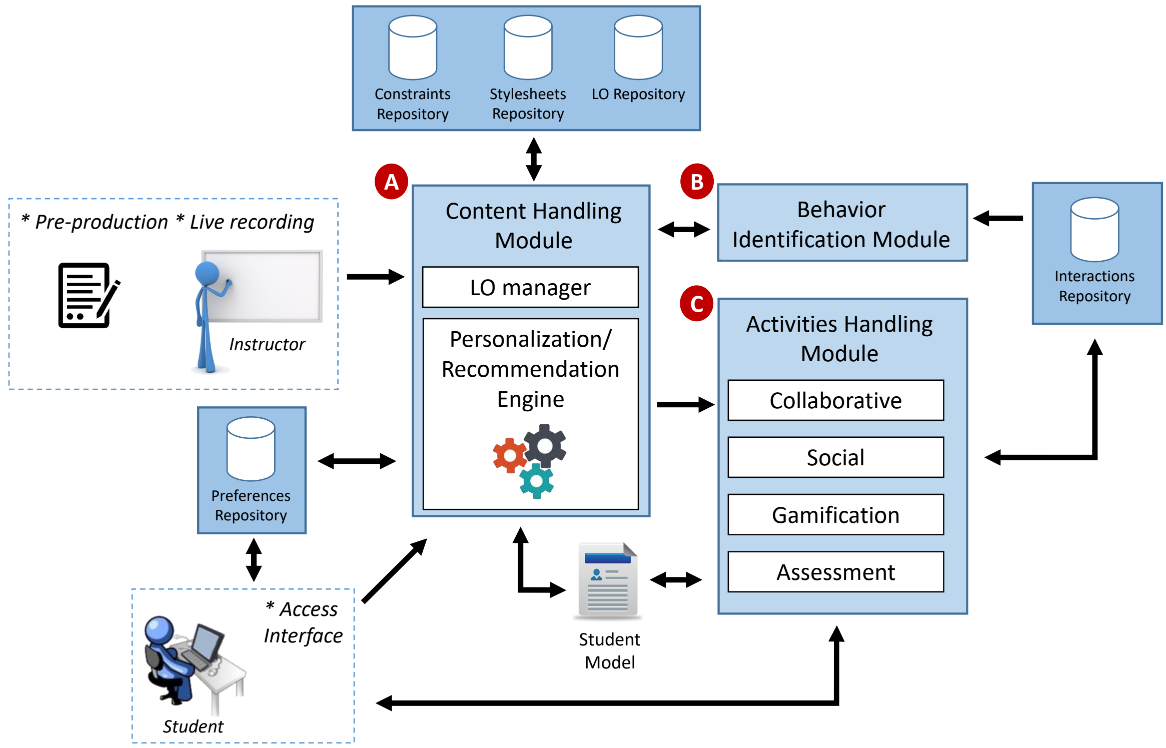



Figure 5 – Architecture Overview.

For storage purposes, AULA provides support for different types of repositories that are responsible for storing specialized information, such as presentation constraints, stylesheets, LOs, users' preferences, and interactions performed throughout the system.

Presentation constraints are pre-defined rules with regard contextual access information. For example, imagine a user's device connected with low bandwidth. In this case, video streaming is not recommended so the captured content should be presented in a personalized way – let's say, just the lecture slides, for fast download and basic browsing features, with no video stream. This kind of personalization is made by means of stylesheets that define different presentation formats during the access phase.

Moreover, to be able to personalize the content, one must have consistent LOs (metadata included), and also relevant information about students. LOs are the ones that should be tailored according to students' needs. Therefore, the "Content Handling Module" (bullet A in Figure 5) has been created to manage LOs, that is, to create, update, and delete them, as well as to customize and recommend such content to students. The LO manager may be understood as the Domain model of an ITS, in which subjects related to the domain knowledge are managed. The personalization/recommendation engine plays the role of the Pedagogical model of an ITS, which uses information of the SM to adapt the content individually.

Furthermore, it is essential to identify and map out student characteristics in order to find individual differences among them, allowing the content to be presented individually to maximize learning. AULA provides the "Behavior Identification Module" (bullet B in Figure 5) for this purpose as a black-box that contributes to the "Content Handling Module", which means that the latter does not know details on how the first is implemented. As a default cognitive feature, the architecture implements a structure to store the Learning Style (LS) of students and LOs according to the Felder-Silverman Learning Styles Model (FSLSM).

In addition to recording and presenting the content of the lecture, the "Activities Handling Module" (bullet C in Figure 5) makes social, collaborative, gamification and assessment features available for students and instructors. Also, a student model that gathers students' characteristics is included.

The general idea of this architecture has already been published (ARAÚJO; DORÇA; CATTELAN, 2017; ARAÚJO et al., 2018 in press). Aiming at facilitating the overall understanding of this architecture, the next sections present the structure and operation of LOs and the resources for the personalization task, separately.

## 3.2 Learning Objects Authoring

LOs authoring is still an arduous and time-consuming task, both in terms of design and preparation of the content itself, as well as the process of filling out their associated metadata. First, it involves an interdisciplinary process, which requires attention to technical and pedagogical aspects (SOLIS; LAVISTE, 2015; BUZATTO et al., 2009). Second, it demands the use of specifications and standards that enable search, retrieval and reuse of such resources in the future. Consistent LOs (content itself and metadata) provide meaningful information that may be used to create personalized experiences with educational content according to students' preferences and their individual differences.

Lectures recorded in ULEs can be regarded as LOs since they are pieces of educational content. The pre-production phase is responsible for setting the base content of the lecture. The live recording phase occurs when the instructor delivers his/her lecture in a classroom. At the end of the class (post-production phase), the lecture's metadata is updated, and the content is prepared to be stored. At that moment, the lecture becomes available to students who start interacting with it.

However, these LOs are coarse-grained as they represent a whole lecture, which is typically more than 1-hour long. Because of that, it decreases the chance of reuse them in the future (BRAGA et al., 2012). Therefore, one more step was included in the LO creation process to refine them, taking advantage of collaborative features foreseen in the architecture.

### 3.2.1 Collaborative Bookmarking

Each lecture consists of a set of slides that can be grouped into different subjects, or topics. Knowing that, a single lecture generates many other LOs, which have been structured in three hierarchical levels: *lecture*, *subject*, and *slide*. A **lecture** consists of several *subjects*, which are composed of several *slides* that are created during the pre-production phase by the instructor who prepares the content for a capture session. The LO is updated in the post-production phase and other LOs are also created to represent each lecture **slide**, which contains the raw media and the annotations made in the electronic whiteboard.

As an example, imagine a lecture whose goal is to teach repetition structures in the context of computer programming. First, it could have a set of introductory content that includes the lecture's title, goal, and agenda. Then, the content could be divided, for example, into different subject matters, such as "For Loops", "While Loops", "Do While Loops", among others. Each subject matter may be presented through different learning resource, as textual definition, visual definition, example, simulation, etc. Finally, the lecture could have a set of concluding content that includes the lecture's summary and references. In this scenario, each subject matter would be one *bookmark*, which comprises a set of *slides*.

Theoretically, a lecture can be defined as a set of $n$ *slides*, with $i$ *slides* representing some introductory content (at the beginning of the lecture) and $n - j$ *slides* representing some concluding content (at the end of the lecture). Additionally, this same lecture could be divided into $k$ *subjects*, as shown in Figure 6. In this way, LOs with different granularity are created: one LO for the whole lecture, each *subject* represents other LOs, and, finally, one LO for each *subject*, and one LO for each *slide*, counting $k + n + 1$ LOs in total.

During the access phase, students and instructors are allowed to label **subjects** within a lecture using the bookmarking feature. They can indicate in which slide a new **subject** begins and label it with a title. Bookmarks created by students and instructors inside a lecture are used to split the lecture into smaller LOs, called *subjects*. Each labeled *subject* becomes a new LO internally, and the most common labels are presented to other students. Figure 7 shows an example of a captured lecture presented to students with a

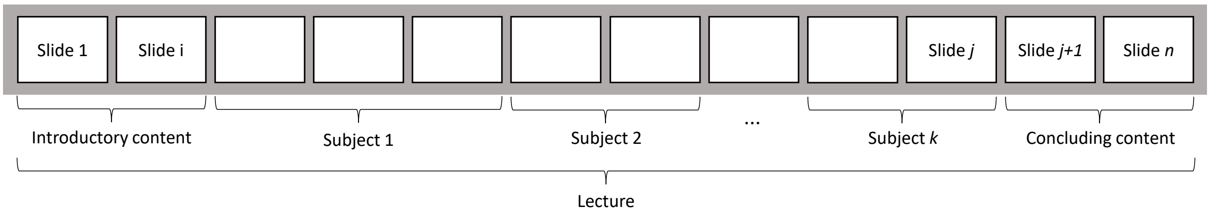



Figure 6 – Structure of a lecture with three hierarchical levels.

bookmark represented by bullet (1). Additionally, users can also collaboratively inform the resource types contained in that the slide, as shown by bullet (2).

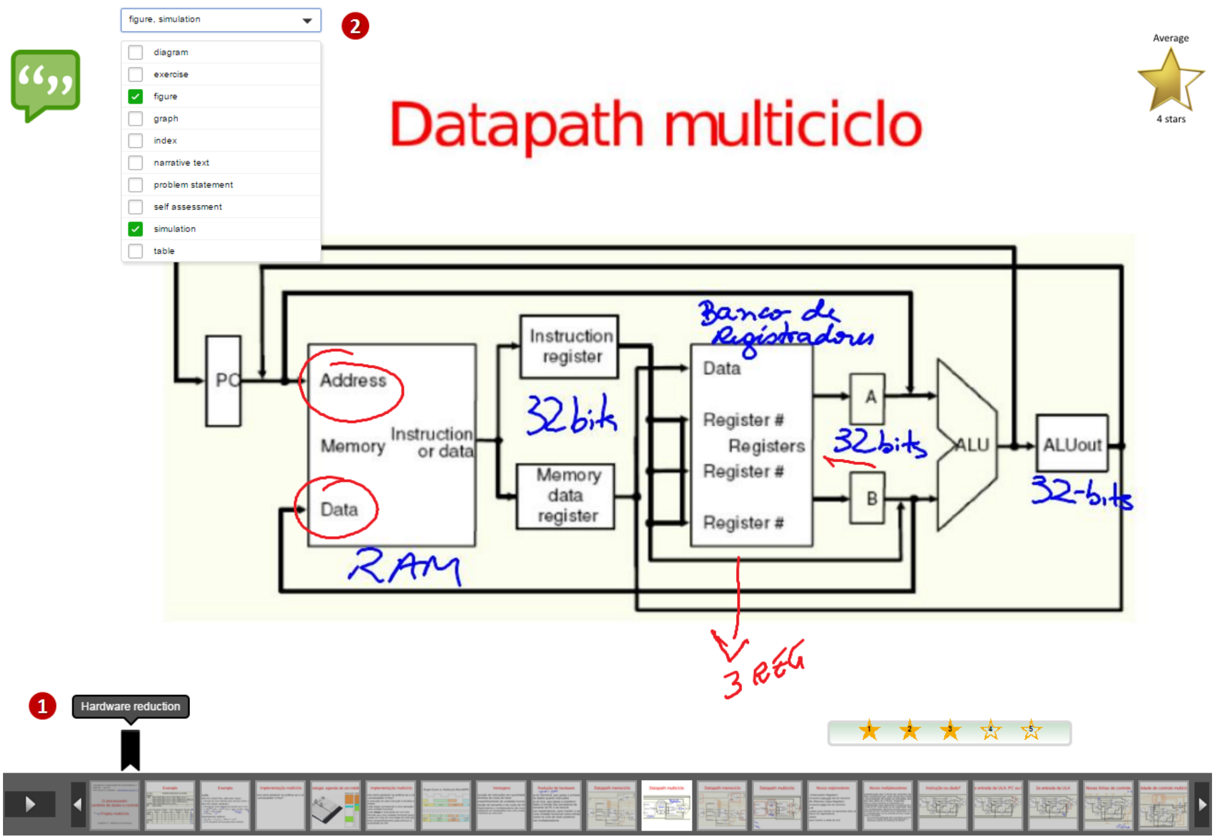
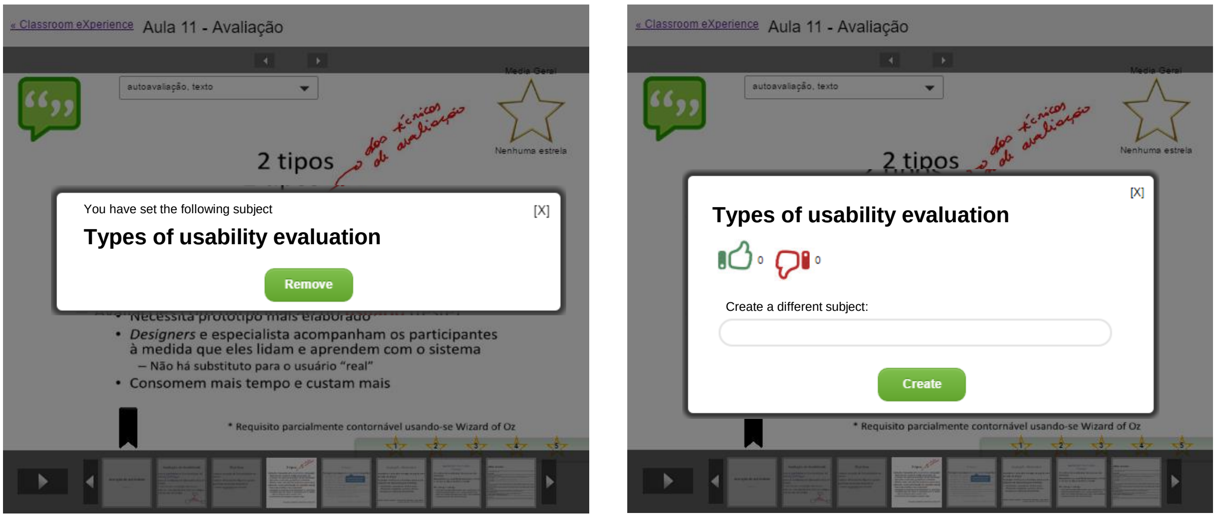



Figure 7 – Visualization of a captured lecture using CX.

Designed to be a collaborative feature, it provides a contextual auto-complete mechanism while labeling the *subject* based on the bookmarks previously created by other users for that specific lecture. Users can also rate the quality of bookmarks created by other users. Thus, when some lecture is opened, the following rules are applied, in order, to retrieve the bookmarks:

1. Bookmarks created by that user;
2. Highly rated bookmarks;
3. Bookmarks with greater number of similar title (lowercase comparison).

When clicking on the bookmark image and there is already a defined one for the respective slide and the user is the owner, he/she can delete it, as shown in Figure 8(a). Otherwise, the user can rate its quality using the buttons "like" and "dislike" ("thumbs-up/thumbs-down" approach) as well as create a new bookmark, as shown in Figure 8(b).




(a) (b)

Figure 8 – Bookmarking feature in the CX.

In this way, it becomes a semi-automatic process for LO authoring in ULEs, including the LOs metadata filling process, which is detailed in the next subsection. A schematic representation of the authoring process is presented by Figure 9, indicating the users' roles at each stage.

### 3.2.2 Semi-automatic Metadata Filling

For searching and recovering an LO in an effective way, its metadata fields must be filled out with the largest possible amount of consistent values – a potentially tough and not intuitive process. Approaches based on completion of extensive forms are quite common and, many times, LOs authors do not know exactly what to fill and end up inputting inconsistent values or merely skipping them (ROY; SARKAR; GHOSE, 2010; FRIESEN, 2004).

The manual filling of metadata requires much time and effort of authors, which already have employed significant effort for developing the LO itself. Because of that, it eventually

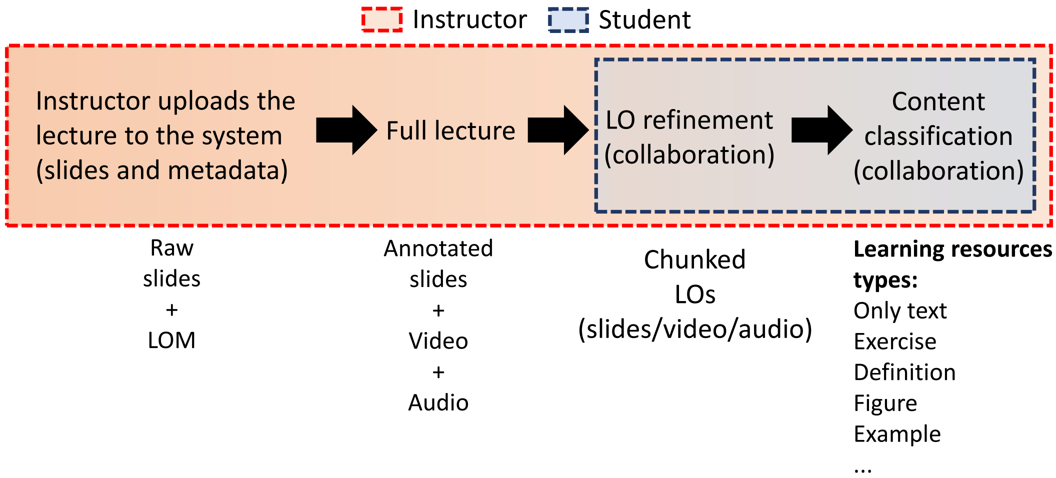



Figure 9 – LO authoring semi-automatic process.

leads to apathy of instructors. Thus, multimedia capture systems can support the semi-automatic filling of LOs metadata, minimizing the time and effort spent on their creation and avoiding erroneous input.

In this work, we use the IEEE Learning Object Metadata (IEEE-LOM) standard (IEEE, 2002) as a base schema to represent the LO metadata, since it is the most widely used in the domain of learning and education (FRIESEN, 2004). However, the vocabulary for the "Learning Resource Type" field includes some other values with higher semantic meanings proposed by CLEO extensions (CLEO, 2003). The reuse property is maintained since this field is specified as an ordered list of learning resource type elements, so the IEEE-LOM default vocabulary is still used in addition to the new ones. Further, the proposed architecture also plays a role as an LO producer, not only a consumer, it means that the architecture does not depend on finding LOs in external repositories.

The metadata filling process is a semi-automatic process in which the values are filled out through three fashions: *(i)* automatically by the system, *(ii)* manually by the instructor, and *(iii)* collaboratively by students.

The automatic process fills 21 IEEE-LOM fields in five different categories, based on the application's domain:

1. General: an identifier number is created for each lecture. The field *Structure* is populated with the value "linear", and the field *Aggregation Level* is filled out with the value "2" (collection of raw media data);

2. Technical: the fields *Format*, *Size*, *Location*, and *Duration* are filled out with information coming from the electronic whiteboard;

3. Educational: the fields *Intended End User Role*, *Context*, and *Typical Age Range* are filled out with the values "learner", "higher education", and "17-" (older than

17 years old), respectively. The field *Learning Resource Type* is first filled out with the value “lecture” by default but other fine-grained values are included later. Regarding the *Semantic Density* field, the instructor may provide such information, or the amount of bookmarks created for the lecture could give a hint on how dense is the LO. The more bookmarks created the more concepts addressed by the lecture and, therefore, the semantic density of the LO is higher.

4. Relation: the fields *Kind* and *Resource.Entry* are filled when LOs are related to each other. Slides are related to subjects and both are related to a lecture;

5. Rights: the fields *Cost*, *Copyright and Other Restrictions*, and *Description* are filled out with copyright information indicating no cost for users; and,

6. Lifecycle: the fields *Version*, *Status*, and *Contribute* are populated with information about the instructor who created the LO, pointing out its versions.

Some information is provided by the instructor when the lecture is being created in the system, as shown in Figure 10. *Title* and *Keywords* are required fields while *Language*, *Description*, *Difficulty*, *Semantic Density*, *Interactivity Type*, *Interactivity Level*, and *Learning Resource Type* are optional fields.

*Difficulty* is filled by a slider bar (1-5) with five possible values: “easy”, “simple”, “medium”, “hard”, and “complex”. *Semantic Density* and *Interactivity Level* also have five possible values: “very low”, “low”, “average”, “high”, and “very high”. The filling options for the *Learning Resource Type* are a subset of the vocabulary presented in Table 2 except by items that do not make sense at this point, such as “lecture”, “slide”, “additional resource”, “assessment”, and “attraction” because they are used by automatic processes at some other time.

Figure 11 shows a schematic representation of the elements hierarchy in the IEEE-LOM data model and indicates which fields are automatically or manually filled out, including the ones with mixed approach.

Finally, students can provide fine-grained information when they access the captured lecture. They can collaboratively point out the metadata *“Learning Resource Type”* contained in each slide, as shown by the number (2) in the Figure 7. It triggers the metadata update process aggregating values of the three hierarchical levels. For usability matter, values presented in *Learning Resource Type* field are a subset of the IEEE-LOM and CLEO vocabulary, as shown by Table 2.

### 3.2.3 Learning Style Estimation for Learning Objects

AULA provides a structure that allows LOs to be classified according to the FSLSM as an extra information attached to them, used when the LOs recommendation is based on students’ LS.

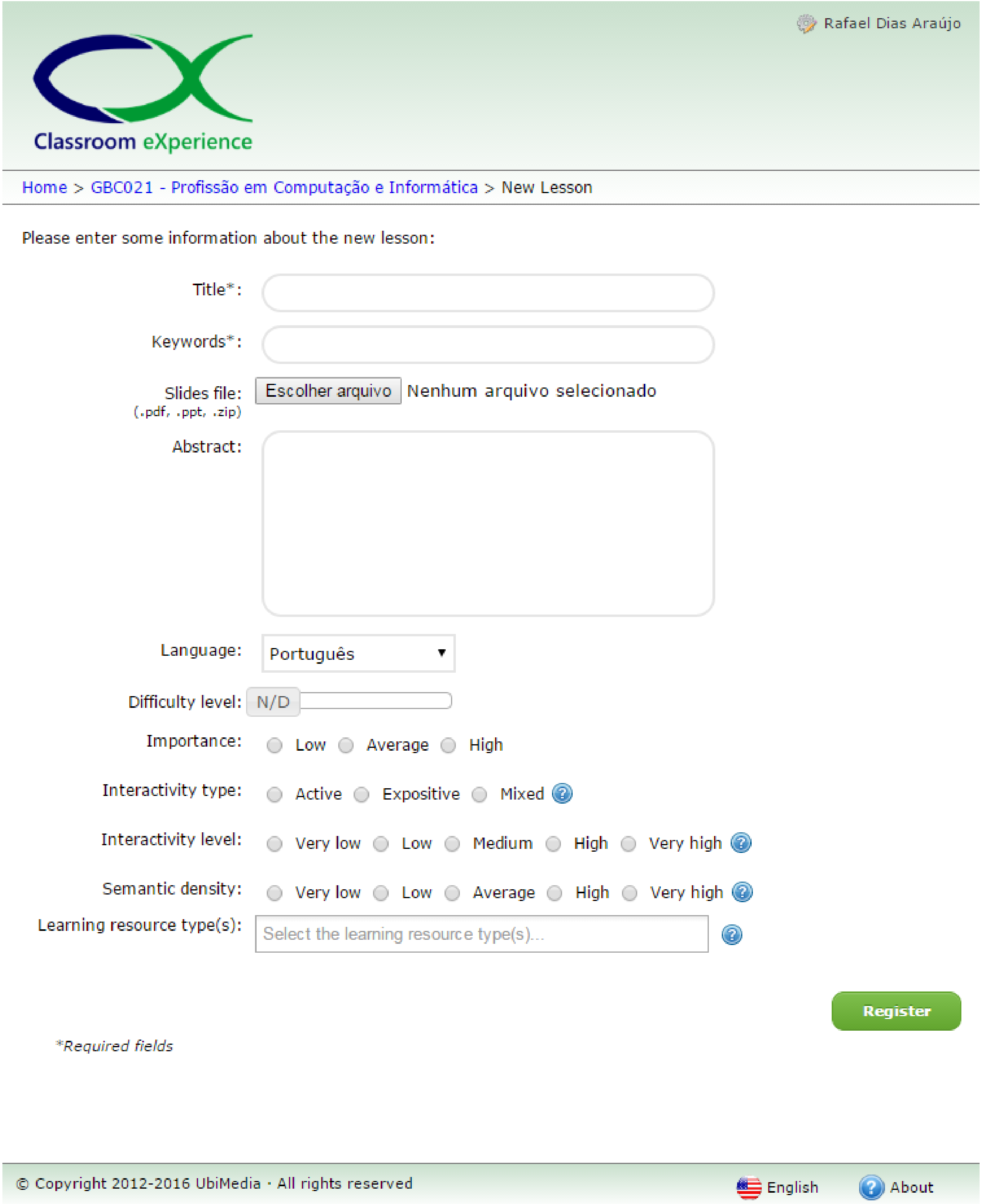



Figure 10 – Creating a new lecture in Classroom eXperience.

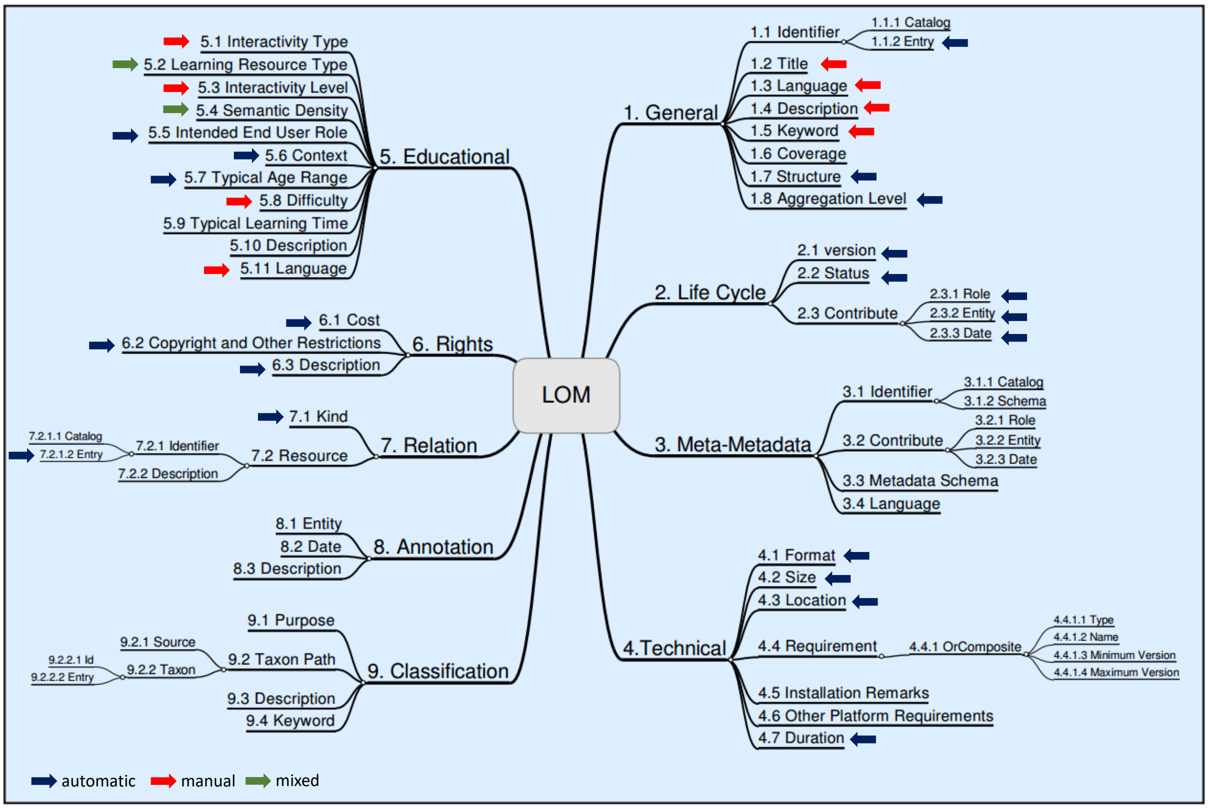



Figure 11 – Schematic representation of elements in the IEEE-LOM data model. Adapted from Barker (2011).

Previous work has mapped out a subset of IEEE-LOM fields that can define different dimensions of the FSLSM and proposed an automatic and dynamic approach to classify LOs (DORÇA et al., 2016). Rules were produced to estimate the LS regarding the relationships between LS and IEEE-LOM fields showed by Table 3.

In addition, the CLEO extended vocabulary for the Learning Resource Type field has also been mapped out to different dimensions of the FSLSM in order to complement the rules of the standard vocabulary, as shown by Table 4.

*Analogy, example, non example, practice* and *scenario* represent CLEO's learning resource types that best suit sensing learners because they tend to be facts-oriented and they prefer concrete and practical content. Intuitive learners are more likely to learn better with abstract content, such as definitions, demonstrations, glossaries, and guidelines.

Reflective learners prefer abstract content in with they can learn through observations in passive way. LOs containing analogies, definitions, demonstrations, examples, non examples, glossaries, notes, presentation, scenarios or summary tend to gratify more such kind of learners. On the other hand, assessments and their items, community resources and practical content are LOs that directly induces productive action, so they are better prepared to active learners.

Table 2 – Vocabulary for the Learning Resource Type field.

| Source | Values | Source | Values |
|---|---|---|---|
| | diagram | | additional resource* |
| | exercise | | assessment* |
| | figure | | attractor* |
| | graph | | community |
| | lecture* | | definition |
| LOM | narrative text | CLEO | demonstration |
| | problem statement | | example |
| | self assessment | | introduction |
| | simulation | | objective |
| | slide* | | outline |
| | table | | overview |
| | | | summary |

* Only for the automatic process.

Visual learners prefer LOs that address information in a visual way, such as illustrations and items that attract their attention (called attractors). Textual or oral content are more pleasing to verbal learners. In this case, assessments, community resources (such as chats), definitions, demonstrations, glossaries, introductions, notes, and objectives are more suitable for them.

Finally, sequential learners prefer to learn in a progressive and linear way. A guidance content is important for this kind of learner. In contrast, global learners like to first get an overview of the content and then make connections between the topics. LOs that contain an outline, overview or summary are good for global learners.

These heuristic rules are checked and the proportionality of rules that matches each LS dimension is stored by eight numeric values – two for each LS dimension – for each LO. For example, consider the hypothetical LO metadata presented in Figure 12(a) and rules presented in Tables 3 and 4. The LS computation for this LO would be the values presented in Figure 12(b), representing 66.7% for Sensing, 33.3% for Intuitive LS, 75% for Visual, 25% for Verbal, 100% for Reflective, and 100% for Sequential.

As previously presented, LOs can be updated and have their metadata information changed. Because of that, the LS is re-computed every time the LO has any of its information updated so these values remain consistent.

### 3.2.4 Content Enrichment

Social features contribute to create a more interactive environment as well as to make the content richer. Previous research developed a multimedia content enrichment model that fosters hierarchical digital artifacts construction (BRANT-RIBEIRO et al., 2014; ARAÚJO et al., 2017). This model has been implemented into the CX platform in the extension phase of its architecture through Web services.

Table 3 – Relationships between LS and IEEE-LOM fields, adapted from DORÇA et al. (2016).

| IEEE-LOM Field | Value | Perception | Input | Processing | Organization |
|---|---|---|---|---|---|
| Structure | collection | – | – | – | global |
| | networked | – | – | – | global |
| | hierarchical | – | – | – | global |
| | linear | – | – | – | sequential |
| | atomic | – | – | – | sequential |
| Format | audio | – | verbal | reflective | – |
| | image | – | visual | reflective | – |
| | text | – | verbal | – | – |
| | video | – | visual | reflective | – |
| | application | – | – | active | – |
| Interactivity Type | active | – | – | active | – |
| | expositive | – | – | reflective | – |
| | mixed | – | – | active reflective | – |
| Learning Resource Type | exercise | – | verbal | active | – |
| | simulation | sensing | – | active | – |
| | questionnaire | – | verbal | active | – |
| | exam | – | verbal | active | – |
| | experiment | sensing | visual | active | – |
| | problem statement | – | verbal | active | – |
| | self assessment | sensing | verbal | active | – |
| | diagram | intuitive | visual | reflective | – |
| | figure | sensing | visual | reflective | – |
| | graph | sensing | visual | reflective | – |
| | index | sensing | verbal | reflective | – |
| | slide | – | – | reflective | – |
| | table | sensing | verbal | reflective | – |
| | narrative text | – | verbal | reflective | – |
| | lecture | – | verbal | reflective | – |
| Interactivity Level | very low | – | – | reflective | – |
| | low | – | – | reflective | – |
| | medium | – | – | active reflective | – |
| | high | – | – | active | – |
| | very high | – | – | active | – |

Users of the platform can also rate slides by using the stars approach to classify how important is each slide for a specific lecture. In the example of a captured lecture shown in Figure 13, the user classified the slide with three stars (bottom-right corner). Still looking at the same figure in the top-right corner, a big star is filled out the average rating considering all users who rated it, in this case, it was four stars.

While accessing the captured content, students and instructors can interact with each other by creating commentaries on slides, asking questions or pointing out some important

Table 4 – Relationships between LS and CLEO extended vocabulary for the Learning Resource Type field.

| IEEE-LOM Field | CLEO value | Perception | Input | Processing | Organization |
|---|---|---|---|---|---|
| Learning | additional resource | – | – | – | – |
| Resource Type | analogy | sensing | – | reflective | – |
| | assessment | – | verbal | active | – |
| | assessment item | – | – | active | – |
| | attractor | – | visual | – | – |
| | community | – | verbal | active | – |
| | definition | intuitive | verbal | reflective | – |
| | demonstration | intuitive | verbal | reflective | – |
| | example | sensing | – | reflective | – |
| | feedback | – | – | – | – |
| | glossary | intuitive | verbal | reflective | – |
| | guidance | – | – | – | sequential |
| | guideline | intuitive | – | reflective | – |
| | illustration | – | visual | – | – |
| | importance | – | – | – | – |
| | introduction | – | verbal | – | – |
| | non example | sensing | – | reflective | – |
| | note | – | verbal | reflective | – |
| | objective | – | verbal | – | – |
| | outline | – | – | – | global |
| | overview | – | – | – | global |
| | practice | sensing | – | active | – |
| | prerequisite | – | – | – | – |
| | presentation | – | – | reflective | – |
| | recall | – | – | – | – |
| | reference | – | – | – | – |
| | reinforcement | – | – | – | – |
| | scenario | sensing | – | reflective | – |
| | summary | – | – | reflective | global |

| ID | Structure | Format | Interactivity Type | Interactivity Level | Learning Resource Type |
|---|---|---|---|---|---|
| 1 | atomic | text<br>image | expositive | very low | figure<br>diagram<br>example<br>slide |

(a)

| Perception | | Input | | Processing | | Organization | |
|---|---|---|---|---|---|---|---|
| Sensing | Intuitive | Visual | Verbal | Active | Reflective | Sequential | Global |
| 0.667 | 0.333 | 0.750 | 0.250 | 0 | 1 | 1 | 0 |

(b)

Figure 12 – Example of an IEEE-LOM and its associated LS.

issue (Figure 13). Comments are eligible for replies and rating, which encourage debate and can be used to measure the comments' relevance. However, comments' rating uses a different approach from slides rating. For comments, the "thumbs-up/thumbs-down" approach that is commonly used in social networks was adopted. In addition, it is possible to create comments related to the course itself. Those comments could be more generic ones that include external references such as course calendar, extra tools, etc.

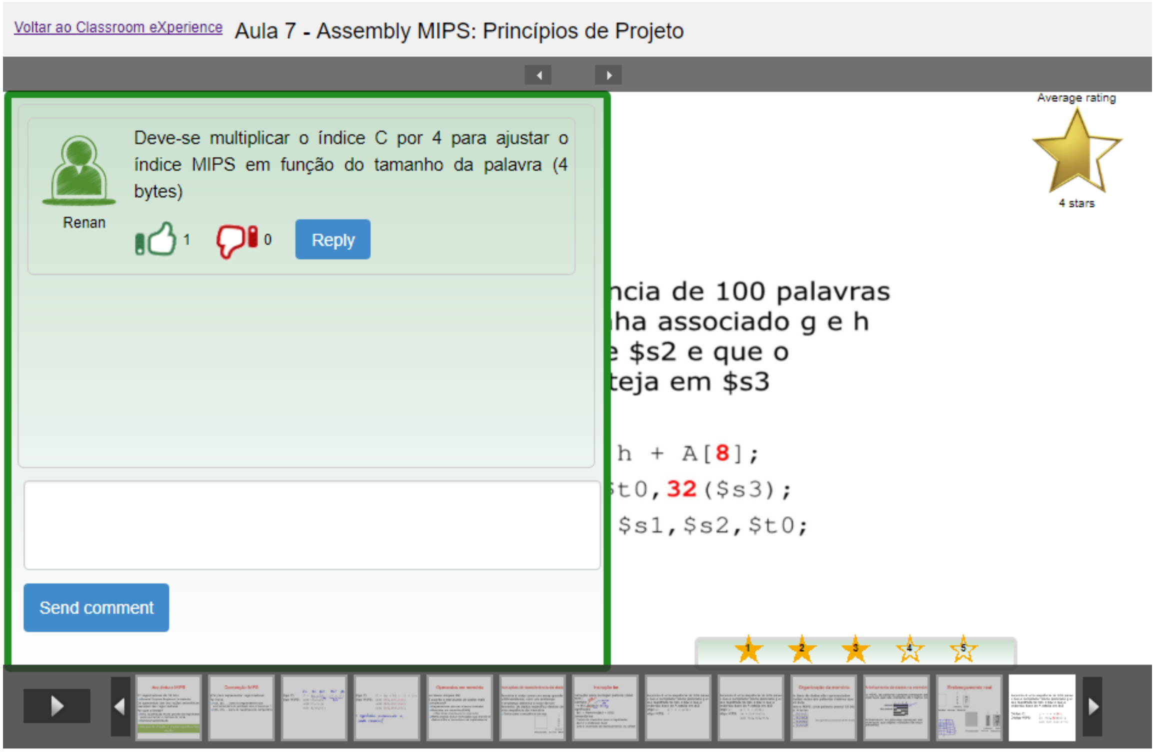



Figure 13 – Example of a commentary on a slide.

The proposed architecture also takes into account the need of additional content, other than the lectures captured in the classroom. Thereby, instructors can provide two different content types as an extra material: videos and quizzes.

Quizzes, or multiple-choice questions, can be created inside a recorded lecture by hovering the mouse over the "Q+" icon, as shown by Figure 14a. They are associated with a slide so students can answer them while reviewing the lecture. Currently, only textual information is allowed, as shown by Figure 14b. Each slide is associated with only one quiz, which is flagged as major for that slide. However, other quizzes can be created to be presented as extra content. Each attempt to answer a quiz is logged and the system presents a feedback indicating whether the answer is correct or not. Students can answer a quiz as many times as they want.

Videos are external content made available through an iframe to students in order to complement the content presented in a specific slide. Each video is manually chosen by the instructor and, currently, only its external Uniform Resource Locator (URL) is

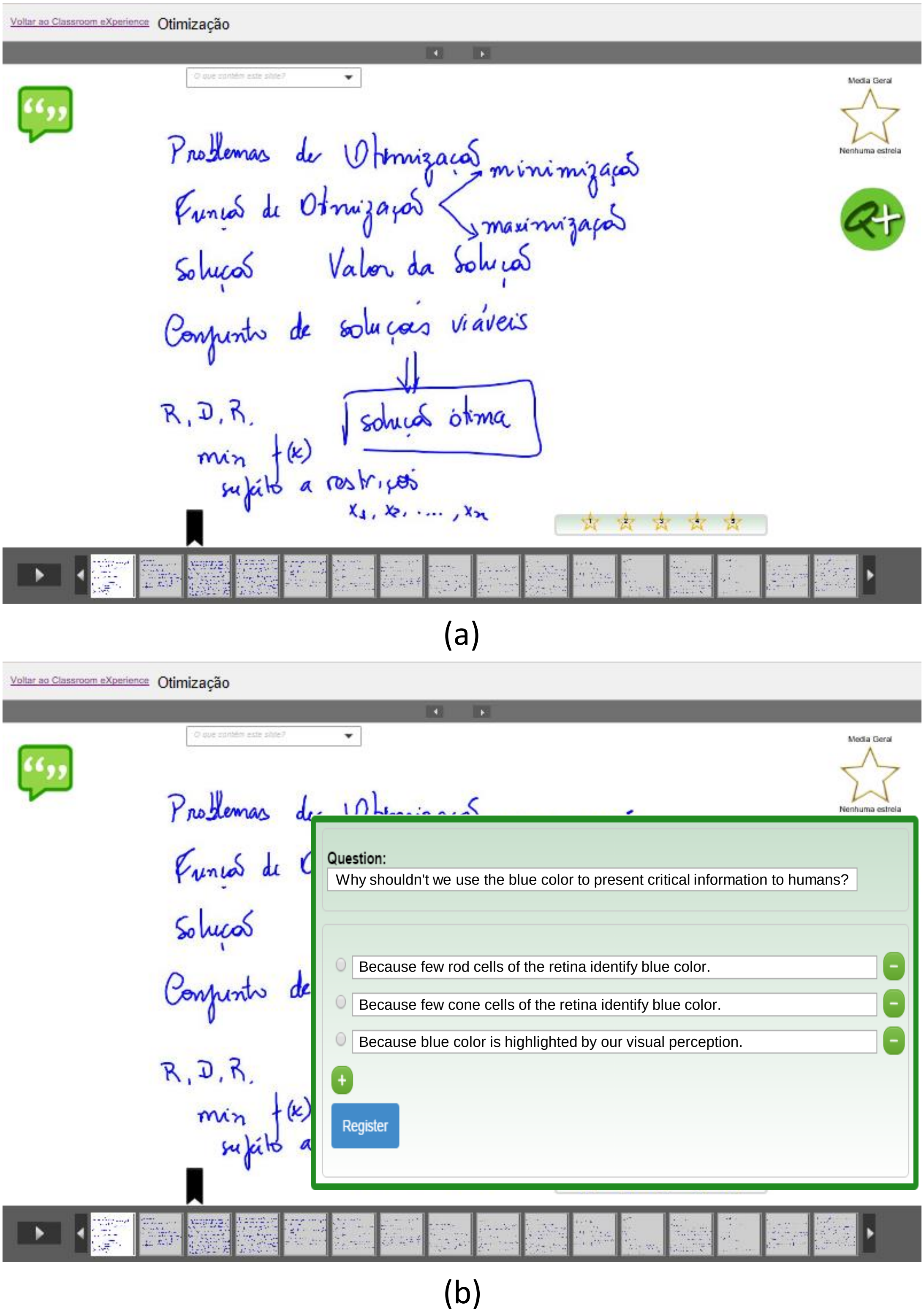



Figure 14 – Creating a new quiz.

informed to link it to a video provider, such YouTube. Nonetheless, some metadata fields are automatically filled out for both quizzes and videos since they can also be considered LOs.

Table 5 shows which metadata is generated in these cases and the respective assigned values for each field. In the future, automatic processes could take charge of analyzing their metadata for recommending these types of LOs at different points of the lecture without the need of creating them manually.

Therefore, all the social and collaborative information gathered by this module enriches the existing digital content, fostering collaborative learning, and also enabling a faster communication channel between students and instructors.

### 3.2.5 CX-LOR: Classroom eXperience Learning Objects Repository

As CX turned out to be a factory of LOs, we decided to create a public repository of LOs, called CX-LOR, freely available to the community, licensed under the Creative Commons Attribution-NonCommercial 4.0 International[1]. Before start using the repository, researchers are asked to send us an e-mail containing the name of the principal researcher, their institution and a justification for the request. Then, a private key is generated to allow them to search LOs.

Once having the private key, it is possible to search for LOs through the main page of the CX-LOR which looks for the desired values in the metadata fields. Then, a list of LOs is displayed in a table that includes a link for the IEEE-LOM, as an XML file, and a link for the content itself, as a ZIP file, as shown in Figure 15. An example of a metadata file in the IEEE-LOM standard generated by the CX platform is shown by Figure 37 in Appendix F.

An Application Programming Interface (API) have also been built make it easier to retrieve LOs. Four different actions have been implemented to search LOs, retrieve an IEEE-LOM, retrieve many IEEE-LOM in a ZIP file, and retrieve an LO. Messages are transmitted in the JavaScript Object Notation (JSON) format. Appendix F shows the definition of each action and its return in Figures 38, 39, 40, and 41, respectively.

Eventually, this repository tends to become larger and larger. Thereby, strategies associated with smart data analysis and machine learning techniques for organizing it will become indispensable ingredients in this context. Studies for clustering LOs based on LS have been conducted (DORÇA et al., 2017; MENDES et al., 2017b; MENDES et al., 2017a).

[1] CC BY-NC 4.0: <https://creativecommons.org/licenses/by-nc/4.0>

Table 5 – Metadata fields and values for quizzes and videos.

| IEEE-LOM field | Quiz | Video |
|---|---|---|
| Identifier | unique number | unique number |
| Title | "Quiz " + id lecture + id slide | "Video " + id lecture + id slide |
| General.Description | question heading | – |
| General.Language | pt-BR | – |
| Structure | atomic | atomic |
| Aggregation Level | 1 | 1 |
| Interactivity Type | active | expositive |
| Interactivity Level | high | low |
| Semantic Density | value depends on the number of topics associated with the respective quiz.<br>“very low”: only one topic;<br>“low”: two topics;<br>“medium”: three or four topics;<br>“high”: five or six topics; and,<br>“very high”: more than six topics; | – |
| Learning Resource Type | assessment<br>additional resource<br>narrative text | additional resource |
| Keywords | filled out with the correct answer for the quiz | – |
| Format | text/html<br>text/plain | video/avi |
| Location | internal URL | external URL |
| Intended End User Role | learner | learner |
| Typical Age Range | 17- | 17- |
| Educational.Context | higher education | higher education |
| Version | 1.0 | – |
| Status | final | – |
| Educational.Language | pt-BR | – |
| Copyright and Other Restrictions | yes | yes |
| Rights.Cost | no | no |
| Rights.Description | All rights reserved to UbiMedia@UFU | All rights reserved to © 2016 YouTube, LLC |
| Contribute.Role | author | – |
| Contribute.Entity | instructor vCard | – |
| Contribute.Date | creation date | – |

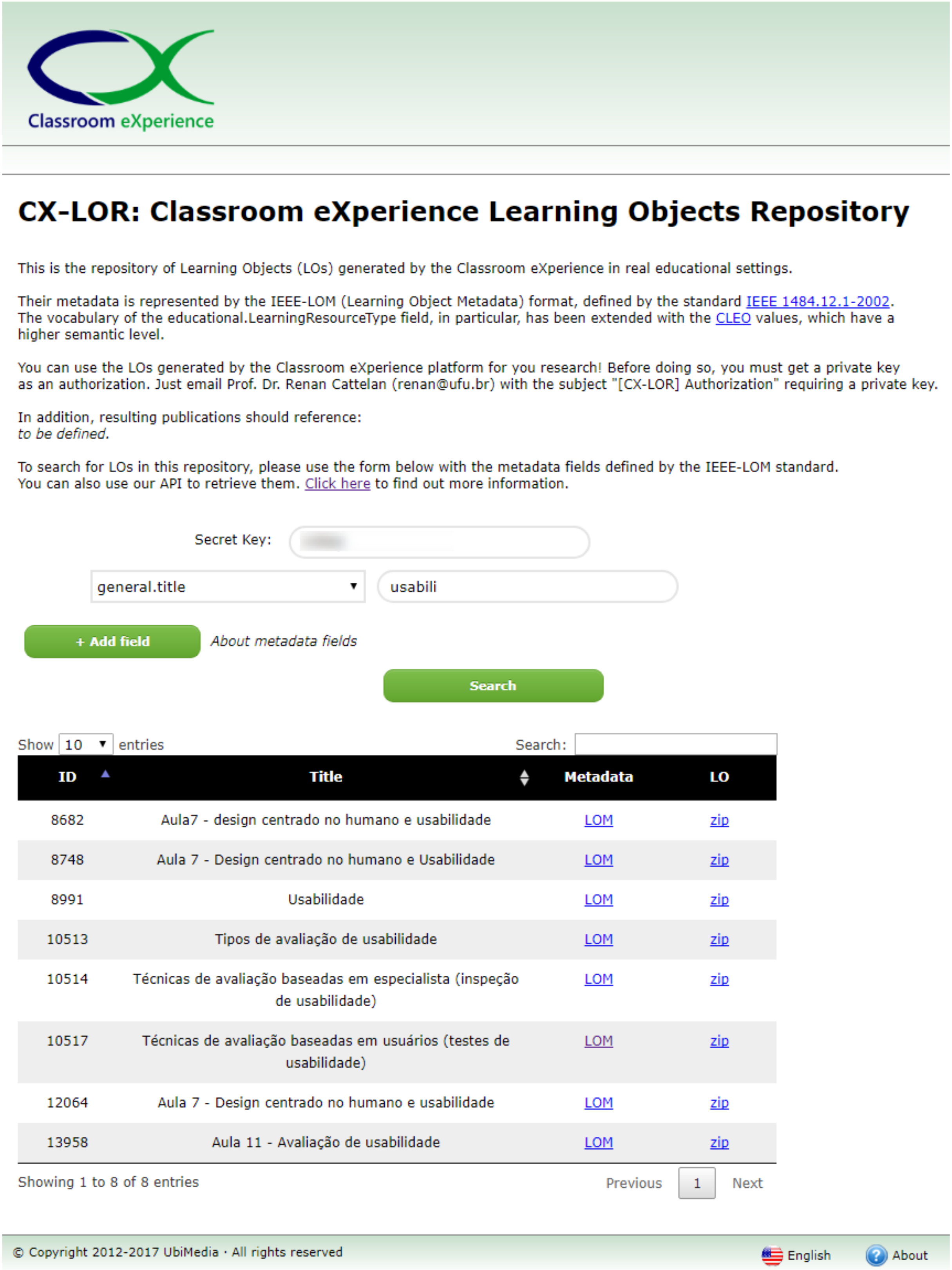



Figure 15 – Home page of the CX-LOR.

## 3.3 Content Personalization

Some resources should be also provided to support content personalization. A Student Model (SM), for example, is a key component that gathers individual information about students. In this way, this section presents an SM that includes the LS information and the types of interactions allowed in the platform.

### 3.3.1 Student Model

Once LOs and their metadata are available, we need to define which students characteristics will be gathered to be able to customize the content individually. These characteristics should be stored in an SM capable of representing students behavior and skills in order to identify what is really relevant for each student.

An SM is one of the fundamental components for personalizing educational content and it should represent not only students knowledge but rather reflect, as closely as possible, their reasoning process (CLEMENTE; RAMÍREZ; ANTONIO, 2011). For example, a student may learn better by solving problems unlike another student who may do better with examples. In addition, contextual information and personal preferences are important to build a better experience in the learning environment.

In this work, the SM contains six classes of information, namely, personal information, contextual information, personal preferences, online interactions, cognitive information, and knowledge information. Thus, the student model is defined as:

$$Student = \{N, C, P, I, L, Q\}$$

where:

$N$: contains personal information, such as name, surname, email, gender, birthday, city, state, country, institution, student ID number, level of education, and a profile picture;

$C = \{d_C, b_C, s_C, dt_C, at_C, p_C, r_C\}$: contains contextual information, such as type of device, device's bandwidth, screen resolution, access' date and time, user's available time, place, and reason, respectively (ARAÚJO et al., 2013);

$P$: contains personal preferences, in this case represented by conditional preferences stored by means of CPref-SQL rules (AMO; RIBEIRO, 2009);

$I = \{< o, t >\}$: list of online interactions $t$ taken place on the LO $o$;

$L$: a set of cognitive information, in this work represented by student's learning style;

$Q$: student knowledge information which contains a set of attempts to quizzes.

Regarding online interactions, the architecture provides support for different types of activities. They comprise important information as basis for analysis and identification of students' individual differences. There are four activities groups with distinct features, as listed below:

- Social: slides rating and specific comments on slides and general comments on the course;
- Collaborative: users can define fine-grained LOs while creating bookmarks for the lecture as well as refine their metadata by providing information related to Learning Resource Types;
- Assessment: students can answer quizzes while reviewing a recorded lecture and every attempt is stored, updating their knowledge in the model according to the answer;
- Gamification: students earn points and badges according to their activities (FERREIRA et al., 2015).

Additional studies with scope beyond what is presented here have been conducted to explore the potentialities of the SM for predicting academic performance (FERREIRA et al., 2017; FERREIRA et al., 2017b; FERREIRA et al., 2016; FERREIRA et al., 2016) as well as designing an open student model that allows students and instructors to access the information inferred by the SM (FERREIRA et al., 2017a).

### 3.3.2 Learning Style Estimation for Students

Since AULA provides infrastructure to compute the LSs of LOs, it is interesting to estimate students' LSs as well. This would enable the architecture to connect LOs to students, based on LSs. Likewise, the storage structure is similar to the one for LOs composed of eight numeric values representing the tendency of preference for one of the LS dimensions.

This gives a probabilistic nature to the LS information (DORÇA et al., 2013), which means that the student LS is not a unique choice neither a fixed one. Rather, it means that students tend to prefer one or more LS and that preference can evolve over time. In this way, students' LS is represented as shown by (1).

$$\begin{aligned} LS_{student} = \{&(PrA, PrR), (PrS, PrI), (PrVi, PrVe), (PrSeq, PrG) \\ &| PrA + PrR = 1, PrS + PrI = 1, PrVi + PrVe = 1, PrSeq + PrG = 1\} \end{aligned} \tag{1}$$

where:
$PrA$: likelihood of preference for the Active LS
$PrR$: likelihood of preference for the Reflective LS
$PrS$: likelihood of preference for the Sensing LS
$PrI$: likelihood of preference for the Intuitive LS
$PrVi$: likelihood of preference for the Visual LS
$PrVe$: likelihood of preference for the Verbal LS

$PrSeq$: likelihood of preference for the Sequential LS
$PrG$: likelihood of preference for the Global LS

It is important to note that this information can be updated using static or dynamic approaches. In static approaches, those values are initialized only once, usually when the student enrolls in the course. In dynamic approaches, those values are not only initialized but updated over time, representing changing of preferences.

In this work, each LS is initialized with a 50% value in order to minimize the cold start problem, which indicates that the system does not know the students' preferences. Our first approach for updating those values is to use the Index of Learning Styles (ILS) for assessing students' LS in a distributed way among usage sessions during the semester. It consists of presenting a set of four questions – one for each LS dimension – each time students log into the system, as shown by Figure 16(b). This approach prevents students from getting tired and demotivated given the size of the entire questionnaire (44 questions).

The probability of preference to the LS corresponding to the answered alternative is increased by $I = P/Q$, where $P$ is the initial probability of each LS, that is 50%, and $Q$ is the number of questions related to each dimension. Since the ILS instrument contains 11 questions for each dimension, each time students answer a question, 50/11 points ($\sim$4.55%) is added to the LS represented by the answer and, on the other hand, this value is subtracted from its opposite LS. For example, consider the LS of a particular student that has just been initialized with 50%. He/she answers a specific question related to the Active/Reflective dimension and it happens that his/her answer goes toward the Active LS. Thus, the student model is updated to $(PrA, PrR) = (0.545, 0.455)$.

Each answered question gives some points to the gamification module as a way to motivate students to answer them. Once answered all 44 questions, students earn a specific badge for this task. Figure 16(a) shows a popup that appears only once to inform the student about the ILS.

### 3.3.3 Types of Interactions

The "Interactions Repository" is responsible for storing users' interactions, including user ID, access context, timestamp, and interaction types $t$. Other stored information is specific for each interaction type. Those interactions are collected through asynchronous web-service calls and stored in a relational database. Currently, the following types of interactions are gathered:

- LOGIN: when users log into the system;
- LECTURE_OPEN: when a user opens a lecture. Class ID and lecture ID are also included in this log;

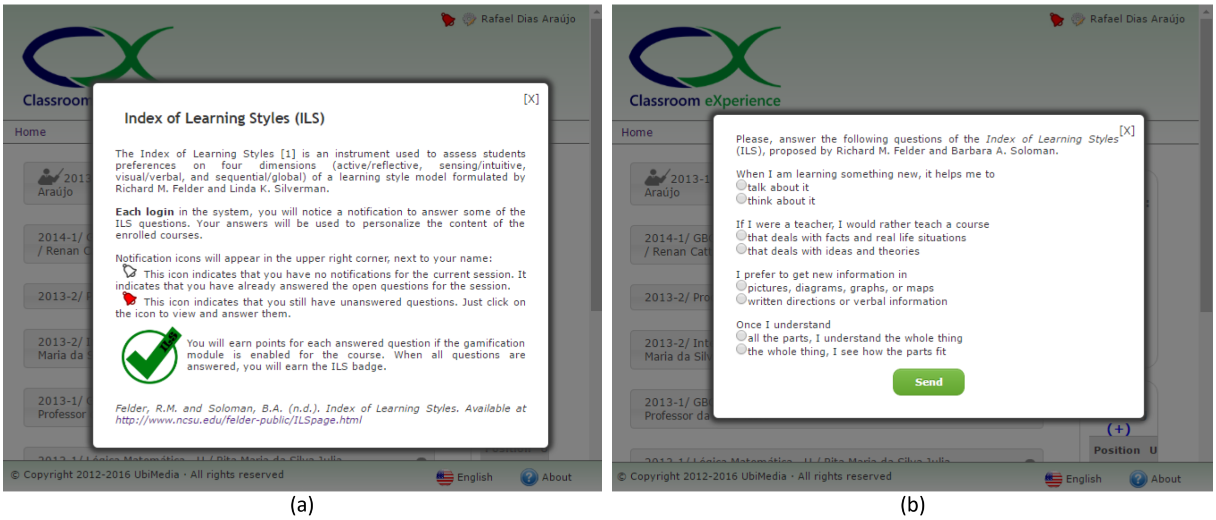



Figure 16 – ILS popup information and some of the ILS questions.

- ❏ SLIDE_VISUALIZATION: every time users view a different slide of the lecture. Class ID, lecture ID, and media ID (slide) are also stored;
- ❏ LECTURE_CLOSE: when a user closes a lecture (only when clicking on the specific link to close it). Class ID and lecture ID are also included;
- ❏ SUBJECT_CREATION: when users create a new bookmark. Class ID, lecture ID, and media ID (slide) are also stored;
- ❏ SUBJECT_DELETION: when users remove a bookmark. Class ID, lecture ID and media ID (slide) are also stored;
- ❏ LRT_CHECK: when a user checks a different Learning Resource Type for a slide. Class ID, lecture ID, and media ID (slide) are also stored;
- ❏ LRT_UNCHECK: when a user unchecks a Learning Resource Type of a slide. Class ID, lecture ID, and media ID (slide) are also stored;
- ❏ SUBJECT_LIKE: when users like an existing bookmark. Class ID, lecture ID, media ID (slide), and the ID of the user who created the bookmark;
- ❏ SUBJECT_DISLIKE: when users dislike an existing bookmark. Class ID, lecture ID, media ID (slide), and the ID of the user who created the bookmark;
- ❏ ADDITIONALCONTENT_CLICK: when users click to visualize additional content. Class ID, lecture ID, and media ID (slide) are also stored;

- ADDITIONALCONTENT_VIDEOCLICK: when a user clicks on a video link (as additional content). Class ID, lecture ID, media ID (slide), and the link pointing to the video are also stored;

- ADDITIONALCONTENT_QUIZCLICK: when a user clicks on a quiz link (as additional content). Class ID, lecture ID, media ID (slide), and the quiz ID are also stored;

- QUIZ_OPEN: when a user opens the quiz related to a specific slide. Class ID, lecture ID, media ID (slide), and the quiz ID are also stored;

- QUIZ_ANSWER: when users answer a quiz. Class ID, lecture ID, media ID (slide), the quiz ID, and an extra information indicating whether the answer was right or wrong are also stored;

- COMMENT_COURSE: when a comment is created for a course. Class ID is included;

- COMMENT_SLIDE: when users write a comment for a specific slide. Class ID, lecture ID, and media ID (slide) are included;

- COMMENT_LIKE: when a comment is liked by the user. Class ID, lecture ID, and comment ID are also stored;

- COMMENT_DISLIKE: when a comment is disliked. Class ID, lecture ID, and comment ID are also stored;

- COMMENT_REPLY: when a user replies to a comment. Class ID, lecture ID, and comment ID are included;

- RATING_SLIDE: when users rate a specific slide. Class ID, lecture ID, and slide ID are also stored;

- ILS_ANSWER: when users answer the ILS questions. It also stores the question ID and the answer ID;

- CHANGE_VISUALIZATION: when the user changes the lecture visualization from the original ordering to the personalized one (only available when the personalization is enabled).

This repository can be used to automatically identify students behavior to provide input to the SM in order to contribute to improve recommendations in the future.

### 3.3.4 Strategies for Content Personalization and Recommendation

Once defined both the type of content that we are working with and the way that users are represented, it is possible to design algorithms and rules to fit the content according to users' needs.

The first level of personalization occurs based on users' access context in which presentation rules define the best way to present the content. For example, if the user accesses the content using a device with a low screen resolution, it is better to present a textual content rather than detailed slides. This kind of rules is used to create a ranking of stylesheets; however, the user is free to choose no matter which one. Figure 17 shows a popup window with the ranked display formats based on the access context. Details of this level of personalization are not presented here as it is not a direct contribution of this thesis but an extension of it, described in (ARAÚJO et al., 2013; ARAÚJO, 2013).

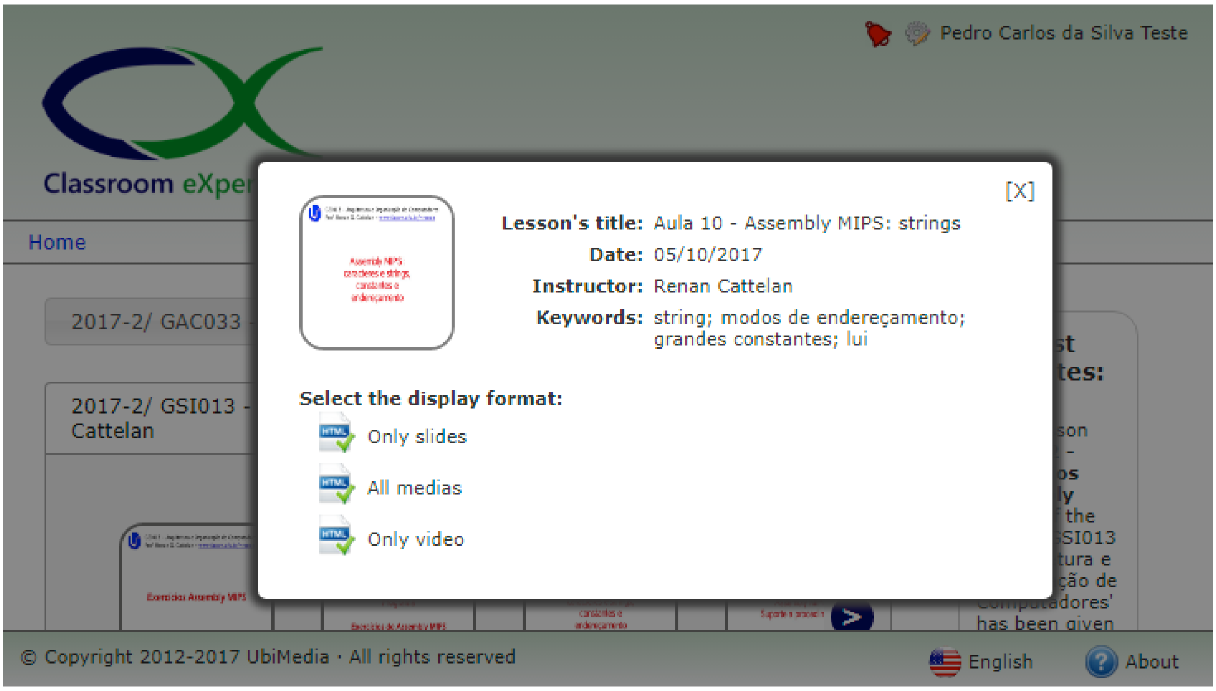



Figure 17 – Rank of display formats for accessing a lecture in the CX.

The second level of personalization occurs inside a lecture based on the output of the "Behavior Identification Module". As a case study, we implemented an approach based on LS for validating the architecture. Basically, as each lecture is an ensemble of LOs, the lecture could be reordered and built according to the LS of each student.

Consider a lecture captured in the classroom. Eventually, it will be sliced into different *subjects*, generating new LOs containing a set of slides, as explained in Section 3.2. Once those slides have their metadata filled and their LS is computed, they can be ranked and presented in a different order for each student.

Let $o$ be an LO, $P$ be the proportionality of rules – presented by Table 3 – satisfied by $o$ considering a specific learning style dimension, and $LS$ be the probability stored in the student model for each LS dimension. The relevance $R$ for an LO $o$ is given by Eq. (2), as the sum of values obtained by $o$ in each of the eight LS dimensions.

$$R(o) = \sum_{i=1}^{8} (P_i \times LS_i) \tag{2}$$

This equation has been adjusted to consider the proportionality of rules matched by LOs for each LS rather than the absolute number of matched rules presented in previous research (DORÇA et al., 2016). This adjustment prevents specific LS that have a higher number of defined rules from being unduly highlighted in comparison to those with fewer rules.

For a better understanding of the relevance computation of LOs regarding a specific student, Algorithm 1 presents the steps for generating a ranking of LOs that better suits students' LS, and Algorithm 2 shows how the proportionality of rules is computed.

**Algorithm 1** Learning Objects relevance computation according to students' LS.

**Require:** List of LO metadata $O = \{o_1, o_2, ..., o_n\}$ and $LS_{student}$.
  **for all** $o \in O$ **do**
    $P \leftarrow$ ComputeLSProportionality($o$)
    $relevance \leftarrow 0$
    **for** $i = 1$ to 8 **do**
      $relevance+ = (P[i] * LS_{student}[i])$
    **end for**
    $R[i] = relevance$
  **end for**
  $sort(O, R)$ //Sorts the list of objects $O$ according to $R$
  **return** O

**Algorithm 2** ComputeLSProportionality

**Require:** LO metadata $o$.
  **for** $i = 1$ to 8 **do**
    $P[i] \leftarrow 0$
  **end for**
  **for** $i = 1$ to 7 **do**
    $N \leftarrow$ counts the number of rules satisfied by $o$ for the $LS_i$
    $K \leftarrow$ counts the number of rules satisfied by $o$ for the $LS_{(i+1)}$
    $P[i] \leftarrow N/(N + K)$
    $P[i + 1] \leftarrow 1 - P[i]$
    $i = i + 2$
  **end for**
  **return** P

Using this computation, LOs that compose the captured lecture may be internally rearranged within topics. Considering the example of a lecture about repetition structures in the context of computer programming. Figure 18(a) shows this lecture in its original order, as designed by the instructor. Imagine two students who have different LS: one of them has tendencies for *sensing* and *visual* LS, the other tends to *sensing* and *verbal* LS. By running this algorithm, the same lecture could be rearranged in two different ways for those students based on the ranking of LOs, as shown in Figure 18(b) and Figure 18(c). Notice that the *subjects* remain in the same order, because they are chained according to the instructor's strategy.

Inside each *subject*, the content is presented according to students' LS. In the first case (Figure 18(b)), the content order (example, diagram, textual definition) matches a sensing and visual LS, since sensing learners prefer to learn from facts, and visual learners learn better through visual content. On the other hand, in the second case (Figure 18(c)), the textual definition appears before the diagram to match a *verbal* learner.

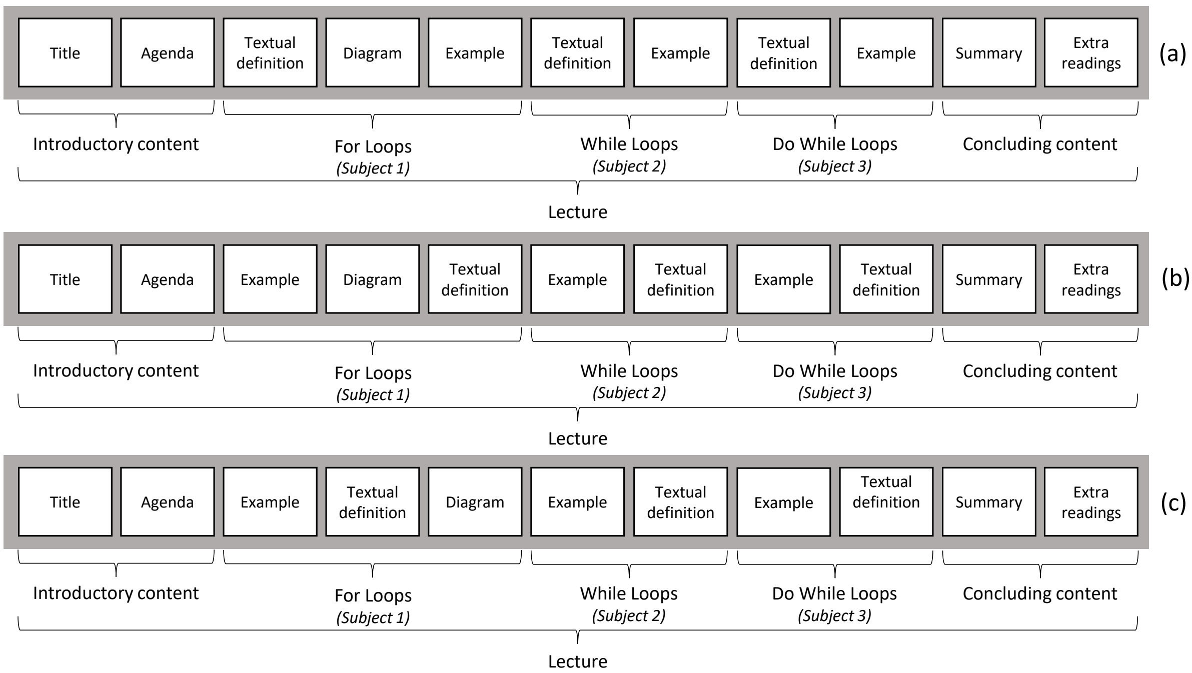



Figure 18 – Examples of a personalized lecture.

Moreover, supplementary material with proper metadata in the IEEE-LOM format can also be recommended and presented as content related to each LOs of the lecture. Although different algorithms can be used for ranking or clustering related content in the repository, no default automatic approach is proposed here, since the goal is to create an infrastructure that make it possible.

In terms of presentation, LOs that compose the lecture are retrieved by means of asynchronous web-services calls as well as their extended information such as ratings, comments, additional content, and presentation order. A sequence diagram (BOOCH;

RUMBAUGH; JACOBSON, 2005) for opening a lecture is presented in Appendix A. As can be noticed, there are specialized components for handling LOs and social features.

All presented features are implemented into the CX platform, which is used as case study for research of our group. Currently, instructors of the Faculty of Computing at Federal University of Uberlândia (UFU) are using this platform for undergraduate and graduate courses in Computer Science, Information Systems, and Information Management majors.

## 3.4 Architectural Components

AULA comprises a set of components with specialized roles. Many of them provides interfaces that allow communication through HyperText Transfer Protocol (HTTP) requests. They use a Data Access Object (DAO) component to persist all the information in the database. Figure 19 shows a components diagram that includes provided interfaces as well as components dependency.

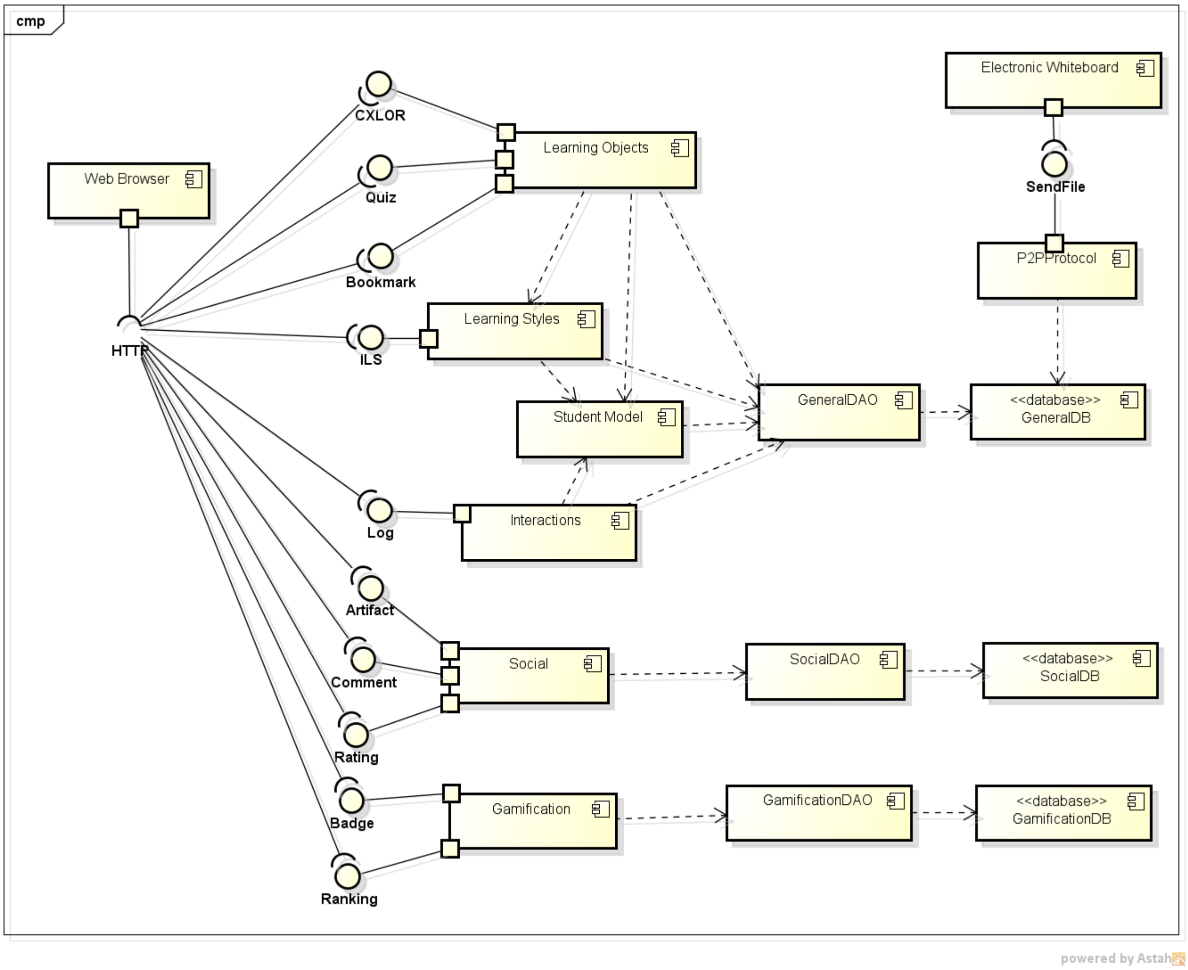



Figure 19 – Components diagram.

### Learning Objects Component

This component is responsible for dealing with learning objects in general. It provides the following interfaces:

- “CXLOR” for retrieving LOs from the repository. It contains four services:

  GET *getLom*: requires an ID of a specific IEEE-LOM (*idlom*) and a secret key (*secretKey*). It returns an eXtensible Markup Language (XML) file representing the metadata.

  GET *getZip*: requires a list of IEEE-LOM ID (*ids*) and a secret key (*secretKey*). It returns a ZIP file containing XML files representing different IEEE-LOM.

  GET *getLO*: requires an ID of a specific IEEE-LOM (*idlom*) and a secret key (*secretKey*). It returns a ZIP file with the files that comprise the LO.

  POST *search*: requires a JSON string containing the IEEE-LOM fields to be searched and a secret key (*secretKey*). It returns a JSON string containing ID and title of found objects. Details are presented in Appendix F.

- “Quiz” for managing quizzes. It contains the following services:

  GET *getQuestion*: requires the lecture ID (*idlesson*), the slide ID (*idslide*), and a flag indicating whether it is the major quiz for the slide or not (*ismajor*). It returns in a JSON string containing the quiz associated with a given slide of a specific lecture, if any exist.

  POST *addQuestion*: it is used to add a new quiz to a specific slide of a lecture. It includes the multiple options of response as well as the correct one. It is allowed only for professors.

  POST *addAnsweredQuestion*: it is used to register an attempt to answer a quiz. The user ID (*iduser*), the question ID (*idquestion*), and the checked option (*answer*) are required.

- “Bookmark” for LOs segmentation. Students and professors can use it for handling bookmarks inside lectures through the following services:

  GET *getLectureSubjects*: requires the user ID (*iduser*) and the lecture ID (*idlecture*). It returns a list of bookmarks of the given lecture.

  GET *getLRT*: requires the language (*lang*) and returns a list of all possible *Learning Resource Types* values in Portuguese (pt) or English (en).

  GET *getLRTmedias*: requires the lecture ID (*idlecture*) and returns a list of *Learning Resource Types* of a specific media.

GET *getSubjectLikeByUser*: requires the user ID (*iduser*), the lecture ID (*idlecture*), and the slide ID (*idslide*). It returns the user's like and dislike interactions for the bookmark, if it exists.

GET *getMediaRanking*: requires the user ID (*iduser*) and the lecture ID (*idlecture*). It computes the relevance of LOs for a specific student and returns an ordered list of LOs. Currently, this computation is based on LS of the FSLSM.

POST *addSubject*: it adds a new bookmark for a lecture. It requires the user ID (*iduser*), the lecture ID (*idlecture*), the slide ID (*idslide*), and a title for the bookmark (*title*).

POST *deleteSubject*: requires the user ID (*iduser*), the lecture ID (*idlecture*), and the slide ID (*idslide*) for removing a bookmark from a lecture. Only the bookmark creator (owner) can delete it.

POST *addLRTmedia*: requires the lecture ID (*idlecture*), the slide ID (*idslide*), and the *Learning Resource Type* ID (*idlrt*) to associate a *Learning Resource Type* value to a slide.

POST *deleteLRTmedia*: requires the lecture ID (*idlecture*), the slide ID (*idslide*), and the *Learning Resource Type* ID (*idlrt*) to delete a *Learning Resource Type* value from a slide.

Further details are presented in Section 3.2.

### Learning Styles Component

This component is responsible for collecting students LS as well as processing all information about LS for both students and LOs. The Learning Objects components depends on this component to compute the LS of each LO. Currently, it provides the ILS interface with two external services:

GET *getilsquestions*: it requires the student to be logged in (iduser) to return the unanswered ILS questions. The questions are available in Portuguese and English.

POST *saveilsanswers*: it saves the answers for the ILS questions for a specific user (iduser) and updates the student model.

### Student Model Component

This component is responsible for storing students' characteristics to provide input for personalization and recommendation algorithms. The Learning Objects component depends on this component to be able to compute the relevance of LOs to each student. Also, it updates the student model with the quizzes answers. The Learning Style component also depends on this component to update the LS of a specific student based on his/her answers to the ILS questions. The interactions component also depends on this component to update the student model with the performed interactions. Details are presented in Section 3.3.

#### Interactions Component

This component is responsible for handling all performed interactions. It stores the user ID, the interaction type, and some relevant information about where the interaction happened, such as lecture ID, media ID and class ID (or group ID). Details are presented in Subsection 3.3.3.

#### Social Component

This component handles all social and collaborative interactions, such as comments and slides rating, in a loosely-coupled manner. Basically, it provides three interfaces:

- "Artifact" for handling all kinds of artifacts, which are abstraction to elements that may contain social interactions such as slides, courses, and the comments themselves;
- "Comment" to register/retrieve comments and replies on artifacts;
- "Rating" to register/retrieve ratings on artifacts (slides and comments);

It uses the SocialDAO component to store this information in a separate database. Details are presented in (ARAÚJO et al., 2017; BRANT-RIBEIRO et al., 2014; MENDONÇA et al., 2014).

#### Gamification Component

This component implements the rules of the gamification module and provides interfaces for retrieving the ranking of students' scores (*Ranking*) and their earned badges (*Badge*). It uses the GamificationDAO component to store this information in a separate database. As it is beyond the scope of this work, it is detailed in (FERREIRA et al., 2015).

#### Electronic Whiteboard Component

This is a Java Web Start component used for capturing strokes on the electronic whiteboard. When started, it downloads the set of slides from the server for a specific lecture. After finished, it synchronizes all media streams and send it back to the server through a peer-to-peer protocol.

#### P2PProtocol Component

This component is a peer-to-peer protocol which is in charge of transmitting and storing the content captured in the classroom to the servers. Eventually, it updates LOs metadata. Details of the protocol can be found in (ARAÚJO et al., 2012).

Chapter 4

# Evaluation

This chapter presents the experiments performed to evaluate the approach proposed in this thesis. Different experiments were performed in order to check the feasibility of the proposed architecture. Section 4.1 presents the first experiment that was designed to evaluate the way in which LOs are created. Then, the personalization of the generated LOs was experimented with fictitious data and presented in Section 4.2. Finally, Section 4.3 presents a case study performed in real educational settings to evaluate the proposed architecture and its impact on the learning process.

The Ethics Committee of UFU – American IRB equivalent – approved the participation of students in this study[1] and all participants have agreed with the consent form presented at the beginning of each semester.

## 4.1 Learning Objects Authoring

This experiment aimed at evaluating how ULEs can support the LOs authoring process and the use of a collaborative bookmarking approach to refine them, supporting the research question Q1. Participants were undergraduate students majoring Information Systems and, also, graduate students in Computer Science enrolled in the Human-Computer Interaction (HCI) course offered by Faculty of Computing of the Federal University of Uberlândia, Brazil. In addition, HCI experts also evaluated the quality of the generated metadata, aiming at validating the results. In total, 30 students plus three experts in the HCI field participated in this study. The results have been already published in (ARAÚJO et al., 2014; ARAÚJO et al., 2016; ARAÚJO et al., 2016).

### 4.1.1 Research Design

First, the professor of the HCI course taught his classes using the Classroom eXperience (CX) as a complementary tool during the semester. Then, two different HCI

[1] CAAE 46909515.4.0000.5152

lectures were chosen for this experiment: “Usability Evaluation” and “Task Analysis”. So, all participants had prior contact with the content, as both lectures were taught before the experiment took place. From now on, the lectures will be called “Lecture A” and “Lecture B”, respectively.

This experiment was divided in four phases: (I) Creating *bookmarks*, (II) Evaluating *bookmarks*, (III) Redefining *bookmarks*, and (IV) Experts evaluation, as shown by Figure 20. Nine graduate students participated in the phase I. Phases II and III counted on 21 undergraduate students and the last phase, IV, included three HCI experts.

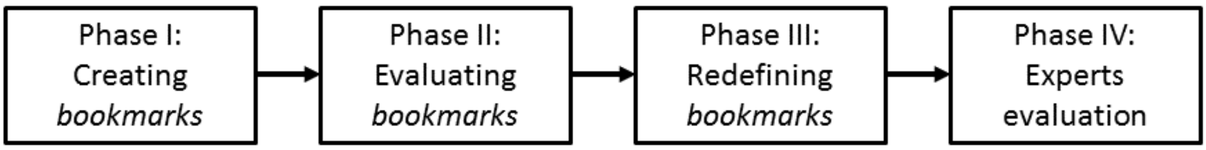



Figure 20 – Phases of the experimental study.

At the end of phases I, II and III, a questionnaire with eight affirmatives were presented to the participants to evaluate them in a 7-points Likert scale. The questionnaire P1 shown in Appendix B was used in phases I and III. The questionnaire P2 shown in Appendix C was used in phase II.

We chose to use a 7-points Likert scale for the same reason as having a longer interval for the allocation of responses, allowing us to make calculations in order to be able to understand the variability of opinions among users. The affirmatives were prepared in accordance with concepts about quality and software evaluation (ISO/IEC, 2011), as presented by Table 6.

Table 6 – Evaluation criteria for phases I, II and III.

| Category | Description | Phases |
|---|---|---|
| Correctness | Perception of correctness of the *bookmarks*. | I, II, III |
| Effectiveness | Accuracy and integrity for users to achieve the goals of the LO. | I, II, III |
| Utility | Perception of a feature to be useful to users achieve their goals. | I, II, III |
| Usability | Ease of viewing and navigation between different concepts inside a lecture. | II |
| Satisfaction | User satisfaction in a given context. | I, II, III |
| New feature | Possibility to define the hierarchy of *bookmarks*. | I, III |

In phase I, participants were asked to navigate and define *bookmarks* for the lectures A and B. In order to get more accurate data, participants were divided into two groups, one with five and another with four people. At the end, the created *bookmarks* were put together and, in case of overlapping, the ones with more “likes” were picked. If there was still a tie, the instructor of the course chose one of them.

In phase II, we chose a within-subjects design with counterbalancing (LANE, 2006) in order to minimize the residual effects. Participants were randomly divided into two groups so that only one of the two lectures was seen with *bookmarks* for each group, as shown in Figure 21. The goal of this phase was to evaluate the quality of the *bookmarks* previously created in phase I and also their usefulness if compared with a lecture without such information.

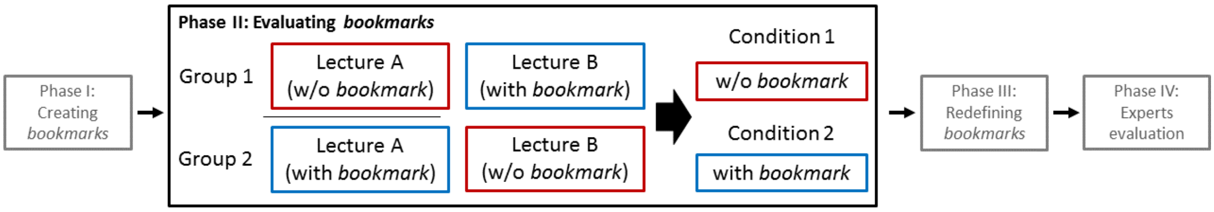



Figure 21 – Within-subjects design for the phase II of the experimental study.

In phase III, the same students who participated in phase II were invited to create *bookmarks* for the lecture that they saw without *bookmarks*. Thereby, half of the participants defined *bookmarks* for the Lecture A and half for the Lecture B. Finally, in phase IV, distinct LOs created in phases I and III were randomly presented to HCI experts to evaluate the quality and consistency of the associated metadata.

Five affirmatives were presented to experts, who were asked to answer them in a 5-points Likert scale for each LO. The affirmatives were created based on the Learning Object Review Instrument (LORI) (NESBIT; BELFER; LEACOCK, 2004; VARGO et al., 2003) and also used concepts about quality and software evaluation (ISO/IEC, 2011), as shown in Table 7. Note that only LOs metadata is evaluated, not the content itself.

Table 7 – Affirmatives presented to experts in phase IV.

| | Affirmatives | Category |
|---|---|---|
| 1 | The metadata of this LO is consistent with its content. | Consistency |
| 2 | All metadata information is correct. | Correctness |
| 3 | This LO contains well-divided subjects (*bookmarks*). | Granularity |
| 4 | This LO has a well-defined learning goal. | Learning Goal Alignment |
| 5 | This LO can be reused in a different course/context without modification. | Reuse |

### 4.1.2 Results and Discussion

During the phase I, 54 LOs were created, 36 of them were associated to the Lecture A and 18 to the Lecture B. After removing duplicates and disambiguation conducted by the instructor, lectures A and B had 24 and 12 associated LOs, respectively. On average, students spent 13:05 minutes working on Lecture A and 4:28 minutes working on Lecture B in this phase.

In phase III, students created 26 LOs for the Lecture A and 11 LOs for the Lecture B. It turned out that about 50% of them were similar to those created in the phase I. On average, students spent 18:19 minutes working on Lecture A and 4:46 minutes working on Lecture B in this phase. Table 8 shows statistical information regarding the responses obtained from the questionnaires answered by students involved in phases I and III.

Table 8 – Mean, standard deviation and coefficient of variation of the responses of graduate and undergraduate students for the questionnaires administered in phases I and III.

| Affirmatives[1] | Phase I | | Phase III | |
|---|---|---|---|---|
| | $\bar{x} \pm s$ | $CV(\%)$ | $\bar{x} \pm s$ | $CV(\%)$ |
| 1 | 5.56 ± 1.42 | 25.63 | 5.73 ± 1.42 | 24.80 |
| 2 | 4.56 ± 1.59 | 34.90 | 5.64 ± 1.21 | 21.40 |
| 3 | 5.00 ± 1.66 | 33.17 | 4.91 ± 1.64 | 33.42 |
| 4 | 4.56 ± 1.67 | 36.59 | 5.64 ± 1.21 | 21.40 |
| 5 | 3.67 ± 1.41 | 38.57 | 4.18 ± 1.60 | 38.29 |
| 6 | 5.67 ± 1.22 | 21.61 | 5.73 ± 1.10 | 19.27 |
| 7 | 4.78 ± 1.86 | 38.84 | 4.82 ± 1.47 | 30.53 |
| 8 | 6.44 ± 0.73 | 11.27 | 5.27 ± 1.68 | 31.84 |

[1] $\bar{x} \pm s$: Mean and standard deviation; $CV$: Coefficient of variation.

In general, we can observe that the average response obtained in both phases remained above the central point of the scale. This suggests that participants were more likely to agree with the presented affirmatives, showing that the presented approach was well received by students. In particular, it is possible to highlight the contextual autocomplete feature (observed by the affirmative 6) obtained one of the highest acceptance rates among students' responses. This indicates that this feature proved to be relevant to the participants as it had a high approval rate in both phases.

Also, we can notice that graduate students had a high agreement rate regarding the possibility of creating hierarchical *bookmarks* (affirmative 8). This case had the highest level of homogeneity among all responses from the questionnaire, resulting in a $CV =$ 11.27%. It shows similar opinions among participants regarding this affirmative. This is a relevant result because this feature can be used to indicate that some topics (or LOs in this case) are sub-items of others, allowing the generation of more concise and structured LOs.

The lowest reviews in both phases are related to the affirmative 5, indicating that students might not be totally willing to create *bookmarks* for all captured lectures. However, users do not need to create *bookmarks* for all of them since the proposed approach has a collaborative nature, so the LO structure is built as users create and share as many *bookmarks* as they wish.

In total, 21 students evaluated the quality, utility, and usability of the created *bookmarks*, as shown in Table 9. In general, the average of their responses remained above the central point of the scale, which suggests that participants were more likely to agree with the presented affirmatives. The highest mean was obtained by affirmative 4, which comprised the perception of correctness of *bookmarks* created by participants in phase I. The lowest mean was in the affirmative 5, which is related to perception of utility of the functionality for better understanding of the lecture's structure. Nevertheless, the mean is still above the central point of the scale, indicating opinions toward the agreement.

Table 9 – Mean, standard deviation and coefficient of variation of the responses of undergraduate students for the questionnaire administered in phase II.

| Affirmatives[1] | $\bar{x} \pm s$ | $CV(\%)$ |
|---|---|---|
| 1 | 5.76 ± 1.09 | 18.94 |
| 2 | 5.62 ± 1.47 | 26.08 |
| 3 | 5.05 ± 1.50 | 29.70 |
| 4 | 5.95 ± 1.07 | 18.00 |
| 5 | 4.86 ± 1.71 | 35.23 |
| 6 | 5.43 ± 1.40 | 25.77 |

[1] $\bar{x} \pm s$: Mean and standard deviation; $CV$: Coefficient of variation.

Finally, three HCI experts – Professors in institutions of higher education in Brazil – evaluated the metadata generated for each LO in the previous phases. Table 10 shows the results of their responses (Likert scale: 1-"Strongly disagree" to 5-"Strongly agree") the affirmatives: (1) The metadata of this LO is consistent with its content; (2) All metadata created is correct; (3) This LO has a well-defined learning objective; and, (4) This LO can be used in other courses/contexts without modification. The mean of all responses reached values greater than 4, which means that the experts agreed that the created metadata values were correct, consistent, and could be used in different courses.

Table 10 – Mean, standard deviation and coefficient of variation of the responses of experts (phase IV).

| Affirmatives[1] | $\bar{x} \pm s$ | $CV(\%)$ |
|---|---|---|
| 1 | 4.32 ± 0.80 | 0.19 |
| 2 | 4.39 ± 0.78 | 0.18 |
| 3 | 4.30 ± 0.89 | 0.21 |
| 4 | 4.32 ± 0.83 | 0.19 |

[1] $\bar{x} \pm s$: Mean and standard deviation; $CV$: Coefficient of variation.

Additionally, they were asked about how well the *bookmarks* collaboratively created inside each lecture reflected their covered topics. Overall, they found that there was a good amount of *bookmarks* that well represented the topics of the lectures.

## 4.2 Content Personalization - Experiments with Simulated Data

Experiments with simulated data – LOs and students – were done aiming at ranking LOs that best fits students' LS. Heuristics were created from the relationship established between some metadata fields and the learning styles of the FSLSM, and then implemented as an expert system for classifying LOs according to LS. Those rules do not include the CLEO extended vocabulary. The results have been already published at (CARVALHO et al., 2014; DORÇA et al., 2016; CARVALHO et al., 2017).

Each rule satisfied by a learning object increases its relevance for the LS that the rule is related to. As each student also has a certain probability for each LS, then these values are multiplied by the number of rules that matched the LS of an LO. Then, the sum of those values gives the overall relevance of the LO to a specific student.

To validate the feasibility of this approach, a functional prototype was implemented to allows us to set up different values for each LS dimension of a simulated student in order to create a ranking of LOs that best fit that student.

For example, consider a student set up with the following LS values in the student model represented by Equation (1), presented in the Subsection 3.3.2:

$$LS_{student} = \{(0.1, 0.9), (0.7, 0.3), (0.55, 0.45), (0.8, 0.2)\}$$

Figure 22 shows a ranking of the most relevant LOs computed by a version of the Equation (2) in which $P_i$ is replaced by $Q_i$. In this case, the term $Q_i$ represents the number of rules satisfied by the LO for the dimension $i$ instead of the proportionality of matched rules.

Different experiments were performed by changing the LS of the simulated student and computing the relevance of LOs. Then, a ranking of LOs recommended to that student was produced. By regarding the LOs metadata ranked first in the list and the simulated student set up, we were able to conclude that such objects really met the student's LS and they were probably better than the ones in the tail of the list for that context. Since there are four LS dimensions, 16 combinations are possible. All of them were tested in different setups for students. As we changed the values for the simulated student, the ranking of LO also changed but still remained consistent (CARVALHO et al., 2014; DORÇA et al., 2016).

Since those experiments using synthetic data produced consistent ranking of LOs for different student profiles, we implemented the proposed approach in a real-world system used as an educational complementary tool, called CX, and we have run some experiments to validate our approach in real educational settings, which are presented in the next section.

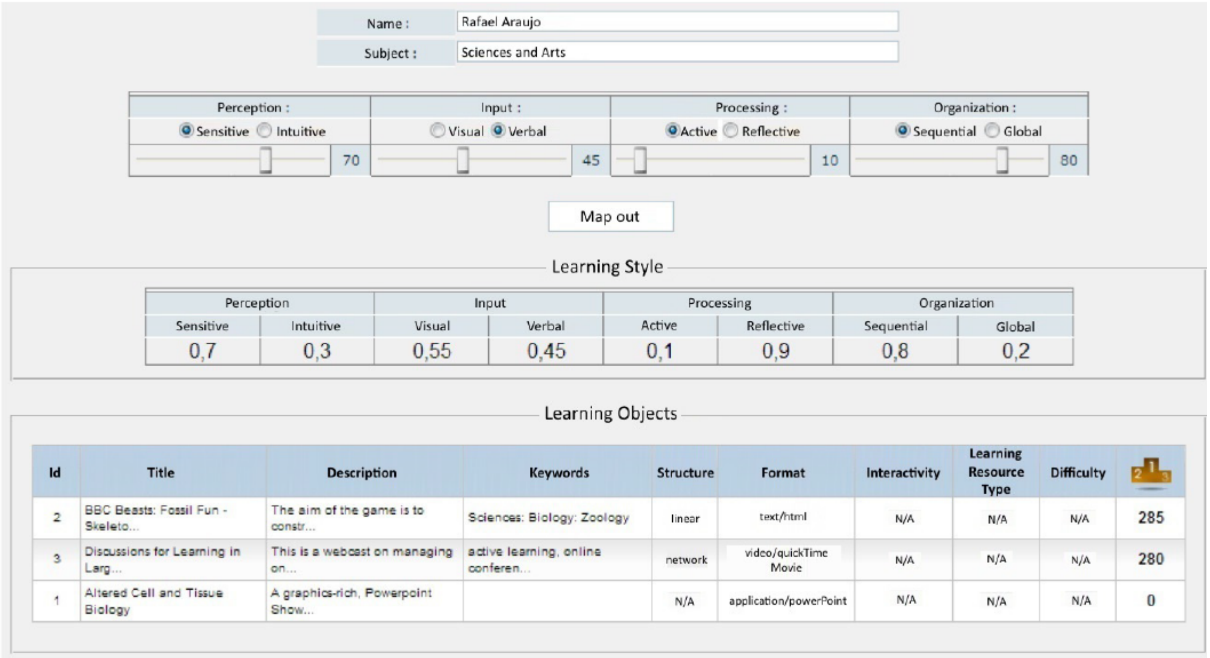



Figure 22 – Prototype system used for ranking LOs according to students' LS (DORÇA et al., 2016).

## 4.3 Content Personalization - Case Study with the Classroom eXperience

The goal of this experiment is to evaluate the approach proposed in the Subsection 3.3.4 for content personalization considering students LS, supporting the research question Q2. The next subsection presents some preliminary exploratory analysis using simulated data. Then, a one-semester long study with real students was performed using the CX platform. For assessing students' LS, a permission to use the Index of Learning Styles (ILS) was granted by Dr. Richard Felder (Annex A). A manuscript containing the results is being prepared to be submitted to the Computers in Human Behavior journal.

### 4.3.1 Research Design

During the first semester of 2017, undergraduate students from four different courses related to Computer Science and Information Systems majors used the CX platform. In total, 95 out of 115 students participated in this study. 20 students either did not use the system or had very few interactions (zero or one) throughout the semester. Table 11 shows the number of students who used the system in each course.

After collecting data, some statistical analyses were performed. First, students' LS were discussed and analyzed regarding the distribution of different interactions with the system among different LS. In addition, we would like to explore the effects of the

Table 11 – Number of students in each course considered in the study.

| Course | N |
|---|---|
| Computer Organization and Architecture (COA) | 37 |
| Human-Computer Interaction (HCI) | 35 |
| Mathematical Logic (MathL) | 12 |
| Software Engineering (SE) | 11 |
| Total | 95 |

personalization approach on students' grades in this context as well as the relationship between grades and different activities performed in the system. Figure 23 shows the analyses pipeline.

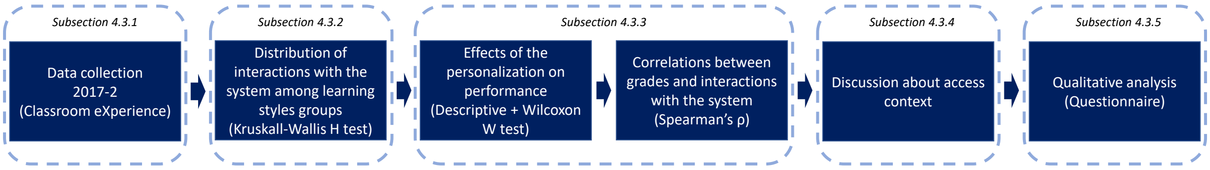



Figure 23 – Pipeline of the performed analyses.

Previous studies show a certain behavior in this complementary tool in which students' interactions with the system tend to happen mainly before the exams. In this sense, the research design was divided into three different course setups based on how many face-to-face exams were proposed by professors in each course to minimize this effect. Students' LS were assessed through the approach presented in the Subsection 3.3.2.

Setups 1 and 2 counted on a pretest (Pre) that was administered just before the beginning of the course and a post-test (Pos) that was administered when the course ended, both containing ten multiple choice questions related to each course content. Also, students of all courses answered a subjective questionnaire (UQ) at the end which was administered to evaluate their perception about utility and usability of the platform, as well as their own study behavior.

In addition, some variables representing students' interactions with the system were collected. Table 12 describes each usage variable extracted from interactions with the CX platform.

Three other scale variables (0 to 10) representing the scores obtained on exams where also considered in the analyzes: (1) course's final grade (GRADE), (2) partial grade when the personalization algorithm was disabled (DIS_PGRADE), and (3) partial grade when the personalization algorithm was enabled (ENA_PGRADE).

Table 12 – Data gathered from interactions with the CX platform.

| Variable | Description |
|---|---|
| TT_LOGIN | Total number of login sessions in the semester. |
| TT_LECT_OPEN | Amount of lecture opening in the semester. |
| TT_COLAB | Amount of collaborative and social activities performed by students, including bookmark creation and exclusion, check/uncheck of learning resource types, comments and slides ratings. |
| TT_QUIZANSWER | Total number of quizzes attempts. |
| TT_QUIZ_LOGIN | Average number of answered quizzes per login session. |
| TT_QUIZ_1ST_CORRECT | Number of answered quizzes in which the first attempt was correct. |

### Setup 1: HCI and SE

Professors of the HCI and Software Engineering (SE) courses proposed two face-to-face exams (in classroom) during the semester. The semester was divided into four timeslots, two before the first exam and two between the first and the second exams. The timeslot just before the first exam had the personalization algorithm enabled and the one just before the second exam has it disabled, as shown by Figure 24.

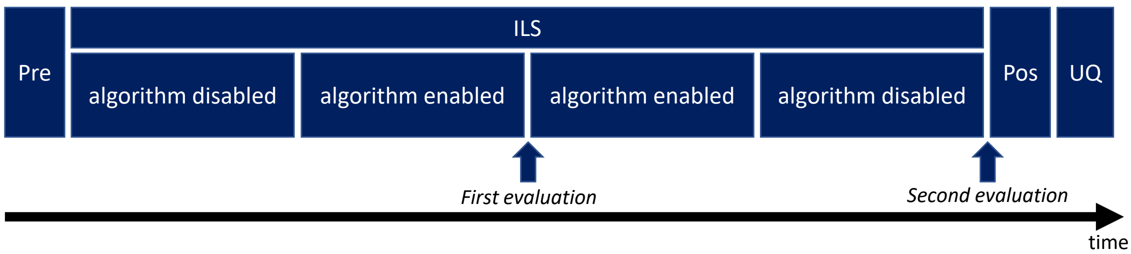



Figure 24 – Experimental design for the HCI and SE courses.

For this case, the score obtained on the first exam was considered as a partial grade for the period with personalization (ENA_PGRADE) and the score obtained on the second exam was considered as a partial grade without personalization (DIS_PGRADE).

### Setup 2: COA

The Computer Organization and Architecture (COA) course had three face-to-face exams (in classroom) during the semester. In this case, the semester was divided into three timeslots, one before each exam. The personalization algorithm was disabled in the extremes periods of the course, that is, before the first exam and between the second and third exams. Only the timeslot between the first and the second exams had the personalization algorithm enabled, as shown by Figure 25.

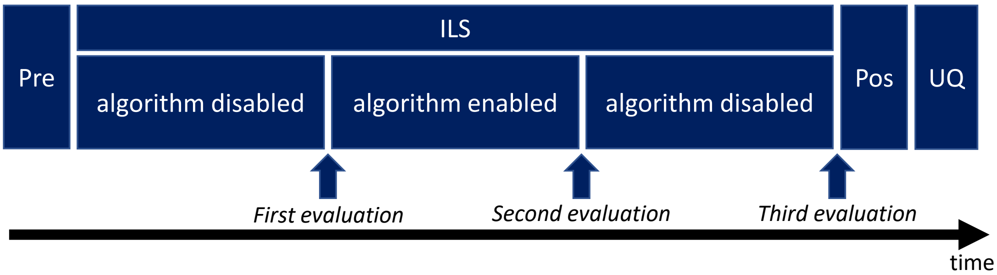



Figure 25 – Experimental design for the COA course.

The score variable representing the partial grade of the period without personalization (DIS_PGRADE) was computed as the mean between the scores obtained on the first and the third exam. On the other hand, the score obtained on the second exam was considered a partial grade for the period with personalization (ENA_PGRADE).

### Setup 3: MathL

The Mathematical Logic (MathL) course also had three face-to-face exams (in classroom) and three timeslots during the semester. However, the setup was the opposite of setup 2 to consider two periods for the research condition enabled. Thus, the personalization algorithm was enabled in the extremes timeslots of the course, that is, before the first exam and between the second and third exams. The timeslot in the middle (between the first and the second exams) had the personalization algorithm disabled, as shown by Figure 26. The professor did not have enough time to prepare the pretest and the post-test for this course, so they were not administered.

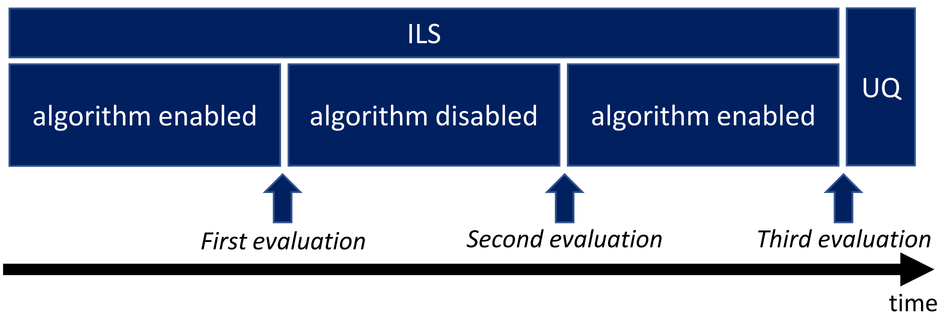



Figure 26 – Experimental design for the MathL course.

The second exam's score was considered as a partial grade for the period without personalization (DIS_PGRADE) and the mean score obtained on the first and third exams was considered as a partial grade for the period with personalization (ENA_PGRADE).

### 4.3.2 Learning Styles

In total, 548 questions from the ILS were answered by 34 different students (out of 95). Of those, only 4 students answered the full questionnaire (44 questions). Figure 27 shows the mean values of each LS dimension assessed in each course, considering only those who answered at least one question. The values indicate how likely, in the average, the first LS of the dimension is preferred. For example, in the COA course, the value 0.48 for the Processing dimension indicates a 48% of preference for the Active LS.

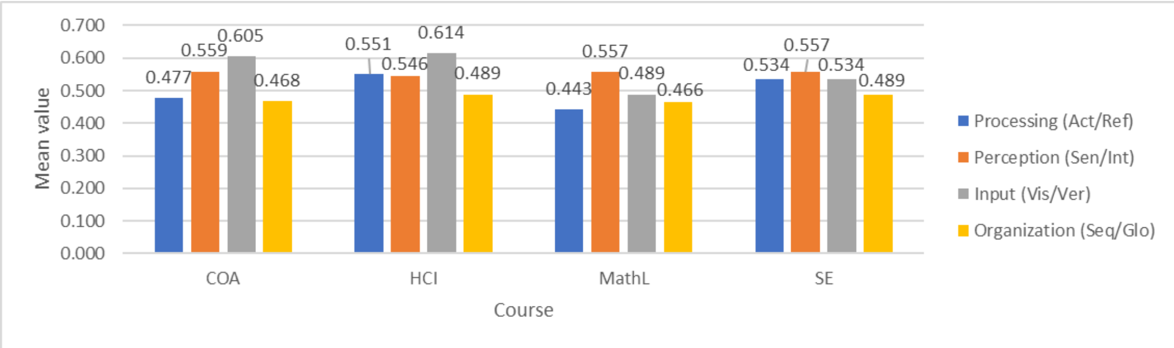



Figure 27 – Mean values of LS dimensions in each course.

Remember that each LS is represented by a value that ranges from 0 to 1 and two LS of the same dimension are complementary to each other, that is, the sum of the LS values of the same dimension must add up to exactly 1. For example, Active and Reflective LS belong to the same dimension (Processing). So, adding the Active and Reflective values should be equal to 1.

Using a data-driven approach, we were willing to explore the behavior of groups of students with different LS regarding their interactions with the system. Since our student model implements a probabilistic approach for LS, we do not have an explicit classification of LS for each student. In this way, we decided to establish some ranges to their LS in a way to analyze and compare how different groups interact with the system. If none or only one question was answered, then the student was classified in the completed balanced category. If the student answered up to six questions towards a specific LS, he/she was classified as balanced for that LS. More than six responses towards a specific direction represented a strong preference for the LS. Table 13 shows the chosen classification ranges.

As 61 students did not answer any question from the ILS, their LS values remained at 0.5, which actually represents "No preference" for any of them. For the purpose of this analysis, they were removed to not draw erroneous conclusions for this group. Therefore, 34 students were considered.

The distribution of interactions with the platform within each LS dimension (with five LS classifications) was tested using the Kruskal-Wallis H test, which is used to compare

Table 13 – LS classification.

| Range | Classification |
|---|---|
| $0.75 <= x <= 1.00$ | Strong preference for the LS |
| $0.55 < x < 0.75$ | Balanced preference for the LS |
| $0.45 <= x <= 0.55$ | Balanced preference |
| $0.25 < x < 0.45$ | Balanced preference for the opposite LS |
| $0 <= x <= 0.25$ | Strong preference for the opposite LS |

three or more independent samples. It assumes that the samples come from identical populations (null hypothesis). This test is a non-parametric method that was chosen because it does not assume a normal distribution of the residuals. Table 14 shows the results for the Kruskal-Wallis H test.

Table 14 – Kruskal-Wallis H test results comparing the distribution of interactions with the platform among different LS.

| LS dimension | Statistics[1] | (A) | (B) | (C) | (D) |
|---|---|---|---|---|---|
| Processing (Act/Ref) | $X^2(df)$ | 4.805(3) | 6.032(3) | 10.486(3) | 9.549(3) |
| | $p$-value | 0.187 | 0.110 | 0.015* | 0.023* |
| Perception (Sen/Int) | $X^2(df)$ | 6.089(3) | 3.397(3) | 9.188(3) | 8.292(3) |
| | $p$-value | 0.107 | 0.334 | 0.027* | 0.040* |
| Input(Vis/Ver) | $X^2(df)$ | 9.902(3) | 2.351(3) | 9.062(3) | 9.146(3) |
| | $p$-value | 0.019* | 0.503 | 0.028* | 0.027* |
| Organization (Seq/Glo) | $X^2(df)$ | 0.109(2) | 1.346(2) | 1.574(2) | 1.532(2) |
| | $p$-value | 0.947 | 0.510 | 0.455 | 0.465 |

[1] $X^2$: chi-squared statistic; *df*: degrees of freedom; *p*-value: Asymp. Sig. (2-sided); * Statistically significant at the 0.05 level; (A): TT_LOGIN; (B): TT_COLAB; (C): TT_QUIZANSWER; (D): TT_QUIZ_1ST_CORRECT.

Three of four LS dimensions have shown statistically significant results, indicating to reject the null hypothesis of the test. The Organization dimension was the only one that did not present statistically significant results.

The Kruskal-Wallis H test indicates that at least one sample is different from the other. However, it does not identify which sample is that. In this way, pairwise comparisons between groups should be performed in order to identify exactly where the differences lie. Although the test indicated to reject the null hypothesis for both the total amount of answered quizzes and the amount of correct answers in the first attempt among different LS groups of three dimensions (Processing, Perception and Input), post-hoc tests showed significant differences for only a few pairs of LS, as shown by yellow edges in Figure 28.

As can be seen, students who were classified with balanced LS for both dimensions, Processing and Perception, answered a different amount of quizzes from those students who had LS measured slightly towards Active and Sensing. Active-Balanced students

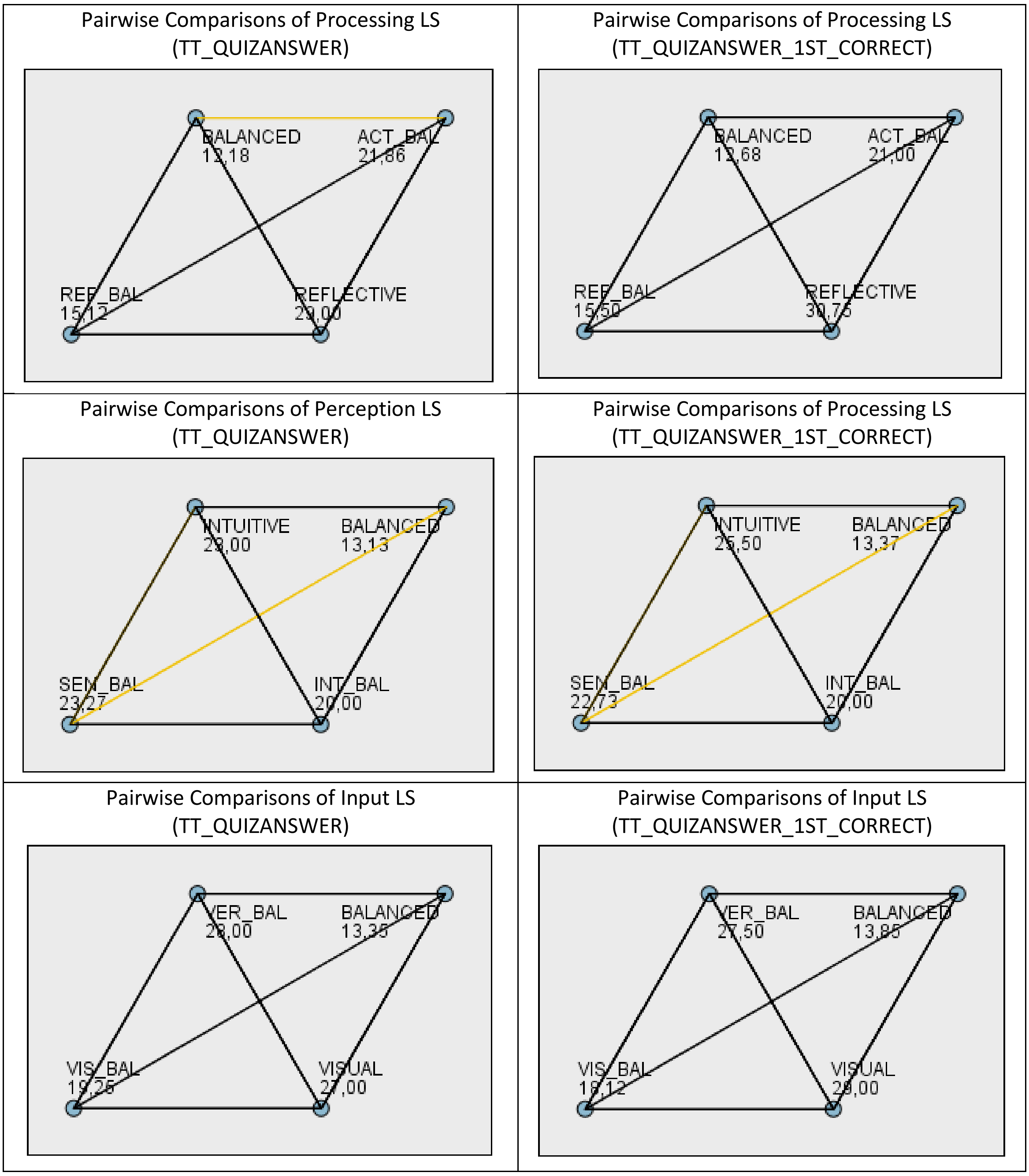



Figure 28 – Pairwise comparisons to verify significant differences in the amount of interactions carried out by students in each LS group.

answered much more quizzes (Median=12.5) than Balanced students (Median=0). Similarly, Sensing-Balanced students also answered much more quizzes (Median=24) than Balanced students (Median=0). It is interesting to note that statistically significant differences were not found between opposite LS of the same dimension. Box-plots charts showing the distribution of interactions by each LS are presented in Appendix E.

### 4.3.3 Effects on Students' Performance

In order to evaluate the periods with and without personalized content aiming at answering the research question Q2, we compared students' grades obtained on the exams for each specific period. For comparing them, the Wilcoxon signed-rank test was performed, which is a non-parametric statistical hypothesis test used when comparing two related samples. In this case, the samples are composed by the grades representing repeated measures for the same individual. Table 15 shows some descriptive statistics, such as mean, standard deviation, minimum, maximum, and median values for DIS_PGRADE and ENA_PGRADE variables, as well as the results for the Wilcoxon signed-rank test for each course.

Table 15 – Statistics for the grades obtained during the periods with and without personalization.

| Course | Variable | N | $\bar{x} \pm s^1$ | Min | Max | Med | $Z(p)^2$ |
|---|---|---|---|---|---|---|---|
| COA | DIS_PGRADE | 37 | 5.005 ± 2.325 | 0.40 | 9.40 | 5.20 | -2.745(0.006) |
| | ENA_PGRADE | 37 | 6.130 ± 3.145 | 0.00 | 10.00 | 6.40 | |
| HCI | DIS_PGRADE | 35 | 6.994 ± 2.052 | 0.00 | 9.60 | 7.20 | -2.663(0.008) |
| | ENA_PGRADE | 35 | 6.206 ± 1.720 | 2.40 | 9.20 | 6.40 | |
| MathL | DIS_PGRADE | 12 | 7.000 ± 2.185 | 3.50 | 10.00 | 7.50 | -1.140(0.254) |
| | ENA_PGRADE | 12 | 6.370 ± 2.756 | 2.00 | 9.75 | 6.87 | |
| SE | DIS_PGRADE | 11 | 5.180 ± 1.601 | 2.00 | 7.50 | 5.00 | -2.677(0.007) |
| | ENA_PGRADE | 11 | 6.500 ± 1.612 | 4.50 | 9.00 | 6.50 | |

[1] $\bar{x} \pm s$: Mean and standard deviation; [2] $Z(p)$: Wilcoxon signed-rank test (two-tailed) statistic and its significance (p-value).

Using a graphical representation, Figure 29 shows a boxplot graph comparing the two periods (with and without personalization) for each course. At a first glance, it seems that the personalized content had a positive impact on students' grades.

To verify this assumption, the Wilcoxon signed-rank test was performed to compare two related samples (scores on exams). Since the samples did not follow a normal distribution, a non-parametric statistical hypothesis test was used.

The Wilcoxon's null hypothesis says that the median difference between pairs of observations is zero. In this case, the pairs of observations are the grades obtained in two conditions: while the content personalization was enabled and while the content personalization was disabled.

Results showed that the grades obtained on the exam carried out in the period with content personalization were statistically higher than the grades obtained on the exam carried out in the period without content personalization for both courses, COA ($Z = -2.745; p < 0.01$) and SE ($Z = -2.677; p < 0.01$). If we look at the median values, the period with content personalization had a median grade around 20% higher than the

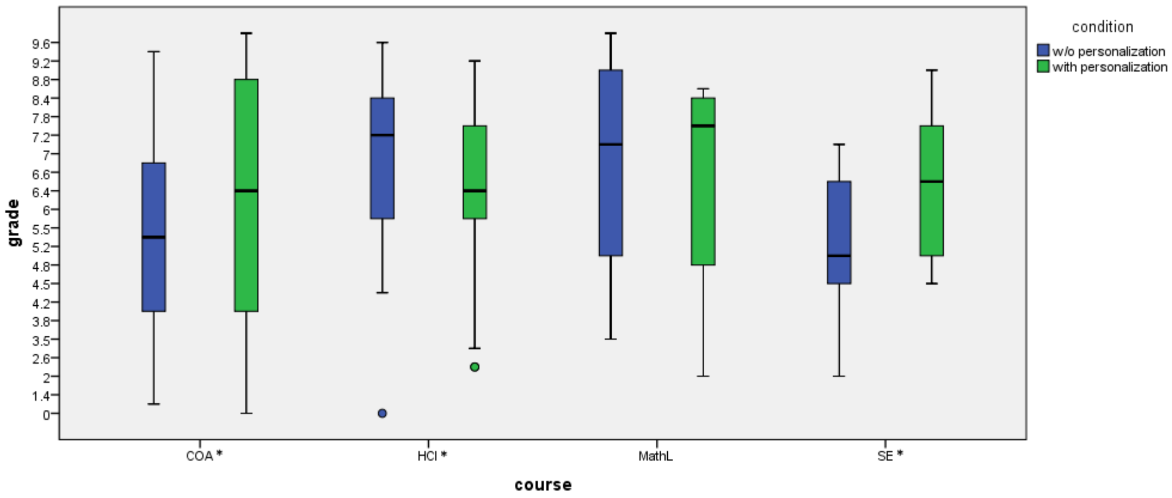



Figure 29 – Boxplots showing the grades obtained while experimenting the content personalization approach in the CX platform. *Statistically significant difference.

other period.

However, in the HCI course, the results showed the opposite, i.e., the grades obtained on the exam that occurred in the period with content personalization were statistically lower than the grades obtained on the exam that occurred in the period without content personalization ($Z = -2.663; p < 0.01$). For the MathL course, the null hypothesis was retained, i.e., there was no statistically significant difference between the scores obtained on the exams.

Perhaps, the design of each course may impact students' performance depending on the profile of the enrolled students. If we observe the distribution of learning resource types in each course, shown by Figure 30, it is possible to identify the most common types according to the boxes' sizes. The COA course, for example, was mainly composed by exercises, figures and examples. Contrasting to predominant students' LS for this course, Sensing and Visual (see Figure 27), figures and examples match those LS, according to the rules listed in Tables 3 and 4.

On the other hand, in the HCI course, the most common learning resource types were figures, examples and definition, which best fit Reflective, Sensing and Verbal students. However, the LS averages tended to the opposite direction (Active, Intuitive and Visual). Similarly, in the SE course, Sensing LS is predominant, however, the most frequent resources are designed to Intuitive students. Although the personalization approach considers individual preferences, there must be different resource types for each course topic to allow the personalization to be more effective.

Since some differences on the exams' grades were found, the Spearman's rank correlation coefficient (also called Spearman's $\rho$) was computed to check if there are relationships between the grades and variables related to interactions with the system. The resulting

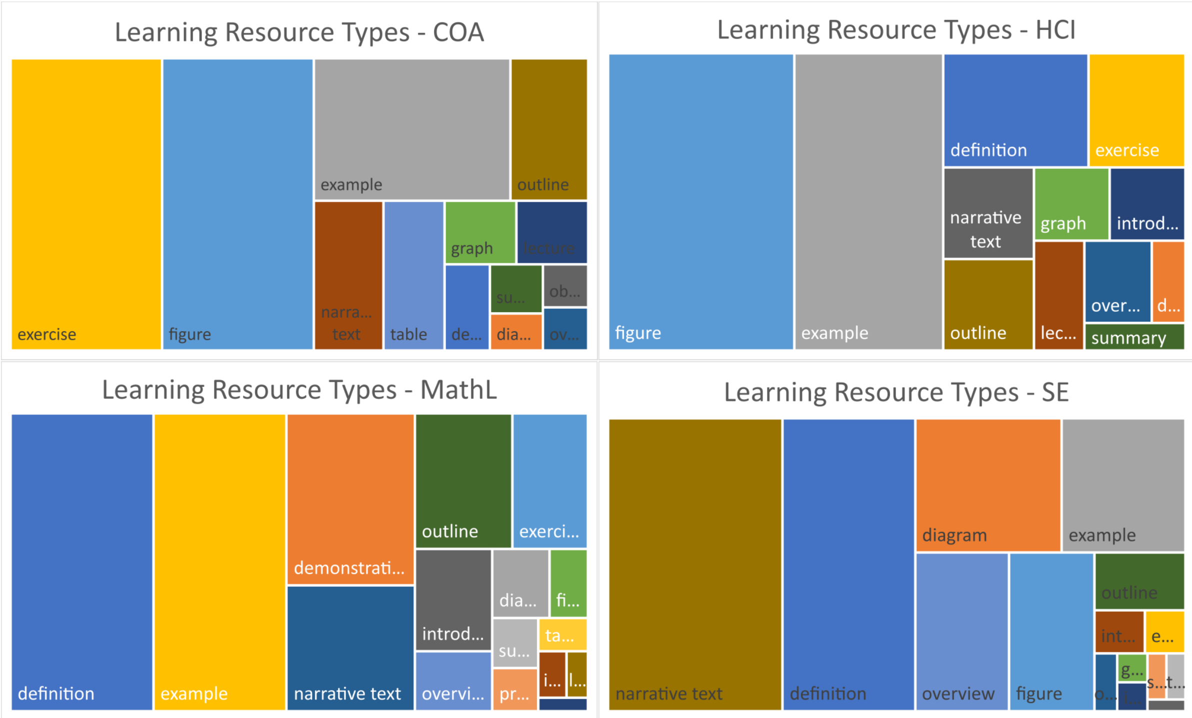



Figure 30 – Learning Resource Types used in each course.

correlation coefficients were classified according to Davis's adjectives (DAVIS, 1971), in which $\rho = 1.00$ indicates a perfect correlation; $0.70 < \rho < 0.99$ represents a very high correlation; $0.50 < \rho < 0.69$ shows a substantial correlation; $0.30 < \rho < 0.49$ indicates a moderate correlation; $0.10 < \rho < 0.29$ represents a low correlation; and, finally, $0.01 < \rho < 0.09$ denotes a negligible correlation.

Both the courses' final grade (GRADE) and the relative gain on the semester (computed as $GAIN = posttest - pretest$) were checked against TT_LOGIN, TT_LECT_OPEN, TT_COLAB, TT_QUIZANSWER, and TT_QUIZ_LOGIN, shown by Tables 16 and 17.

Table 16 – Spearman's $\rho$ correlations between grades, amount of login sessions, and number of lecture opening.

| Variable | Statistics | GRADE | GAIN | TT_LOGIN | TT_LECT_OPEN |
|---|---|---|---|---|---|
| GRADE | Spearman's $\rho$ | 1.000 | 0.202 | 0.374** | 0.233* |
| | Sig. (2-tailed) | - | 0.140 | 0.000 | 0.023 |
| | N | 95 | 55 | 95 | 95 |
| GAIN | Spearman's $\rho$ | 0.202 | 1.000 | 0.447** | 0.074 |
| | Sig. (2-tailed) | 0.140 | - | 0.001 | 0.593 |
| | N | 55 | 55 | 55 | 55 |

** Correlation is significant at the 0.01 level (2-tailed)
* Correlation is significant at the 0.05 level (2-tailed)

Table 17 – Spearman's $\rho$ correlations between grades and amount of collaborative activities, total number of answered quizzes, and number of answered quizzes per login session.

| Variable | Statistics | TT_COLAB | TT_QUIZANSWER | TT_QUIZ_LOGIN |
|---|---|---|---|---|
| GRADE | Spearman's $\rho$ | 0.217* | 0.284** | 0.262* |
| | Sig. (2-tailed) | 0.034 | 0.005 | 0.010 |
| | N | 95 | 95 | 95 |
| GAIN | Spearman's $\rho$ | 0.017 | 0.062 | 0.013 |
| | Sig. (2-tailed) | 0.903 | 0.654 | 0.928 |
| | N | 55 | 55 | 55 |

** Correlation is significant at the 0.01 level (2-tailed)
* Correlation is significant at the 0.05 level (2-tailed)

Positive low correlations were found between the final grade and the following variables: the number of opened lectures in the whole semester ($\rho = 0.233$), total of collaborative activities performed in the system ($\rho = 0.217$), the amount of answered quizzes ($\rho = 0.284$) as well as the number of answered quizzes per login session ($\rho = 0.262$). The final grade and relative gain presented a positive and moderate correlation with the amount of login sessions during the entire semester ($\rho = 0.374$ and $\rho = 0.447$, respectively), both statistically significant at the 0.01 level. It means that students who accessed more the platform have scored better on the exams, which may have also been influenced by the amount of proactive activities performed, such as answered quizzes and collaborative activities in the system.

### 4.3.4 Access Context

As the proposed architecture also captures some contextual information related to the moment when students access the content, it is also reported here. Figure 31 presents some pies charts showing the reasons for login sessions, the location where students accessed the system, the type of device they used, and the available time in login sessions.

Overall, students accessed the CX using a desktop computer (in this case, it could be a laptop as well) at home for ordinary studies and often with little time available for study (up to 15 minutes). Sessions marked as ordinary studies happened mainly at home while sessions marked as missed lesson happened mainly at work, which may indicate that students wanted to learn what was taught in missing classes even when they were not at home. Access to the system for quick review was balanced between home and work, as shown by Figure 32.

Additionally, students had more available time while accessing the system for ordinary studies than when they missed some lesson, as shown by Figure 33. It is important to mention that the availability information may be somewhat biased since the default option

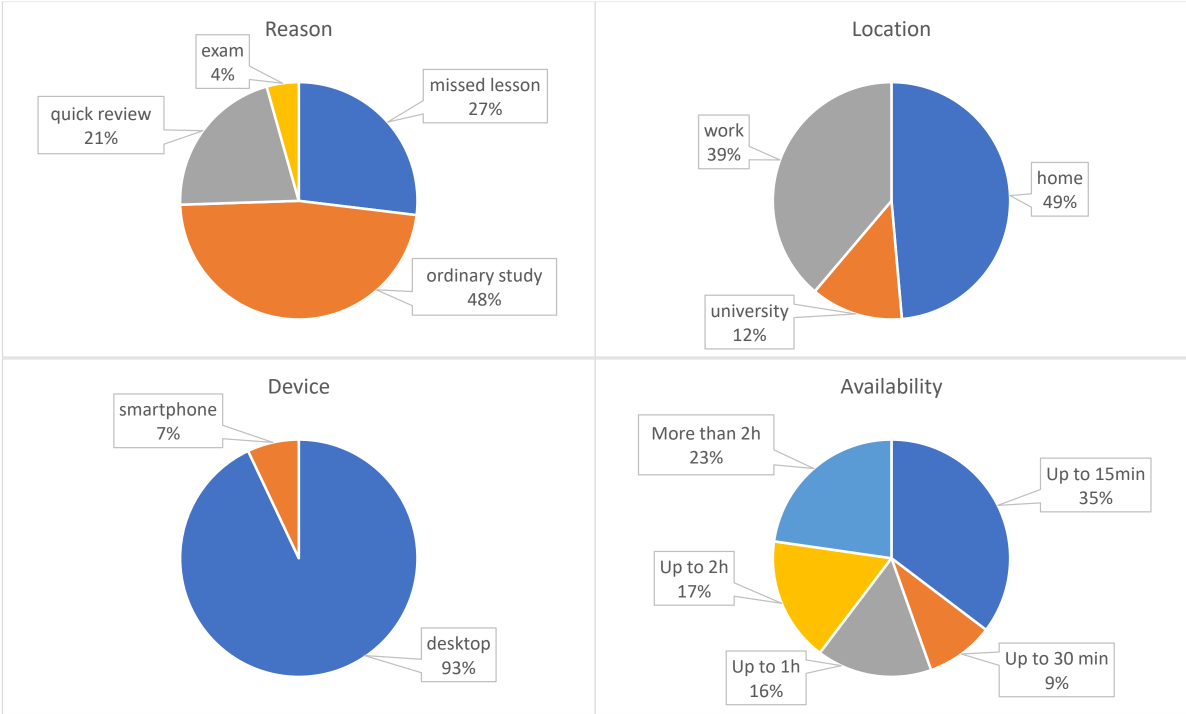



Figure 31 – Reason, Location, Device and Availability information captured as access context dimensions.

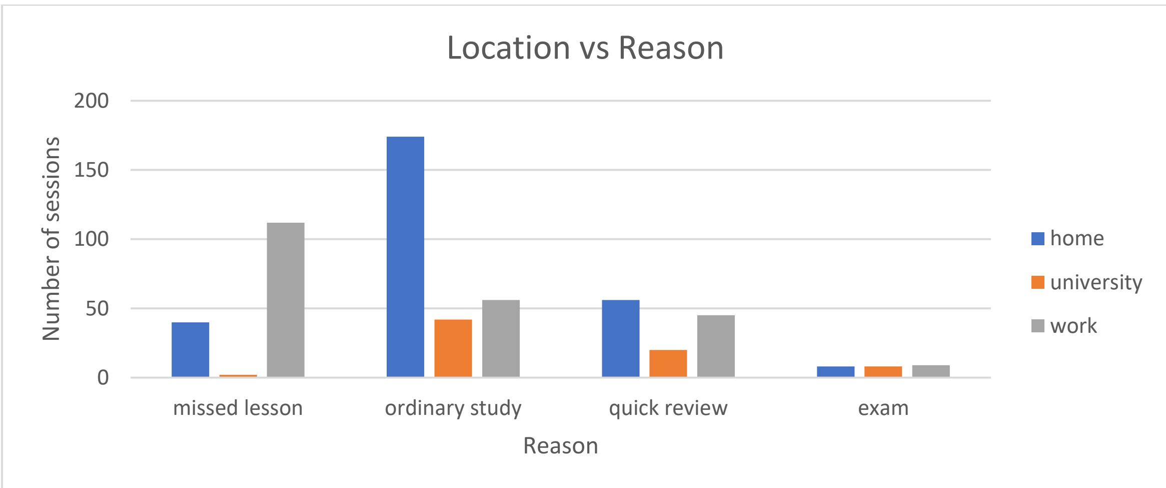



Figure 32 – Distribution of login sessions according to access location and reason.

for the available time was “up to 15 min”. In any case, those results may not be totally untrue as students could also skip informing this information.

Contextual information is important to better tailor the material according students' needs and to design strategies to recommend pieces of content in specific sessions in order to improve the user experience. For example, when a student access the system for a quick review, the lectures could be personalized to show only the most important slides for that session based on ratings or slides with recent discussions, for example.

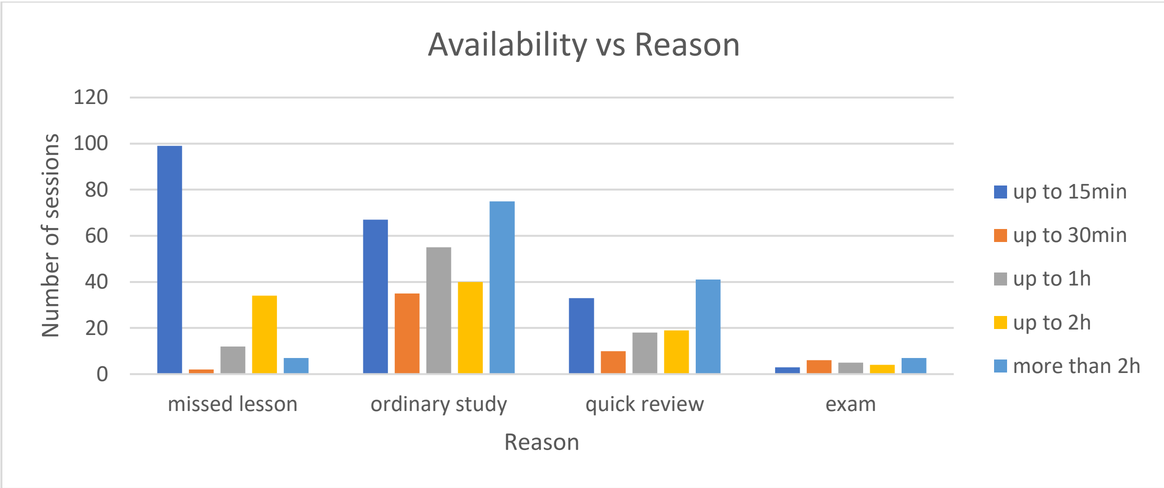



Figure 33 – Distribution of login sessions according to available time for study and access reason.

### 4.3.5 Qualitative Evaluation

By the end of the semester, participants also answered a questionnaire to evaluate their experience as users of the system. The administered questionnaire included questions related to frequency of use, usability, general utility and usefulness of specific features for learning. Appendix D presents the full questionnaire.

In total, 89 out of 115 students answered it. Of these, 42 individuals (47.2%) answered that they used the system many times, 40 individuals (44.9%) said that they used it few times, and 7 students (7.9%) declared they did not use at all. Those who did not use the system or used it a few times were asked about the reason it happened. Five statements were presented to be evaluated in a 7-point Likert scale ranging from "1-Strongly Disagree" to "7-Strongly Agree". Table 18 shows the means, the standard deviations and the coefficients of variation for those statements.

Table 18 – Descriptive statistics of answers related to the reasons why students did not use the CX platform.

| Items[1] | N | $\bar{x} \pm s$ | $CV(\%)$ |
|---|---|---|---|
| Q2.1 | 41 | $2.27 \pm 1.80$ | 79.49 |
| Q2.2 | 41 | $3.27 \pm 1.76$ | 53.88 |
| Q2.3 | 41 | $2.15 \pm 1.41$ | 65.53 |
| Q2.4 | 41 | $4.59 \pm 1.92$ | 41.94 |
| Q2.5 | 26 | $2.50 \pm 1.73$ | 69.05 |

[1]N: number of responses; $\bar{x} \pm s$: Mean and standard deviation; $CV$: Coefficient of variation.

The affirmative that students most agreed was the fourth one (Q2.4), which said *"I found sufficient the content presented in the classroom"*. Although the mean value of responses for this statement ($\bar{x} = 4.59$) is above the scale midpoint, no very high mean for these statements was found, which leads us to believe that there was no consensus on the main reason for not using the system. However, it seems that students have used other materials from the internet, outside the CX platform, since they gave a moderate rating for the statement Q2.2 ($\bar{x} = 3.27$).

An extra space was provided to allow participants to write other reasons than those presented in the statements. Some students stated that they prefer to use the Moodle[2] environment, which have been used in many other courses they were enrolled, so they were already familiar with it. Other students stated they "did not study much" or they "had many other work to do". Finally, some students would like to download the content from the platform for offline study, which we believe it is not an issue but an expected part of students' adaptation process, since CX explores the dynamics of ULEs over existing models based on static documents.

Other statements were arranged into four dimensions in order to evaluate different aspects of the user experience: *"Usability"*, *"Frequency of Use"*, *"General Utility"*, and *"Utility of Specific Features for Learning"*. In order to check the internal consistency of these dimensions, the Cronbach's $\alpha$ coefficient (CRONBACH, 1951) was computed for each of them and the results are shown in Table 19.

The dimensions named *"Usability"*, *"General Utility"*, and *"Utility of Specific Features for Learning"* presented a high reliability coefficient. It is important to note that some researchers believe that a "good" $\alpha$ coefficient depends on the theoretical knowledge of the scale in question. However, many studies claim that values higher than 0.7 represents an indicative of high internal consistency of the instrument (CORTINA, 1993; NUNNALLY, 1994).

The idea behind the assertions of *"Frequency of Use"* dimension was to find out which points in time was preferred to use the platform, according to students' own assessment. However, its $\alpha$ coefficient was very low and indicates that the assertions created to measure this dimension may have caused confusion and misunderstanding among participants. In this case, this dimension was not analyzed to avoid mistaken conclusions.

Another dimension was created to group five questions regarding the way students changed their behavior of study. This group has been named *"Behavior of Study"*, however, it was analyzed differently since it was designed in the form of questions rather than assertions.

Lastly, items Q5.7, Q7.8, Q7.9, Q7.10, Q11, Q11.1, and Q11.2 are related to a proposed Open Student Model using charts for performance visualization that is subject of other research (FERREIRA et al., 2017a).

[2] Moodle: <https://moodle.org>

Table 19 – Questionnaire responses statistics for the user experience assessment groups.

| Groups | Items | $N$ | $\bar{x} \pm s$ | $CV(\%)$ | $\alpha$ |
|---|---|---|---|---|---|
| | Q3.1 - I was able to access the lectures without difficulty. | 82 | 6.07 ± 1.38 | 22.67 | |
| | Q3.2 - Overall, I found it easy to use the CX. | 82 | 6.32 ± 1.11 | 17.57 | |
| Usability | Q3.3 - I quickly learned how to use the CX. | 82 | 6.32 ± 0.98 | 15.51 | 0.801 |
| | Q3.4 - Navigation on the CX was clear. | 82 | 6.05 ± 1.14 | 18.89 | |
| | Q3.5 - Overall, I liked the CX interface. | 82 | 5.49 ± 1.57 | 28.67 | |
| | Q4.1 - I used to go to the CX for studies just before each class. | 79 | 2.06 ± 1.61 | 78.13 | |
| | Q4.2 - I used to go to the CX for studies right after each taught class. | 79 | 2.18 ± 1.54 | 70.83 | |
| Frequency of Use | Q4.3 - I used to go to the CX for studies every 1 or 2 weeks of taught classes. | 79 | 4.11 ± 2.11 | 51.19 | 0.025 |
| | Q4.4 - I used to go to the CX for studies every 3 or 4 weeks of taught classes. | 79 | 4.59 ± 2.05 | 44.70 | |
| | Q4.5 - I used to go to the CX only before the exams. | 79 | 4.97 ± 2.08 | 41.84 | |
| | Q5.1 - I found it useful to use the CX for studies outside the classroom. | 74 | 6.50 ± 0.97 | 14.90 | |
| | Q5.2 - Accessing the CX for studies after classes helped me to reinforce the taught content. | 74 | 5.50 ± 1.69 | 30.73 | |
| General Utility | Q5.3 - The CX interface helped me to understand the structure of each lecture. | 74 | 4.92 ± 1.86 | 37.89 | 0.814 |
| | Q5.10 - I would like to use the CX in other courses. | 74 | 6.20 ± 1.31 | 21.18 | |
| | Q7.1 - The CX helped me to identify my weaknesses. | 74 | 3.93 ± 1.95 | 49.51 | |
| | Q7.2 - The CX helped me to plan my studies. | 74 | 4.74 ± 2.04 | 43.03 | |
| | Q5.4 - Creating bookmarks for dividing the lecture in different subjects has positively influenced my learning in the course. | 74 | 4.86 ± 1.88 | 38.69 | |
| | Q5.5 - The possibility of creating comments for each slide has positively influenced my learning in the course. | 74 | 5.15 ± 1.95 | 37.86 | |
| | Q5.6 - Slides rating using stars has positively influenced my learning in the course. | 74 | 5.36 ± 1.97 | 36.71 | |
| Utility of Specific Features for Learning | Q5.7 - Visualizing my performance through charts has positively influenced my learning in the course. | 74 | 4.04 ± 1.98 | 48.89 | 0.825 |
| | Q5.8 - Having quizzes to be answered has positively influenced my learning in the course. | 74 | 5.07 ± 1.79 | 35.38 | |
| | Q5.9 - The gamification feature (score ranking and badges) has positively influenced my learning in the course. | 74 | 4.51 ± 1.92 | 42.65 | |

[1] $N$: number of responses; $\bar{x} \pm s$: Mean and standard deviation; $CV$: Coefficient of variation; $\alpha$: Internal consistency of scale measured by Cronbach's alpha.

### Usability

The *"Usability"* dimension counted on five assertions about how easy it was to use the CX platform for accessing the lectures and navigating through them. Figure 34 shows the distribution of responses for these affirmatives. As can be noticed, a very high percentage of responses are concentrated at the highest levels of agreement ("Strongly agree" and "Agree"), which means that, in general, students liked to use the CX interface and found it easy to use.

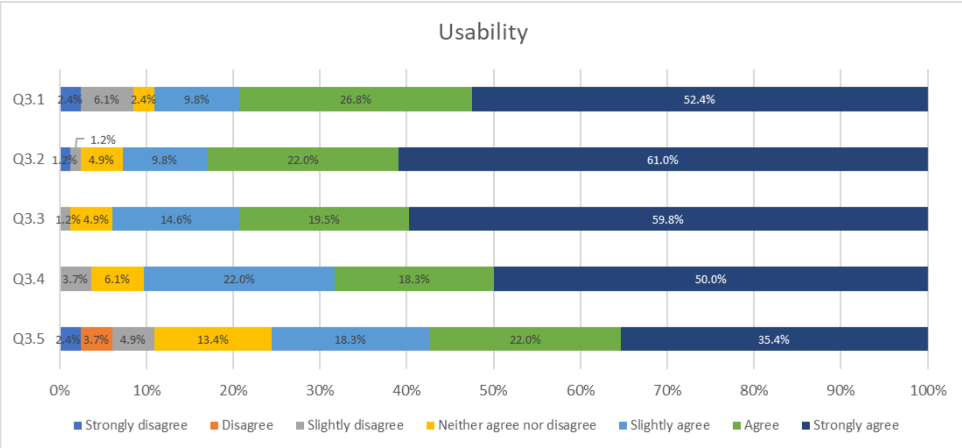



Figure 34 – Students agreement levels for the assertions related to the platform usability.

### General Utility

Regarding the general utility of the platform, six affirmatives were presented. The distribution of responses is shown by Figure 34. More than 97% of respondents found the CX platform useful while studying outside the classroom, and 3/4 of respondents found it useful to reinforce what they learned in classroom. It shows that this kind of tool can complement students' learning in some way by reinforcing the taught content and to help them to understand the structure of the classes. An interesting point to note is that approximately 90% of participants would like to use this tool in other courses.

On the other hand, the assertion Q7.1 ("The CX helped me to identify my weaknesses") obtained the lowest agreement level among respondents in this dimension, 46.2%. However, it does not mean that students disagree with it since 20.5% of respondents neither agree nor disagree. In addition, the mean value of responses for that assertion was 3.93, as can be seen in Table 19, which is higher than the scale midpoint.

### Utility of Specific Features for Learning

The importance of specific features for students learning has also been assessed. Six affirmatives pointing out the role of some implemented features, such as collaborative

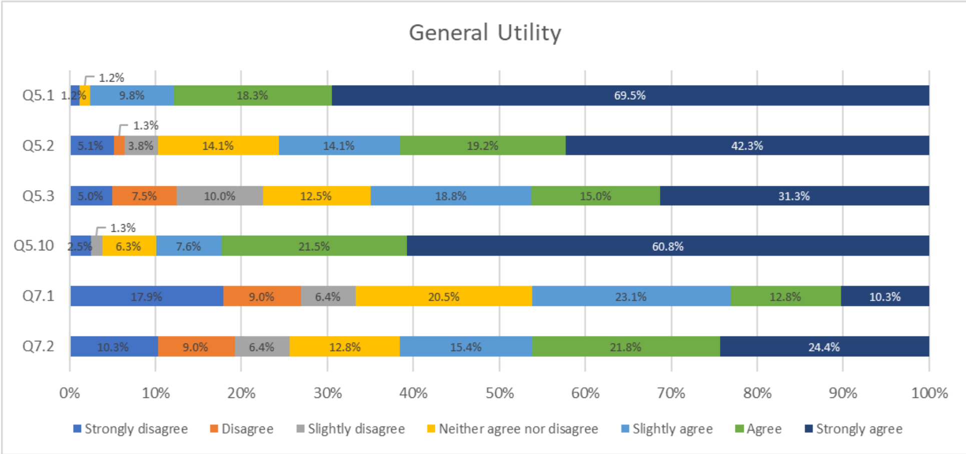



Figure 35 – Students agreement levels for the assertions related to CX general utility.

bookmarking, comments, slides rating, quizzes, performance visualization, and gamification were presented in the questionnaire. Again, the agreement levels were higher than the disagreement levels overall, as shown by Figure 36. Social and collaborative features have stood out. More than 60% of respondents believe that the slides rating functionality positively influenced their learning ("Agree" or "Strongly agree"). The slides' comments feature also got a high agreement level (55.7%). The mean values of responses for these affirmatives were 5.36 and 5.15, respectively.

In addition, more than 60% of respondents agreed, somehow, that having quizzes in the platform and the ability to create bookmarks for each lecture positively influenced their learning in the course.

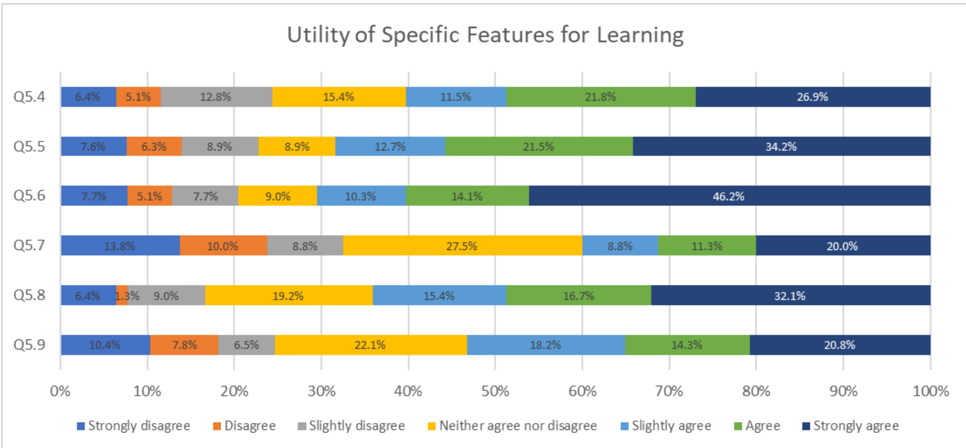



Figure 36 – Students agreement levels for the assertions related to the utility of specific features.

Additionally, two other questions specifically related to the personalized slides reordering were asked to participants: Q10 - *"Did you like the way the system rearranged the lectures slides?" (1-Yes; 2-No; 3-I haven't noticed)* and Q10.1 *"How much did this feature positively impact your learning in the course? (1-Very little to 7-Very much)"*. 47% of respondents (N=37) answered that they liked this feature and the same amount of respondents said they did not notice that slides were rearranged, which answer the research question Q2.1. Only five respondents answered they did not like this feature. Of those who have noticed it (like it or not), 73.8% of students agreed that this feature positively influenced their learning (Mean=4.9; SD=1.72).

Besides that, the system's interface also provided students with a feature to change the lecture visualization to the original sequence as created by the instructor. 95% of the students did not use this feature, which confirms that many students have not noticed that the slides were rearranged.

### Behavior of Study

Participants were asked how the use of such a tool has changed the way they studied for the course regarding frequency of study, collaboration with colleagues, motivation, competitiveness, and search for extra material. In our context, competitiveness is related to gamification artifacts provided in the platform, in which students were able to track their peers' scores. The responses ranged from "Very little (1)" to "Very much (7)". Descriptive statistics are presented in Table 20.

Table 20 – Descriptive statistics of responses for questions in the "Behavior of Study" group.

| Items[1] | N | $\bar{x} \pm s$ | $CV(\%)$ |
|---|---|---|---|
| Q7.3 - Frequency of study | 79 | 3.68 ± 1.87 | 50.82 |
| Q7.4 - Collaboration | 79 | 3.44 ± 2.16 | 62.76 |
| Q7.5 - Motivation | 79 | 4.38 ± 1.80 | 41.21 |
| Q7.6 - Competitiveness | 79 | 3.20 ± 1.86 | 58.07 |
| Q7.7 - Search for extra material | 79 | 4.93 ± 1.98 | 40.19 |

[1]N: number of responses; $\bar{x} \pm s$: Mean and standard deviation; $CV$: Coefficient of variation.

According to participants, the use of the CX made them more motivated to study and to look for extra materials different from those presented in the classroom. However, the competitiveness aspect got the lowest scores, which means that it was not enjoyed very much by students.

### Open-Ended Questions

*Q8. Can you cite some other specific situation where there was a positive contribution to your learning while using the CX?*

The goal of this question was to identify in which contexts or scenarios students find value in the used platform as a complementary tool for their learning. Actually, many students answered this question by pointing out the features they most found relevant thus overlapping question Q12. However, some interesting contexts were listed. First, annotations made in the electronic whiteboard were useful both in and outside the classroom to prevent students from losing any important detail while copying what the professor writes and also in situations in which they missed classes:

> "I missed some classes. Luckily, I had access to the teacher's notes."
> "When I missed classes, I could keep up with the course."
> "In case of missing classes, the CX allows you to view the slides used in class in a way that is almost as clear as if we were in the classroom, thanks to the teacher's notes."
> "No specific situation, but the fact that we can focus on the class without wasting time copying stuff is something valuable."
> "For me, the best part is the one the professor writes in the CX and it stays there, so you do not have to write it down, just paying attention."
> "The possibility of having the professor's notes on each slide had a huge contribution."
> "Information that was sometimes lost or unnoticed on the board, remained saved in the CX."

Scenarios in which students used the social and collaborative features provided by the platform, such as slides rating and commentaries, also attracted attention:

> "When I was studying, the comments on the slides written by the professor helped to remember what was said in the class which was not on the slides."
> "Commented slides helped a lot to solve some doubts."
> "There were some exercises before the first exam that, thanks to CX and the comments on the slides having those exercises, I was able to understand them."
> "Yes, on a slide that I had trouble, the professor added a comment that solved my doubts."
> "Slides ranked as important helped guide my studies."
> "Being able to rate slides using stars contributed to identify the most important parts."

Finally, the importance of the tool for helping students to solve their doubts was pointed out:

> "I was able to quickly have a doubt cleared up using the system. I didn't need to wait for the next class or even send an email to the professor."

*Q9. Can you cite some other specific situation where there was a negative contribution to your learning while using the CX?*

This question aimed at identifying situations in which the CX platform could have a negative contribution to students learning. Overall, the criticism focused on technical aspects of systems that are not yet commercial, such as unavailability and overload:

> "Right before the second exam the system went down. This messed up because I had to use the PDF file which didn't have the comments for the study."
> "I couldn't access it sometimes."
> "It is not good to review the content the day before the exams, because it gets overwhelmed and goes down."

Nevertheless, the system has always been monitored, especially during exams' periods to prevent these problems to happen. In addition, some students complained about usability aspects, which can be corrected promptly:

> "A bug that causes the slide bar not to disappear, which hinders part of the material's visualization."
> "Slide navigation takes time to fade out and sometimes it gets in front of some information on the slide."

*Q12. Please, list up to 3 features you liked most in the CX.*

Many different features appeared in the answers. The most cited feature was the slides rating using stars. According to students, they were able to identify the most important content. Professor's annotations and the possibility of creating comments for each slide also appeared frequently in the answers, followed by quizzes and the system's ease of use. In short, content enrichment somehow was the most remarkable aspect. Some examples:

> "The possibility of interacting with the materials through comments, ratings."
> "The annotation system directly on the whiteboard."
> "The interface is much cleaner than in Moodle."
> "Comments and interaction with slides."
> "Clean design."
> "Possibility of creating bookmarks."
> "Gamification and individual performance evaluation as well as regarding the rest of the class."

*Q13. Please, list up to 3 features you did not like in the CX.*

Finally, participants were asked to list which features they did not like. Some students complain that it is not possible to download the content for offline study. However, it is considered in the platform architecture because it has been designed to explore the dynamics of UbiComp over existing models based on static documents. In this way, we do not consider an issue, but a particularity that is part of students' adaptation process.

Other participants pointed out the page that collects contextual access information manually every time right after the log in page is quite unpleasant. Indeed, the information collected in this page could be either handled by some automatic approach or changed to some other place ahead in the system. Only three dimensions of the access context (available time, place, and reason) are manually collected.

As a suggestion for future work, the available time could be first compared to the time scheduled for the class. The place in which students access the system could be associated to the Internet Protocol (IP) address, for example. Lastly, some rules could be created to set up the access reason, for example, if the student has missed classes. Other than that, it could be asked further in a notification area in the system.

Some other answers are reported here:

> "Lack of more Quizzes on slides."
> "Auto-play on slides.""
> "The interface color."
> "Lack of a better mobile version."
> "Missing explanation on how main features work."
> "Scores and badges."

Overall, the received feedback was valuable and can guide the construction of a new iteration. For instance, usability of the slides navigation may be improved to make the slide transition smoother, without overlapping annotations as well as indicating the current position in the slide set. Further, dissemination actions should be planned and taken during the semester to encourage the use of the system.

After all analysis, we argue that ULEs provide support for automatic creation of structured LOs as well as using their metadata values to classify them according to the FSLSM. Fields like format, structure, learning resource types, interactivity type, and interactivity level of the LO are the most significant for this task. In addition, the CLEO vocabulary provided values with greater semantic meaning in this context. Finally, the metadada fields can be either inferred by the system or collaboratively inputted by the users. Some other fields that are manually informed could be used to automatically populate the metadata of similar LOs, particularly those which are hierarchically related.

Lastly, a qualitative analysis was used to find answers for research questions Q1 and Q1.1, while the research questions Q2 and Q2.2 were answered using both quantitative and qualitative analyzes.

# Chapter 5

# Conclusion

This work proposed a computational architecture that blends the concepts of Ubiquitous Learning Environments (ULEs), Adaptive Educational Hypermedia (AEH) and Intelligent Tutoring Systems (ITSs) to generate structured LOs and present them in a personalized way to students. Also, it aims at facilitating the interaction between instructors and students outside the classroom. The architecture, which was named Adaptive and Ubiquitous Learning Architecture (AULA), complies with the main goal of this work.

The first specific goal was addressed by the semiautomatic process designed for creating LOs and their metadata using the IEEE-LOM standard along with the CLEO extensions. An experiment in real educational settings was conducted to evaluate how ULEs support the LOs authoring process and the use of a collaborative bookmarking approach to refine them. Results have shown that the presented approach was well received by students, in particular, the contextual auto-complete feature – one of the highest acceptance rates among students' responses. The lowest scores indicate that students might not be totally willing to create *bookmarks* for all captured lectures. However, they do not need to create *bookmarks* for all lectures thanks to the collaborative nature of the proposal. In addition, experts stated that there was a good amount of *bookmarks* that well represented the topics covered by the lectures.

The second specific goal concerning the design of a cognitive module for handling learning styles according to the FSLSM was addressed through an approach that classifies the generated LOs according to LS. Heuristics that map LOs metadata fields to LS were presented. Moreover, students' LS is accessed using a partitioned version of the ILS which was created to update the probabilistic student model.

The third specific goal was accomplished by implementing the proposed approach into the Classroom eXperience (CX) platform which has been used as a complementary tool in courses of the Faculty of Computing at Federal University of Uberlândia. Results presented in Chapter 4 showed that students who were classified towards Active and Sensing LS answered much more quizzes than students who were classified towards a Balanced LS. In addition, partial grades obtained on the exam carried out in the period with content personalization based on LS were statistically higher (≈20%) than the grades obtained on the exam carried out in the period without content personalization for two of four courses. One of them had lower grades in the period with content personalization and the other had no statistically significant difference between the scores obtained on the exams, which could be affected by the design and nature of each course.

Regarding the access context, students mainly accessed the CX using a desktop computer at home for ordinary studies and often with little time available for study (up to 15 minutes). Results obtained from a user experience evaluation questionnaire showed that, in general, students liked to use the CX interface and found it easy to use. More than 97% of respondents found the platform useful while studying outside the classroom, and 75% of them found it useful to reinforce what they learned in classroom. About 90% of participants pointed out that they would like to use such a tool in other courses. Among all features, the group including social and collaborative ones – such as slides ratings, slides comments, and bookmarking – were the most praised by the students.

Finally, the creation of a free LOs repository for the research community, named CX-LOR, was presented in Subsection 3.2.5 to comply with our last specific goal. A Web interface and API were built to allow users to query the repository and retrieve metadata of real educational material in the IEEE-LOM format.

As observed, such tools have the potential to change the traditional paradigm of teaching, in which the instructor is the only entity to provide content, to a scenario where students have a more active role in the production of knowledge. Computational and technological resources that assist people to carry out everyday tasks are often found everywhere. In the educational domain, it is no different and computers can assist both instructors and students in their activities. Devices scattered in classrooms can capture educational activities through different medias, so the experience can be revisited in the future. In addition, social and collaborative functionalities allow for the enrichment of content and provide input to intelligent techniques for content to be properly tailored to users' needs.

## 5.1 Contributions

Given the difficult and time-consuming task of authoring LOs as well as the complex problem of tailoring them according to students' needs, this research proposed a computational architecture for adaptive hypermedia applications that takes into account contextual, social, collaborative, and cognitive information in order to recommend e personalize educational content to students.

The architecture includes a collaborative approach for LOs authoring in ULEs as well as an algorithm to personalize them according to students' LS. This architecture has been evaluated through a case study in real educational settings and with real users using the

CX platform.

Additionally, the following contributions may be listed as a result of this thesis:

- Relationship mapping between the CLEO vocabulary extension for the "Learning Resource Type" field of the IEEE-LOM standard and the FSLSM;
- A repository of LOs created in this environment;
- Establishment of research collaboration with the Personalized Adaptive Web Systems Lab[1] of the University of Pittsburgh, headed by Dr. Peter Brusilovsky.

## 5.2 Publications

The following scientific publications are directly related to this doctoral project:

- Araújo, R. D., Ferreira, H. N. M., Dorça, F. A., Cattelan, R. G. *A Hybrid Architecture for Adaptive, Intelligent and Ubiquitous Educational Systems.* Book chapter accepted for publication in the book entitled *Digital Technologies and Instructional Design for Personalized Learning*, edited by Dr. Robert Zheng and published by IGI Global (in press).
- Araújo, R. D., Dorça, F. A., Cattelan, R. G. *Towards an Adaptive and Ubiquitous Learning Architecture.* Short paper published in the Doctoral Consortium of the 17th IEEE International Conference on Advanced Learning Technologies (ICALT), Timisoara, Romania. (ARAÚJO; DORÇA; CATTELAN, 2017)
- Araújo, R. D., Brant-Ribeiro, T., Mendonça, I. E. S., Mendes, M. M., Dorça, F. A. and Cattelan, R. G. *Social and Collaborative Interactions for Educational Content Enrichment in ULEs.* (2017) Article published the Educational Technology & Society journal. (ARAÚJO et al., 2017)
- Araújo, R. D., Brant-Ribeiro, T., Ferreira, H. N. M., Dorça, F. A., Cattelan, R. G. *Segmentação Colaborativa de Objetos de Aprendizagem Utilizando Bookmarks em Ambientes Educacionais Ubíquos.* Full paper published at the XXVII Brazilian Symposium on Informatics in Education (SBIE), Uberlândia, Brazil. (ARAÚJO et al., 2016)
- Araújo, R. D., Ferreira, H. N. M., Dorça, F. A., Cattelan, R. G. *Learning Objects Authoring Supported by Ubiquitous Learning Environments.* Extended abstract published at the 21st International Conference on Intelligent User Interfaces (IUI), Sonoma, USA. (ARAÚJO et al., 2016)

[1] http://adapt2.sis.pitt.edu/wiki

- Dorça, F. A., Araújo, R. D., Carvalho, V. C., Resende, D. T., Cattelan, R. G. *An automatic and dynamic approach for personalized recommendation of learning objects considering students learning styles: an experimental analysis.* Article published in the Informatics in Education journal. (DORÇA et al., 2016)

- Araújo, R. D., Brant-Ribeiro, T., Freitas, R. S., Dorça, F. A. and Cattelan, R. G. *Autoria automática de objetos de aprendizagem a partir de captura multimídia e associação a estilos de aprendizagem.* Full paper published at the XXV Brazilian Symposium on Informatics in Education (SBIE), Dourados, Brazil. (ARAÚJO et al., 2014)

Further, many other publications took place during the doctoral period since this work includes requirements from each part of the architecture separately. Therefore, efforts were employed in each of the following publications in collaboration with other students:

- Carvalho, V. C., Araújo, R. D., Cattelan, R. G., Dorça, F. A. *OntAES: Uma Ontologia para Sistemas Adaptativos Educacionais Baseada em Objetos de Aprendizagem e Estilos de Aprendizagem.* Full paper published at the XXVIII Brazilian Symposium on Informatics in Education (SBIE), Recife, Brazil. (CARVALHO et al., 2017)

- Dorça, F. A., Carvalho, V. C., Mendes, M. M., Araújo, R. D., Ferreira, H. N. M., Cattelan, R. G. *An Approach for Automatic and Dynamic Analysis of Learning Objects Repositories Through Ontologies and Data Mining Techniques for Supporting Personalized Recommendation of Content in Adaptive and Intelligent Educational Systems.* Short paper published at the 17th IEEE International Conference on Advanced Learning Technologies (ICALT), Timisoara, Romania. (DORÇA et al., 2017)

- Ferreira, H. N. M., Araújo, R. D., Dorça, F. A., Cattelan, R. G. *Uma Abordagem Baseada em Ontologias para Modelagem e Avaliação do Estudante em Sistemas Adaptativos e Inteligentes para Educação.* Full paper published at the XXVIII Brazilian Symposium on Informatics in Education (SBIE), Recife, Brazil. (FERREIRA et al., 2017b)

- Ferreira, H. N. M., Araújo, R. D., Dorça, F. A., Cattelan, R. G. *Open Student Modeling for Academic Performance Visualization in Ubiquitous Learning Environments.* Full paper published at the 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2017, Banff, Canada. (FERREIRA et al., 2017a)

- Ferreira, H. N. M., Brant-Ribeiro, T., Araújo, R. D., Dorça, F. A., Cattelan, R. G. *An Automatic and Dynamic Knowledge Assessment Module for Adaptive Educational Systems.* Full paper published at the 17th IEEE International Conference on Advanced Learning Technologies (ICALT), Timisoara, Romania. (FERREIRA et al., 2017)

- Mendes, M. M., Carvalho, V. C., Dorça, F. A., Araújo, R. D., Cattelan, R. G. *Agrupamento e Recomendação de Objetos de Aprendizagem no Padrão IEEE-LOM Considerando Estilos de Aprendizagem.* Full paper published at the XXVIII Brazilian Symposium on Informatics in Education (SBIE), Recife, Brazil. (MENDES et al., 2017b)

- Mendes, M. M., Carvalho, V. C., Araújo, R. D., Dorça, F. A., Cattelan, R. G. *Clustering Learning Objects in the IEEE-LOM Standard Considering Learning Styles to Support Customized Recommendation Systems in Educational Environments.* Full paper published at the 12th Latin American Conference on Learning Technologies (LACLO), 2017, La Plata, Argentina. (MENDES et al., 2017a)

- Bull, S., Brusilovsky, P., Guerra, J., Araújo, R. D. *Individual and Comparison Open Learner Model Visualisations to Identify What to Work On Next.* Late Breaking results published at the 24th ACM Conference on User Modeling, Adaptation and Personalisation (UMAP), Halifax, Canada. (BULL et al., 2016)

- Çebi, A., Araújo, R. D., Brusilovsky, P., Guyer, T. *Cognitive Traces from the Perspective of Students Navigation Patterns.* Abstract published at the 10th International Computer & Instructional Technologies Symposium, Rize, Turkey. (ÇEBI et al., 2016)

- Ferreira, H. N. M., Araújo, R. D., Dorça, F. A., Cattelan, R. G. *Uma Abordagem Híbrida para Acompanhamento da Aprendizagem do Estudante Baseada em Ontologias e Redes Bayesianas em Sistemas Adaptativos para Educação.* Full paper presented in the IX WAvalia at the V CBIE, Uberlândia, Brazil. (FERREIRA et al., 2016)

- Ferreira, H. N. M., Brant-Ribeiro, T., Araújo, R. D., Dorça, F. A., Cattelan, R. G. *An Automatic and Dynamic Student Modeling Approach for Adaptive and Intelligent Educational Systems using Ontologies and Bayesian Networks.* Full paper published at the 28th IEEE International Conference on Tools with Artificial Intelligence (ICTAI), San Jose, USA. (FERREIRA et al., 2016)

- Brant-Ribeiro, T., Araújo, R. , Mendonça, I., Soares, M. and Cattelan, R. *A User-centered Approach for Modeling Web Interactions Using Colored Petri Nets.* Full paper published at the 17th International Conference on Enterprise Information Systems (ICEIS), Barcelona, Spain. (BRANT-RIBEIRO et al., 2015)

- Carvalho, V., Araújo, R. D., Cattelan, R. G. and Dorça, F. A. *Um Modelo para Recuperação de Objetos de Aprendizagem no Padrão IEEE LOM Utilizando o Protocolo OAI-PMH e Repositórios de Objetos de Aprendizagem Públicos.* Full paper presented in the 7th Brazilian Workshop on Semantic Web and Education at the IV CBIE, Maceió, Brazil. (CARVALHO et al., 2015)

- Ferreira, H. N. M., Araújo, R. D., Souza, P. C., Silva Júnior, S. C. da, Dorça, F. A. and Cattelan, R. G. *Gamificação em Ambientes Educacionais Ubíquos.* Full paper published at the XXVI Brazilian Symposium on Informatics in Education (SBIE), Maceió, Brazil. (FERREIRA et al., 2015)

- Brant-Ribeiro, T., Mendonça, I. E. S., Araújo, R. D., Mendes, M. M., Dorça, F. A. and Cattelan, R. G. *Um Modelo Social e Colaborativo para Extensão de Conteúdo em Ambientes Educacionais Ubíquos.* Article published in the Tecnologias, Sociedade e Conhecimento journal, NIED. (BRANT-RIBEIRO et al., 2014)

- Carvalho, V., Dorça, F. A., Cattelan, R. G. and Araújo, R. D. *Uma Abordagem para Recomendação Automática e Dinâmica de Objetos de Aprendizagem Baseada em Estilos de Aprendizagem.* Full paper published at the XXV Brazilian Symposium on Informatics in Education (SBIE), Dourados, Brazil. (CARVALHO et al., 2014)

- Mendonça, I. E., Araújo, R. D., Mendes, M. M., Brant-Ribeiro, T., Dorça, F. A. and Cattelan, R. G. *Explorando Funcionalidades Sociais e Colaborativas em Ambientes Educacionais Ubíquos.* Full paper published at the XXV Brazilian Symposium on Informatics in Education (SBIE), Dourados, Brazil. (MENDONÇA et al., 2014)

- Resende, D. T., Dorça, F. A., Cattelan, R. G. and Araújo, R. D. *Em direção à recuperação automática de objetos de aprendizagem em repositórios através da associação dos estilos de aprendizagem de estudantes com metadados no padrão IEEE-LOM.* Full paper presented in the 6th Brazilian Workshop on Semantic Web and Education at the III CBIE, Dourados, Brazil. (RESENDE et al., 2014)

## 5.3 Limitations

Some limitations may be pointed out to the proposed approach. First, as our recommendation strategy depends on the variability of LOs, instructors should create different content types for presenting the same topic in order to provide students with different resource types that fit their profile. In addition, the courses are taught in Portuguese, thus the content is mainly created in one single language. Nevertheless, their metadata is entirely in English to comply with the IEEE-LOM, which makes it possible to use the metadata repository for research.

Besides that, activity history from previous instances of the courses is not taken into account in the bookmarking approach. In this sense, it relies on the active participation of users to refine the LO in each semester, although instructors could lead this activity, but that would take more effort from them.

Furthermore, users still need to manually provide some information, such as students' LS through the ILS, although exploratory studies about automatic approaches to collect them have been conducted, it is still an open question. Three contextual access information (location, reason, and available time) is also manually provided. In our studies, we have observed that it is makes students upset because they are asked to provide it every time they log into the system.

## 5.4 Future Work

As future work, machine learning techniques could be applied to improve different parts of this work. For instance, LOs metadata and its structure could be automatically identified or at least some automatic pre-processing could be performed. Furthermore, the LOs repository tends to grow more and more. Thus, designing intelligent algorithms to better organize the repository is a must that would be helpful for recommendation processes as well.

Additionally, the interactions repository may be used to identify individual differences using a data-driven approach in order to provide input data for refining the student model. Behavior patterns that lead to success or failure of the learning process could also be found to improve the individualized learning approach.

Moreover, it is interesting to design and integrate a *Learning Analytics* module to this infrastructure. It has the potential to provide support for an individualized interpretation of students' learning path, their difficulties and study characteristics as well as to monitor students' performance in detail, allowing instructors to identify possible learning gaps.

Regarding the personalization algorithm, it could consider other LOs metadata in addition to LS, such as difficulty level and prerequisites, in order to create a more robust approach towards the idea of ITSs.

The usability should be continuously improved. Some specific points, for example, while capturing contextual access information and while accessing a lecture were pointed out by students as elements that are causing displeasure.

Finally, the proposed approach may be used and evaluated in flipped classrooms scenarios in which interactive and annotated lessons are previously created by professors to allow students to access them before going to the classroom. In such scenarios, although classrooms become places to discuss advanced concepts and to solve practical problems, there is still a need to create LOs and provide mechanisms to personalize and recommend them individually.

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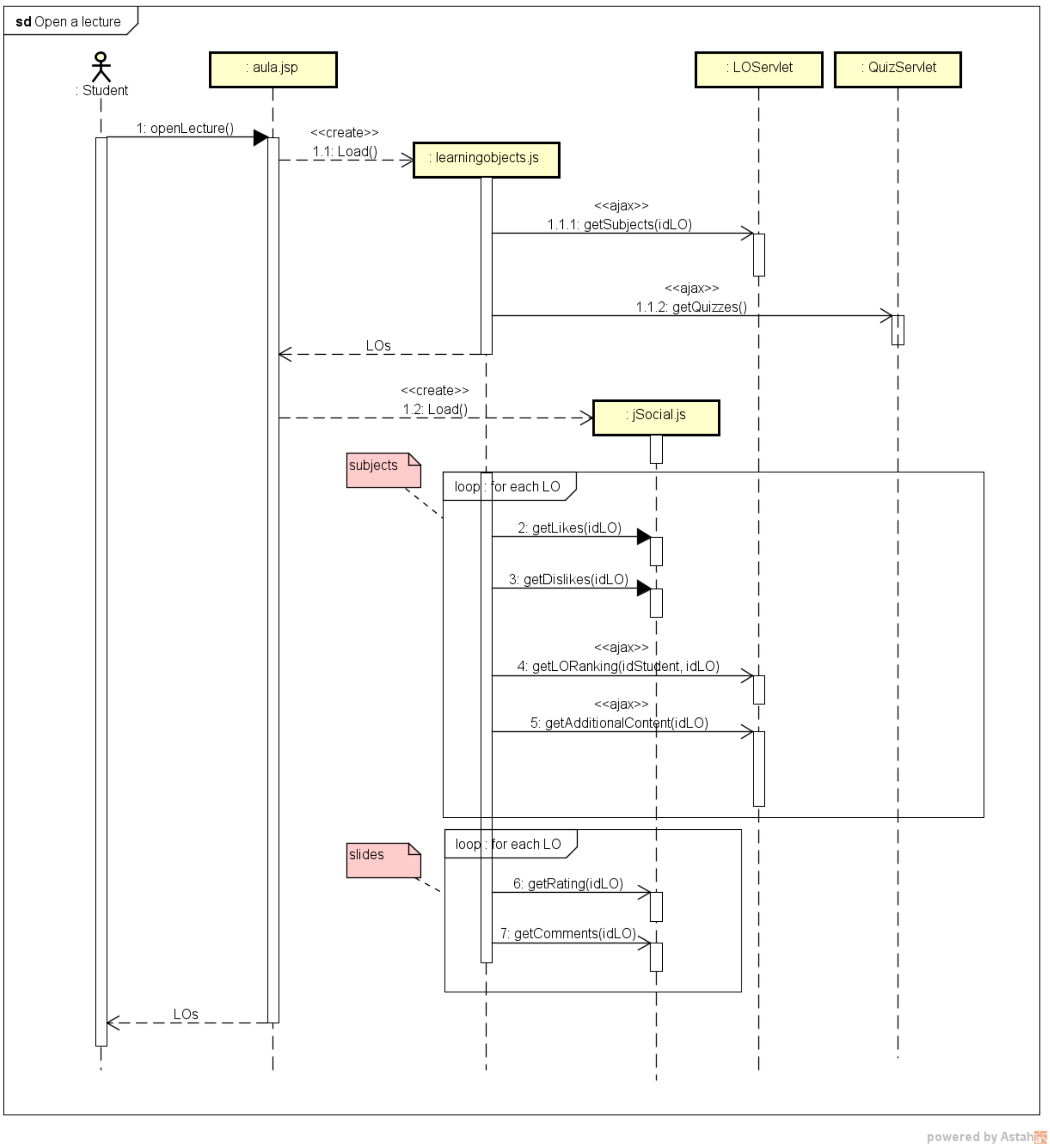
# Appendix

APPENDIX A

# Sequence diagram for opening a lecture

*This is a sequence diagram of the Unified Modeling Language (UML) (BOOCH; RUMBAUGH; JACOBSON, 2005) for opening a lecture. The gamification component is not shown in the diagram.*



# APPENDIX B

# Questionnaire P1

*This is the questionnaire, in Portuguese, used in phases I and III of the experiment 1 presented in Chapter 4, Section 4.1*

## Estudo sobre a funcionalidade "bookmarks (marcadores de tópicos)" do Sistema Classroom eXperience - P1

Bem-vindo(a)!

Este estudo aborda questões relativas à definição e utilização da funcionalidade de bookmarks (marcadores de tópicos) nas aulas disponibilizadas para estudo online.

Responda às questões abaixo com base na utilização do sistema Classroom eXperience (CX). Os resultados não serão identificados e serão utilizados apenas para propósitos de pesquisa.

Cada questão consiste de uma afirmativa, com a qual você pode ou não concordar marcando sua resposta em uma escala que vai de 1 - Discordo totalmente a 7 - Concordo totalmente. Valores intermediários expressam concordância/discordância parcial.

Obrigado por participar deste estudo!

*Obrigatório

Informe o e-mail utilizado para login no CX (essa informação será utilizada apenas para associar suas respostas ao seu perfil do CX e, posteriormente, será anonimizada para ser utilizada na pesquisa): *

Sua resposta

1. A definição de bookmarks é uma boa ferramenta para separar/dividir os diferentes conceitos/tópicos dentro de uma aula. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

2. Poder definir os bookmarks em uma aula fez com que eu entendesse melhor como os conceitos da aula se organizam e como a aula está estruturada. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

3. Tenho certeza que os bookmarks que defini estão corretos. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

4. Eu definitivamente utilizaria a funcionalidade para definir bookmarks nas aulas das disciplinas que estou matriculado. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

5. Eu criaria bookmarks em todas as aulas. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

6. Achei útil o recurso de auto-completar que sugere palavras quando estamos criando um novo bookmark. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

7. Na maioria das vezes em que apareceu essa opção de auto-completar, a sugestão feita pelo sistema foi a mesma que eu já estava pensando em digitar para o bookmark. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

8. Gostaria de poder definir uma hierarquia para os bookmarks, informando quando um bookmark é um subitem de outro. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

# APPENDIX C

# Questionnaire P2

*This is the questionnaire, in Portuguese, used in phase II of the experiment 1 presented in Chapter 4, section 4.1*

## Estudo sobre a funcionalidade "bookmarks (marcadores de tópicos)" do Sistema Classroom eXperience - P2

Bem-vindo(a)!

Este estudo aborda questões relativas à definição e utilização da funcionalidade de bookmarks (marcadores de tópicos) nas aulas disponibilizadas para estudo online.

Responda às questões abaixo com base na utilização do sistema Classroom eXperience (CX). Os resultados não serão identificados e serão utilizados apenas para propósitos de pesquisa.

Cada questão consiste de uma afirmativa, com a qual você pode ou não concordar marcando sua resposta em uma escala que vai de 1 - Discordo totalmente a 7 - Concordo totalmente. Valores intermediários expressam concordância/discordância parcial.

Obrigado por participar deste estudo!

*Obrigatório

Informe o e-mail utilizado para login no CX (essa informação será utilizada apenas para associar suas respostas ao seu perfil do CX e, posteriormente, será anonimizada para ser utilizada na pesquisa): *

Sua resposta

1. A definição de bookmarks é uma boa ferramenta para separar/dividir os diferentes conceitos/tópicos dentro de uma aula. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

2. Eu fui capaz de visualizar facilmente os bookmarks criados, quando eles existiam. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

3. Eu consegui navegar mais facilmente entre os diferentes conceitos na aula que possuia bookmarks. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

4. Na maioria das vezes, eu concordei com os bookmarks existentes e não os alteraria. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

5. Eu consegui entender a organização dos conceitos e a estrutura da aula que possuia bookmarks melhor do que na aula sem bookmarks. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

6. Gostaria que todas as aulas tivessem bookmarks. *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Concordo totalmente |

7. Defina o nível de dificuldade da "Aula 11 - Avaliação". *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Muito fácil | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Muito difícil |

8. Defina o nível de dificuldade da "Aula 12 - Análise de tarefas". *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Muito fácil | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Muito difícil |

# APPENDIX D

# User Experience Questionnaire

*This questionnaire includes qualitative questions to evaluate the user experience regarding frequency of use, utility and usability of the features used in the experiment presented in Chapter 4, Section 4.3. Note that the questionnaire language is Portuguese*

**Questionário de avaliação da plataforma Classroom eXperience (CX)**

1. Você utilizou o CX?
   - ☐ Sim, muitas vezes (neste caso, pular a questão 2)
   - ☐ Sim, poucas vezes
   - ☐ Não

2. Por que você NÃO utilizou ou utilizou o CX poucas vezes?

| | Discordo totalmente | | | | | | Concordo totalmente |
|---|---|---|---|---|---|---|---|
| 2.1. A ferramenta não foi apresentada em detalhes em sala de aula | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2.2. Eu preferi utilizar outros materiais da internet para aprender | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2.3. Eu achei que o CX não me ajudaria a entender o conteúdo | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2.4. Eu achei que o conteúdo apresentado em sala de aula foi suficiente | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 2.5. Eu preferi estudar por livros e materiais impressos | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

2.6. Outros:

________________________________________

________________________________________

________________________________________

3. Sobre a usabilidade do CX:

| | Discordo totalmente | | | | | | Concordo totalmente |
|---|---|---|---|---|---|---|---|
| 3.1. Consegui acessar as aulas sem dificuldade | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 3.2. No geral, achei fácil utilizar o CX | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 3.3. Aprendi rapidamente como utilizar o CX | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 3.4. A navegação no CX foi clara | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 3.5. No geral, eu gostei da interface do CX | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

| | Discordo totalmente | | | | | | Concordo totalmente |
|---|---|---|---|---|---|---|---|
| 4. Sobre a frequência de estudo, eu costumava a acessar o CX: | | | | | | | |
| 4.1. Para estudos imediatamente antes de cada aula | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4.2. Para estudos logo após cada aula ministrada | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4.3. Para estudos a cada 1 ou 2 semanas de aulas ministradas | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4.4. Para estudos a cada 3 ou 4 semanas de aulas ministradas | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 4.5. Somente antes das avaliações | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

| | Discordo totalmente | | | | | | Concordo totalmente |
|---|---|---|---|---|---|---|---|
| 5. Com relação à percepção de utilidade: | | | | | | | |
| 5.1. Achei útil utilizar o CX para estudos fora da sala de aula | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5.2. Acessar o CX para estudos após a aula me ajudou a fixar o conteúdo ministrado | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5.3. A interface do CX me ajudou a entender a estrutura de cada aula | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5.4. A funcionalidade de **criar bookmarks** e dividir a aula em diferentes assuntos influenciou positivamente a minha aprendizagem na disciplina | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5.5. A possibilidade de **criar comentários** para cada slide influenciou positivamente a minha aprendizagem na disciplina | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5.6. A funcionalidade de **classificação em estrelas** dos slides influenciou positivamente a minha aprendizagem na disciplina | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5.7. A funcionalidade de **visualização de desempenho** por meio de gráficos influenciou positivamente a minha aprendizagem na disciplina | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5.8. A funcionalidade de **quizzes** influenciou positivamente a minha aprendizagem na disciplina | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5.9. A funcionalidade de **gamificação** (ranking de pontuação e quadro de medalhas) influenciou positivamente a minha aprendizagem na disciplina | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 5.10. Eu gostaria que o CX fosse utilizado em outras disciplinas. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

| | Discordo totalmente | | | | | | Concordo totalmente |
|---|---|---|---|---|---|---|---|
| 6. Ao comparar o CX com o Moodle, você gostaria que: | | | | | | | |
| 6.1. O CX fosse utilizado no lugar do Moodle | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 6.2. O CX fosse utilizado juntamente com o Moodle | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 6.3. Eu prefiro utilizar apenas o Moodle | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

| | Discordo totalmente | | | | | | Concordo totalmente |
|---|---|---|---|---|---|---|---|
| 7. Sobre seu comportamento de estudos: | | | | | | | |
| 7.1. O CX me ajudou a identificar meus pontos fracos | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7.2. O CX me ajudou a planejar meus estudos | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

| | Pouco | | | | | | Muito |
|---|---|---|---|---|---|---|---|
| Como o CX mudou a forma de você estudar? | | | | | | | |
| 7.3. Frequência de estudo | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7.4. Colaboração com colegas | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7.5. Motivação para estudo | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7.6. Competitividade | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7.7. Procura por material extra | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Como os gráficos de desempenho mudaram a sua forma de você estudar?

| | Pouco | | | | | | Muito |
|---|---|---|---|---|---|---|---|
| 7.8. Motivação para estudo | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7.9. Necessidade de melhora no desempenho | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| 7.10. Competitividade | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

8. Alguma situação específica durante a utilização do CX em que houve uma contribuição positiva para seu aprendizado?

______________________________________________________________________________

______________________________________________________________________________

______________________________________________________________________________

9. Alguma situação específica durante a utilização do CX em que houve uma contribuição negativa para seu aprendizado?

______________________________________________________________________________

______________________________________________________________________________

______________________________________________________________________________

10. Você gostou da reordenação dos slides apresentados pelo sistema?
    - ☐ Sim
    - ☐ Não
    - ☐ Não percebi

    10.1. Quanto essa funcionalidade impactou positivamente a sua aprendizagem na disciplina? Pouco ○ ○ ○ ○ ○ ○ ○ Muito

11. Você gostou da visualização de desempenho por meio de gráficos apresentados pelo sistema?
    - ☐ Sim
    - ☐ Não
    - ☐ Não percebi

Para as questões 11.1 e 11.2, considere os seguintes gráficos:

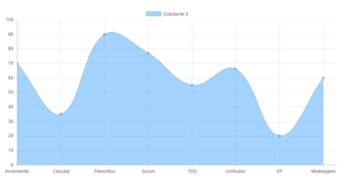


Gráfico de Linha

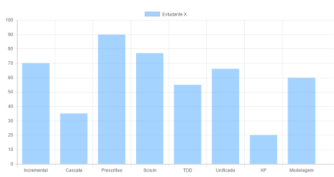


Gráfico de Barra

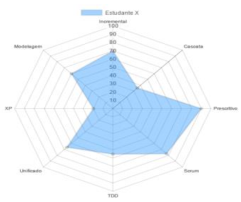


Gráfico de Radar

11.1. Qual tipo de gráfico você prefere para visualizar seu rendimento?
☐ Linha ☐ Barra ☐ Radar

11.2. Qual tipo de gráfico você prefere para visualizar seu rendimento com relação à média da turma?
☐ Linha ☐ Barra ☐ Radar

| | Discordo totalmente | | | | | | Concordo totalmente |
|---|---|---|---|---|---|---|---|
| 11.3. A comparação do meu desempenho com a média da turma influenciou positivamente a minha aprendizagem na disciplina | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

12. Liste até 3 funcionalidades/características que você mais gostou no CX.

________________________________________

________________________________________

________________________________________

13. Liste até 3 funcionalidades/características que você NÃO gostou no CX.

________________________________________

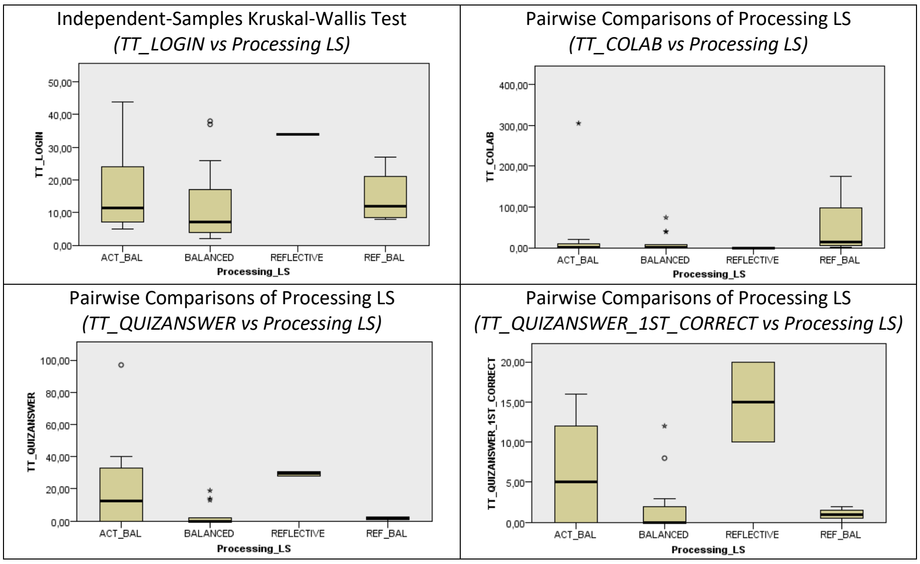
________________________________________

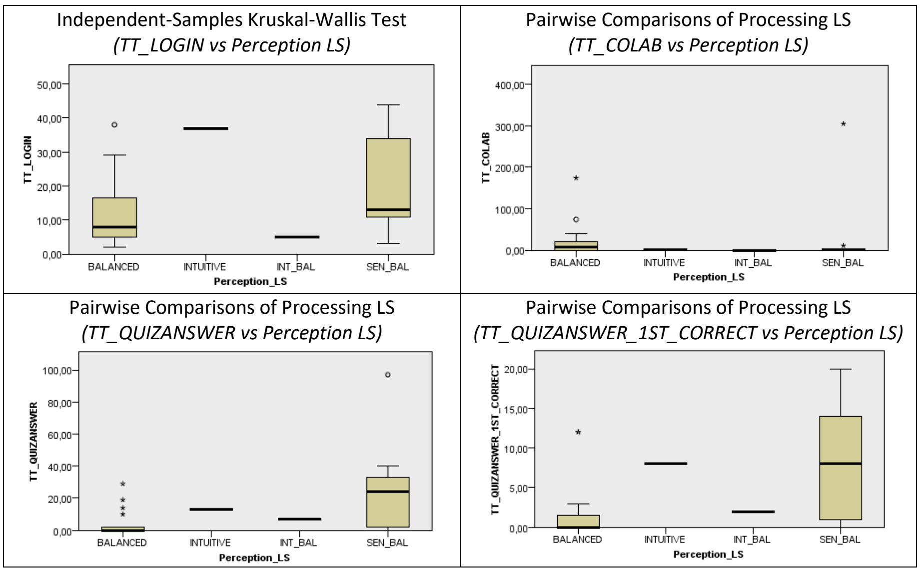
________________________________________

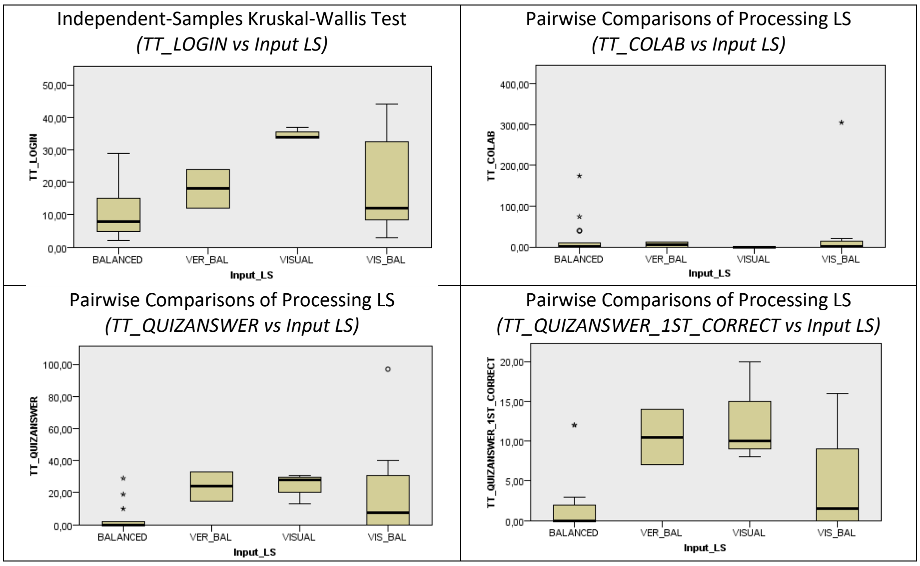
# APPENDIX E

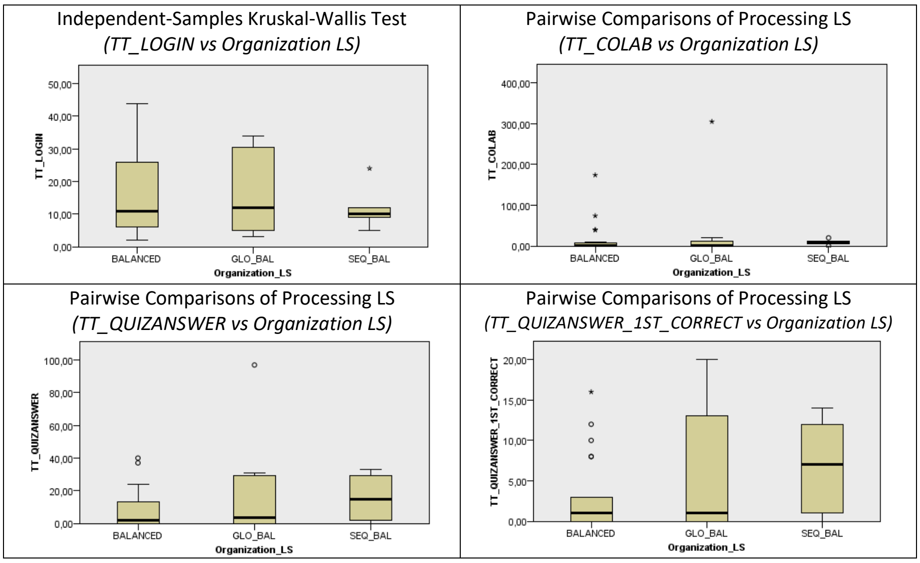
# Further Analysis

*This appendix presents some extra analyzes for the experiment presented in Chapter 4, Section 4.3.*




Independent-Samples Kruskal-Wallis Test
(TT_LOGIN vs Input LS)
TT_LOGIN
Input_LS
BALANCED
VER_BAL
VISUAL
VIS_BAL
Pairwise Comparisons of Processing LS
(TT_COLAB vs Input LS)
TT_COLAB
Input_LS
Pairwise Comparisons of Processing LS
(TT_QUIZANSWER vs Input LS)
TT_QUIZANSWER
Input_LS
Pairwise Comparisons of Processing LS
(TT_QUIZANSWER_1ST_CORRECT vs Input LS)
TT_QUIZANSWER_1ST_CORRECT
Input_LS


Independent-Samples Kruskal-Wallis Test
(TT_LOGIN vs Organization LS)
TT_LOGIN
Organization_LS
BALANCED
GLO_BAL
SEQ_BAL
Pairwise Comparisons of Processing LS
(TT_COLAB vs Organization LS)
TT_COLAB
Organization_LS
Pairwise Comparisons of Processing LS
(TT_QUIZANSWER vs Organization LS)
TT_QUIZANSWER
Organization_LS
Pairwise Comparisons of Processing LS
(TT_QUIZANSWER_1ST_CORRECT vs Organization LS)
TT_QUIZANSWER_1ST_CORRECT
Organization_LS

# APPENDIX F

# CX-LOR

*This appendix presents some elements of the CX-LOR.*


```
  <?xml version="1.0" encoding="UTF-8"?>
- <lom>
  - <general>
        <id>13958</id>
        <title>Aula 11 - Avaliação de usabilidade</title>
        <language>pt-BR</language>
        <description/>
        <keyword>avaliação heurística</keyword>
        <keyword> think aloud</keyword>
        <keyword> percurso cognitivo</keyword>
        <keyword> codescoberta</keyword>
        <keyword> coaching usability</keyword>
        <structure>linear</structure>
        <aggregationlevel>2</aggregationlevel>
    </general>
  - <lifecycle>
        <version>1.0</version>
        <status>final</status>
      - <contribute>
            <entity>BEGIN:VCARD FN:Renan Cattelan TITLE:professor EMAIL\;TYPE=INTERNET:Renan END:VCARD</entity>
            <role>author</role>
            <date>2016-10-05</date>
        </contribute>
    </lifecycle>
  - <technical>
        <format>image/jpeg</format>
        <format>text/html</format>
        <size>13788632</size>
        <location>aula11.zip</location>
        <duration>4992</duration>
    </technical>
  - <educational>
        <interactivitytype>mixed</interactivitytype>
        <learningresourcetype>figure</learningresourcetype>
        <learningresourcetype>table</learningresourcetype>
        <learningresourcetype>narrative text</learningresourcetype>
        <learningresourcetype>lecture</learningresourcetype>
        <interactivitylevel>average</interactivitylevel>
        <semanticdensity>high</semanticdensity>
        <intendedenduserrole>learner</intendedenduserrole>
        <context>higher education</context>
        <typicalagerange>17-</typicalagerange>
        <difficulty>medium</difficulty>
        <language>pt-BR</language>
    </educational>
  - <rights>
        <cost>no</cost>
        <copyright>yes</copyright>
        <description>All rights reserved to UbiMedia@UFU</description>
    </rights>
  </lom>
```


Figure 37 – IEEE-LOM example.

**Action: Search LOs**
Returns: an array of JSON objects containing the LOM ID and LO title.

POST cx.facom.ufu.br/cxlor

```
dataType: "json"
contentType: "application/json; charset=utf-8"

{
   "act": "search",
   "secretKey": "",
   "searchFields": [
      "fieldName": "",
      "fieldValue": "",
      "connector": ""
   ]
}
```

"fieldName": IEEE-LOM field name, including its category.
"fieldValue": string value for the search field.
"connector": choose between "and" or "or".

```
returns:
[
   {
      "id": "",
      "title": "",
   }
]
```

Figure 38 – Definition of the "Search LOs" action in the CX-LOR API.

**Action: Get LOM**
Returns: IEEE-LOM fields in an XML file.

GET cx.facom.ufu.br/cxlor

```
parameters:
   ?act=getlom
   &secretKey=
   &idlom=
```

Figure 39 – Definition of the "Get LOM" action in the CX-LOR API.

**Action: Get many LOM in a ZIP file**
Returns: a .ZIP file containing many XML files (IEEE-LOM).

GET cx.facom.ufu.br/cxlor

```
parameters:
   ?act=getzip
   &secretKey=
   &ids=

   ids: list of IDs separated by a comma.
```

Figure 40 – Definition of the “Get many LOM” action in the CX-LOR API.

**Action: Get LO**
Returns: a .ZIP file with the LO content.

GET cx.facom.ufu.br/cxlor

```
parameters:
   ?act=getlo
   &secretKey=
   &idlom=
```

Figure 41 – Definition of the “Get LO” action in the CX-LOR API.

# Annex

ANNEX **A**

# ILS Certification

*This is the certification of intention to use the Index of Learning Styles for research purposes that was sent to Dr. Richard Felder in November 19th, 2015.*

**CERTIFICATION OF INTENTION TO USE THE *INDEX OF LEARNING STYLES* FOR EDUCATIONAL OR RESEARCH PURPOSES AT NO COST TO USERS**

I certify that:

- I am affiliated with an educational institution and plan to administer the Index of Learning Styles only as part of my teaching, advising, staff development, and/or research activities with that institution.
- I will not charge a fee to anyone who completes the questionnaire under my direction or the direction of anyone working with me.
- I will keep the response sheet with the scoring key for the instrument strictly confidential. I will not share copies of it with anyone not directly involved with administering the instrument, and I will collect completed copies from everyone who takes the instrument.

Signature: Rafael Dias Araújo

Name: Rafael Dias Araújo

Institution: Federal University of Uberlândia, Brazil / University of Pittsburgh, USA

Email: rdaraujox@gmail.com

Please email the signed form to rmfelder@mindspring.com

or mail it to

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