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ORIGINAL ARTICLE

A model for learning objects adaptation in light of mobile and context-aware computing

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Abstract The growth usage of mobile technologies and devices such as smartphones and tablets, and the almost ubiquitous wireless communication set the stage for the development of novel kinds of applications. One possibility is exploiting this scenario in the field of education, so creating more intelligent, flexible and customizable systems. Mobile devices can be used to help students to learn, considering their learning styles, surroundings, devices and profiles. In this way, the main goal of this article is to propose EduAdapt, an architectural model for the adaptation of learning objects considering device characteristics, learning style and other student's context information. To make this adaptation we used inferences and rules in a proposed ontology, named OntoAdapt. We believe that such ontology can help recommending learning objects to students or adapt these objects according to the context (context-aware computing). We evaluate this proposal in two ways. Firstly, we used scenarios and metrics to assess the ontology. Secondly, we developed a prototype of EduAdapt model and submitted to a class of 20 students with the intention of evaluating the usability and adherence to adapted objects, resulting in a 78 % of acceptance. In brief, the evaluation presented encouraging results, indicating that the proposed model would be useful in the learning process.

Keywords Learning style · Dynamic adaptation · e-learning · Mobile computing · Context awareness · Ubiquitous learning

1 Introduction

The constant evolution of mobile devices, nowadays in the form of tablets and smartphones, along with the pervasive connectivity to the Internet, allows teachers and students to access information and educational materials anywhere and at anytime [37]. This perspective, which has been called *Mobile Learning* [20], gives the possibility to provide contents to learners without the need to be in a school environment. Another close related concept is *Ubiquitous Learning*, in which the learning process can occur everywhere integrated with people daily lives [37]. Furthermore, in the learning environment we could explore context awareness, adapting this learning to the users' needs and surroundings [5]. Among the different context data that we could explore in a mobile learning environment, we highlight network infrastructure, hardware capabilities, and learners preferences and styles [34].

Educational contents are numerous and consist of assorted types of media such as videos, audios, and presentations, among others. Some of these learning objects (LOs) [23] are built for fixed devices (typically desktop with fast Internet access), hindering their use on mobile devices. Among the issues that may arise are processing power, intermittent Internet access, network latency, screen

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size and resolution, storage capacity and file type supported. To address this diversity, we could use adaptation [26], automatically modifying learning objects to meet these assorted characteristics. Particularly, we could tailor the learning objects to user preferences and learning capability [12, 28]. For instance, if a learner style is more visual than verbal, we could present the contents in diagrams and use more images and videos, improving his/her satisfaction and increasing interest.

We believe that the strengths of virtual learning systems, targeted at mobile devices, can be improved by mingling context awareness with content adaptation. The context awareness is formed by data regarding users and their surroundings, such as location data, learning objective, knowledge history and preferences, among others. Content adaptation, accordingly, can personalize the learning object to meet this context. For example, consider the following scenario: a learner, driving her car to the University, may need information regarding the course in which she will have an examination in a few minutes. An application in her mobile phone, using context awareness, can suggest a learning object related to the examination. Since the learner is current driving, the object can be adapted to audible format and transmitted via Bluetooth to the car sound system.

Concerning the adaptive systems scope, there is a trend on using ontology to promote adaptive services directed to education [38]. The ontology works in the adaptive system (will be described throughout this paper) like an interaction model between the learner's contexts and the content provided. In this way, ontology can enable rich and better-adapted information to the learner, because of web semantics can explore automatic reasoning using computational tools.

In this article, we propose a model named *EduAdapt*, which uses students' context to adapt learning objects in a way that helps their learning. We try to answer the following problem statement in our research: *Considering the students' context, including their learning styles, surroundings and characteristics of the mobile device used, how could be an ontology based model for adapting learning objects that reach the level of user satisfaction?* To answer this question, the proposed model has to deal with the required adaptations to change the learning objects, including their format and scale, to better adjust them to the student's context. Particularly, we want to investigate whether the use of ontology is suited to the scope of learning objects adaptation. Besides, we want to look into the possibility of developing a prototype, for mobile devices, which incorporate the main model features: using public repositories of learning objects; integrating with learning management systems; adapting objects according to context-aware data, including learning style, device characteristics and surrounding information, such as movement and connection speed.

One of the main contributions of this model is the development of an ontology that describes context, learner profile, learning style and device characteristics. Our aim is to employ the proposed ontology, named *OntoAdapt*, as the core of a mobile learning environment, which can adapt contents considering context-aware information. The idea of proposing an ontology is to semantically represent the mobile learning-related concepts, as well as providing a mechanism that assists in the inferences of learning objects appropriate for the learner. Different from related works, our proposal focuses on context and content, both targeted at mobile learning. OntoAdapt has four main groups of information regarding the learner, learning objects, devices and context. In the process of developing this work, we did not find an ontology suited to this task. Although there is some propositions in the literature [11, 17, 30, 38], these cases were not available to be further extended or reused. Furthermore, in the process of developed the ontology, we reused parts of other four well-known ontologies in their specific domain.

The evaluation of EduAdapt is twofold. Firstly, we assess the ontology considering some user scenarios and evaluation metrics. Here, the employed metrics are used to compare our proposal with a reference ontology, i.e., a golden standard, also defining it in terms of coverage and as counters and statistics about the expressiveness of the language. To accomplish this, we are following the proposition described in *FOEval* [4]. Secondly, we developed a prototype for Apple iOS mobile devices. We used this prototype in an undergraduate course aiming at trying to answer the proposed research question, empirically measuring the level of user satisfaction. We employed a survey, based on the works of [9, 32], composed of ten statements with answers in the Likert scale [21]. We also evaluated the reliability of this survey using the Cronbach alpha approach [15].

The remainder of this article will first describe the methodology used to build the ontology in Sect. 2. The details of OntoAdapt ontology appear in Sect. 3. Both EduAdapt model and its implementation are shown in Sect. 4. Section 5 relates the evaluation of the EduAdapt model, discussing its strengths and weaknesses properly. Section 6 presents related works. Finally, Sect. 7 emphasizes the main conclusions and notes some challenges that we can address in the future.

2 Methodology for developing OntoAdapt

This section describes some aspects of the methodology used to create the OntoAdapt ontology. The methodology is summarized in Fig. 1. We are basing OntoAdapt

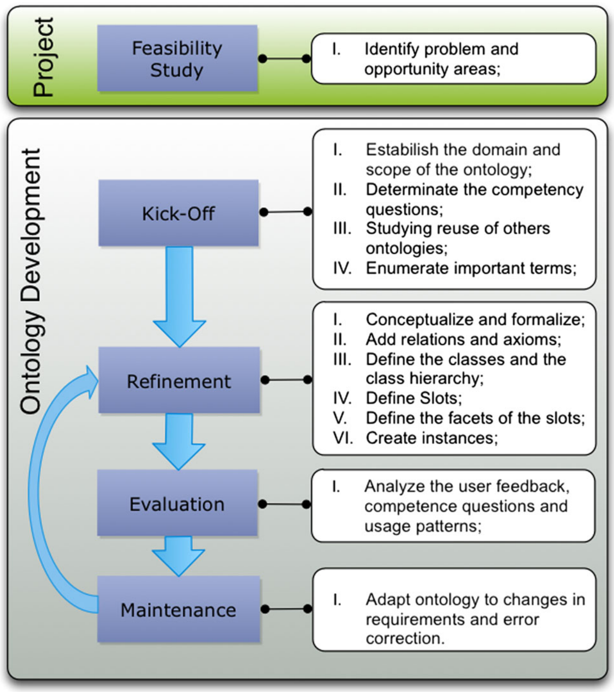


Fig. 1 Methodology used for developing OntoAdapt ontology: a combination of [24, 33] approaches

development in two other works. The first focused on designing an ontology in relation to structural classes, attributes and individuals [24]. The second presented an organization method for projecting an ontology [33]. We can benefit from the strengths of each proposal by merging both methodologies. The final result is a framework for guiding the organization, specification and design of ontologies.

The process for building the ontology was divided into five stages. As depicted in Fig. 1, the process starts with the *Feasibility Study*. In this stage we establish reasons for building a new ontology based on identified problems and opportunities. This stage consists of justifying the need for projecting a new ontology. The next stage initiates the development process. The *Kick-Off* stage comprises the clear definition of both the aim and the scope of the ontology. Based on that, we list some competence questions that the ontology should answer. Furthermore, in this stage we start the list of major terms and consider the reuse of other existing solutions. The *Refinement* stage, in its turn, structures the information generated in the previous stage in the form of an ontology structure. This stage defines classes, their relationships, slots, facets and some instances. Normally, the use of a software for modeling the ontology is recommended in this point. Thus, we are employing Protégé[1] in the scope of this work.

After modeling the ontology, at stage *Evaluation*, we perform some assessments to determine whether the created ontology satisfies the conditions defined in the early stages. Furthermore, we consider user feedback and usage patterns to revaluate the competence questions. To evaluate the built ontology, we use tools that verify the integrity of the issues addressed and the consistency of the data presented in the ontology. The techniques are based on the model FOEval [4] and the metrics provided by the software Protégé. Finally, the *Maintenance* stage aims at changing the ontology to reflect either changes or corrections that may occur throughout its lifetime. Considering the changes that ontologies may need, identified in this stage, it is essential to iterate again from the refinement and evaluation stages.

Using all aforementioned described stages, we developed an ontology that in our view is appropriate for supporting learning objects adaptation in mobile and context-aware computing. The next section details the results of applying this methodology on the development of OntoAdapt.

3 Ontology proposal

The proposed ontology for adaptation of learning objects takes into account four broad groups of information (also called domain ontologies [18]). We present a general view of the main groups of information in Fig. 2. First, we have information regarding the *Student*, including personal data, preferences, profile and academic background. Second, the group *LO* stores information with reference to learning objects, including their contents, domains, types and related evaluation. *Device* constitutes the third general group, dealing with device characteristics used by the learner. Finally, the *Context* group makes relations between the surrounding of the learners, with respect to the environment in which they are currently located, and the educational context that can be extracted from Learning Management Systems (LMS) such as Moodle®.[2]

Figures 3, 4, 5 and 6 illustrate the concepts covered by the OntoAdapt ontology. Each concept is covered in a particular subsection. These figures were developed based on the diagrams proposed by Henze et al. [18]. In the diagrams, the classes filled with orange background depict concepts imported from external ontologies.

3.1 Student

We need to know information about the learner, i.e., the student, in order to offer adaptation. This includes the

[1] http://protege.stanford.edu.

[2] http://moodle.com.

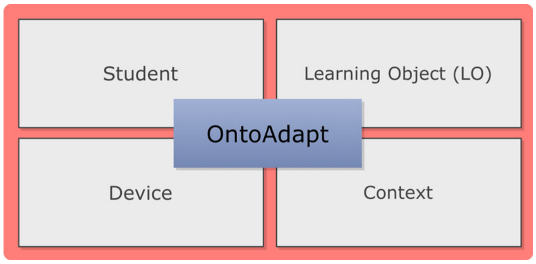


Fig. 2 OntoAdapt general view

current surroundings, enrolled course, history (including previous interactions) and preferences (user profile). Figure 3 summarizes the main classes and relations. *Student* class is based on the Friend of a Friend Ontology (FOAF)[3] and incorporates its classes and relations. The use of FOAF enables to build relations between people and information using the web. The FOAF information that is most important for OntoAdapt is personal information such as name, interests, directions and friends.

The property *hasLearningStyle* allows to represent the learning style, due to composition of different elements in the *Learning Style*, based on [12]. Thus, the learning style is captured through the Index of Learning Style (ILS).[4] The ILS, created by Felder and Soloman, can be seen as a questionnaire based on a web platform to evaluate the learner preferences. The questionnaire is divided into 44 questions classified according to the way the learner captures information. The classification consists of four dimensions with 11 items each: Active/Reflective, Sensing/Intuitive, Visual/Verbal or Sequential/Global. The four dimensions can be summarized as follows [12]:

- Active and Reflective: Active Learners tend to retain and understand best by doing something, while Reflective Learners prefer to think about it quietly first;
- Sensing and Intuitive: Sensing Learners tend to like learning facts, although Intuitive Learners prefer to discover possibilities and relationships about the facts;
- Visual and Verbal: Visual learners remember best when see pictures, flowcharts, films and demonstrations. However, Verbal Learners get more out of words, written and spoken explanations;
- Sequential and Global: Sequential learners tend to gain understanding in linear steps, where each step follows logically from the previous one. Nevertheless, Global learners tend to understand in large jumps, absorbing material almost randomly without seeing connections, and then suddenly integrating the main idea.

Considering the state of the art on the ontologies area, it is observable that there are other proposals for measuring learning style. We choose the Felder–Silverman approach because it is widely used by the academic community, as can be seen in [2]. These dimensions are used in OntoAdapt to help adapting or choosing the appropriate LO to each learner. Finally, we added the relation between *Device* and *Context* classes, which is described in the following sections in detail.

3.2 Device

Here, we are presenting the *Device* class for adaptation purposes. In other words, we need to know the characteristics of learners' mobile devices to adapt content for them. In this way, we can map the current available features and consider them in customizing the content. Figure 4 depicts the main classes and relations regarding *Device*. Firstly, we establish a relation between *Device* and *Student* classes. The main class describes the characteristics of the device, including information about hardware, software and communication capabilities such as the version and kind of the operation system, screen size and network connections.

Hardware specifications are stored in the *Device* class. The *DeviceNetConnection* property stores the main interfaces available in the device such as Internet connectivity (via WiFi or cellular network), bandwidth and other available interfaces (such as Bluetooth and NFC). The property *hasMidiaType* stores the media supported by the device. Finally, *DeviceType* property stores data related to the type of the user device.

3.3 Context

The *Context* class specifies the user surroundings (see Fig. 5). We have reused *CoBrA* [8], an ontology that defines a set of vocabularies for describing places, events, people and presentation events. Here, we are only using the representation of *Place*. This class includes some properties such as latitude, longitude and *hasPrettyName* property to indicate location. In addition, OntoAdapt added the class named *Activity* for storing the kind of activity that the user is engaged at a specific time.

OntoAdapt models two kinds of activities: *ActivityRunning* and *ActivityStationary*. The former is employed when the user is running or in movement, while the second is used when the user is immobile. Through these definitions the system can offer audible LO for when the learner is in movement or visible LO for when the learner is stationary.

[3] http://www.foaf-project.org.

[4] http://www.engr.ncsu.edu/learningstyles/ilsweb.html.

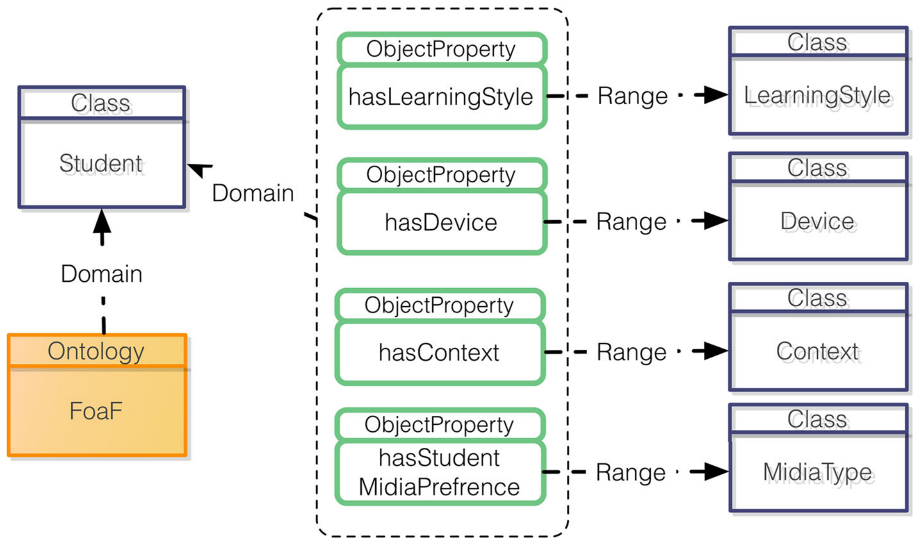


Fig. 3 Ontology describing the Student class

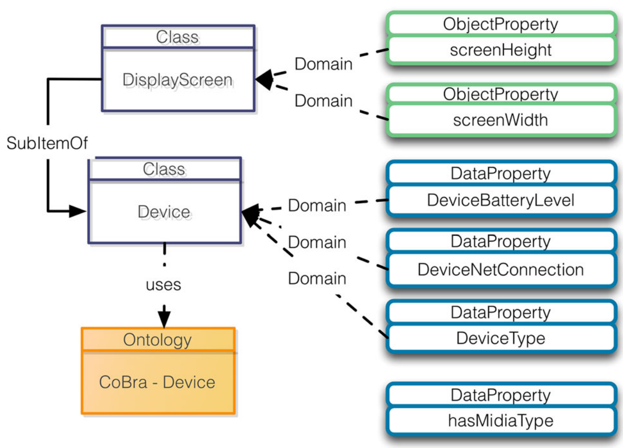


Fig. 4 Ontology describing user devices

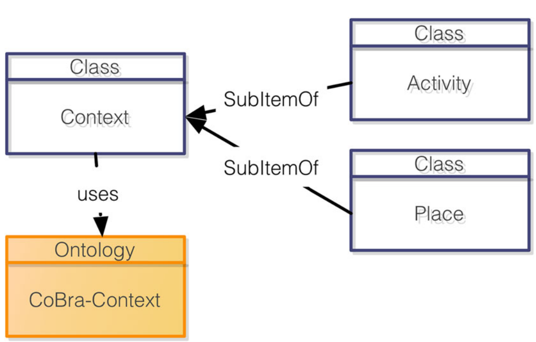


Fig. 5 Ontology describing user context

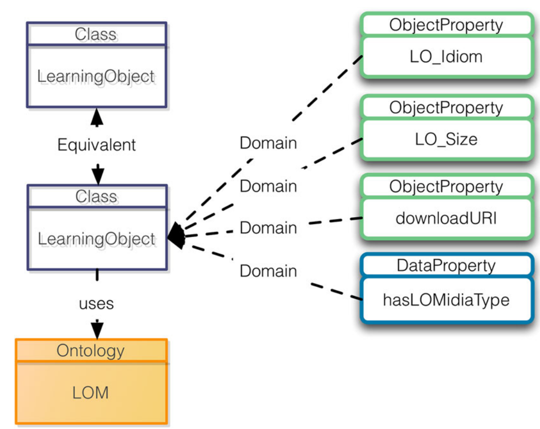


Fig. 6 Ontology to describe learning objects

3.4 Learning object

We must model and represent the learning objects in order to choose and adapt the most appropriate content to a learner. Figure 6 shows the main classes to represent this idea. One of the main initiatives to make standards to learning objects is the Learning Object Metadata (LOM) [11], which comes from the Learning Technology Standard Committee of Institute of Electrical and Electronic Engineers (IEEE). The LOM data model specifies aspects of a learning object to guarantee that the content from one platform can be used in another platform [6]. Considering that this eases interoperability, here we are reusing LOM ontology in the OntoAdapt context. We added some properties for helping the adapt process in the OntoAdapt ontology. *LO_Idiom* stores the idiom of an LO; *LO_Size* stores the size of the learning object; *downloadURI* refers to a place that the LO is located in a public or local repository and, finally, *hasLOMidiaType* is the property that stores the media kind of the LO.

4 EduAdapt model and implementation

The EduAdapt model provides learning object adaptation considering the student profile and other student-related context information, such as location, time and device characteristics. Regarding the learner profile, we considered a user model that comprehends knowledge, interests, objectives, individual characteristics and environment [7]. The EduAdapt model is a software architecture that provides services to ubiquitous computing environments helping the learning. Figure 7 illustrates the proposed architecture.

The EduAdapt architecture has four main components that communicate in order to capture and analyze context, resulting in the delivery of an adapted LO. First, the student must be engaged in some LMS, such as Moodle, and using a specific community related to a course. Letter "A" in Fig. 7 shows the connection of EduAdapt to this LMS. This integration allows the identification of student needs, stored in a correspondent module in this component, using the LMS logs, which stores all the actions of the student in the LMS. These data help searching keywords, for instance in forum messages or chats, to indicate possible doubts or needs that a student could have about a specific subject. With the identification of those keywords, we choose LOs with matching metadata identifying the main subject.

Once detected the student needs, EduAdapt chooses an LO that matches this necessity. For that, we need access to a repository of learning objects. The more LOs we have access in this phase, the better we can select. For that purpose, in EduAdapt model we created an integration with various LO repositories. In Fig. 7 we represent this integration in the component identified with the letter "B." We used the *OAI-PMH* protocol [22] to obtain LO metadata, offering more content to the learners.

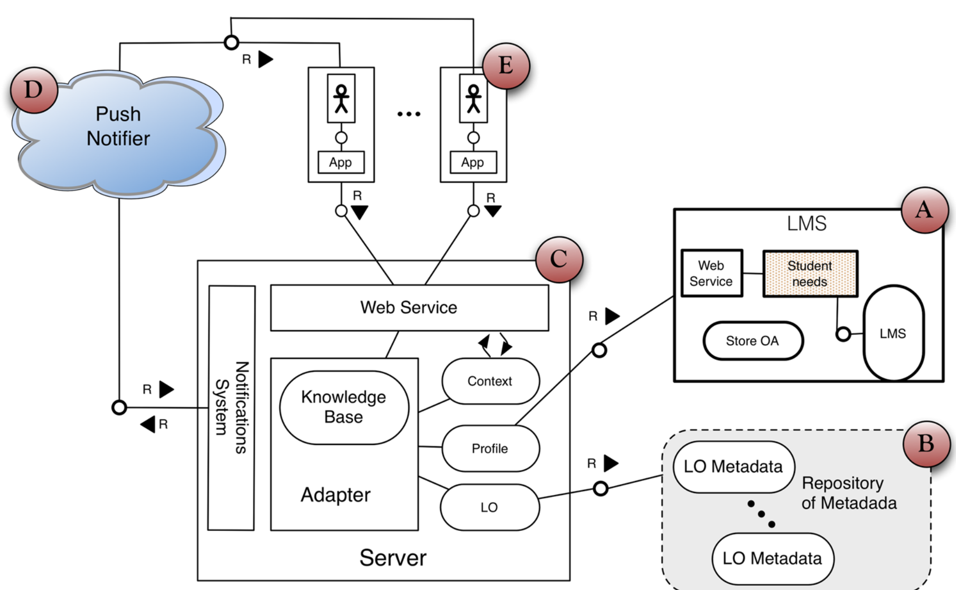
After detecting the student needs, and having the options of educational content that match those needs, the server sends a notification (using the module notification system in component "C" of Fig. 7). This notification follows the unidirectional flow presented in Fig. 8. A message is prepared in the server and sent to the Push Notifier Service, PNS (component "D"), which sends the notification to the application installed in a mobile device.

When receiving a notification, the client App (symbolized by letter "E" in Fig. 7) collects data regarding learners' context and their preferences. This information is sent to the server via Web Services to be used afterward with the OntoAdapt ontology to choose and adapt the LO properly. Using rules and inferences, the server determines the best LO to be sent to the student and, if necessary, adapts to a proper media type or format. Finally, the client app is notified to present the adapted LO to the student. Aiming at summarizing these steps, Fig. 9 shows a general view of the LOs adaptation process in EduAdapt. This process is detailed in the next subsection.

4.1 EduAdapt adaptation process

The adaptation process starts in the client, by gathering the current learning context. This information consists of the device characteristics, including the device model, the battery level, available storage capacity, screen size and operating system version. This information is useful to choose de appropriate LO according to devices limitations, such as screen size and multimedia capabilities. Besides these characteristics, the client sends information regarding

Fig. 7 EduAdapt architecture



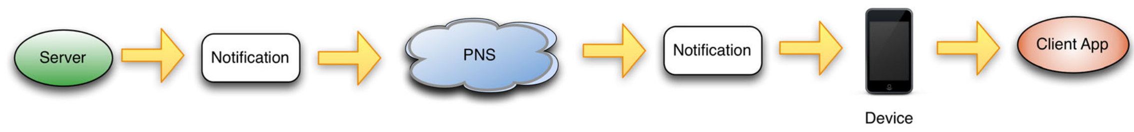


Fig. 8 Push notification flow

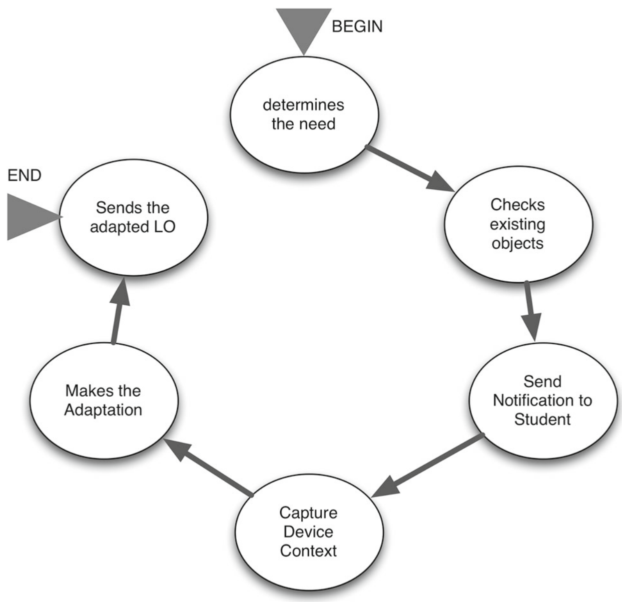


Fig. 9 General view of LO adaptation process in EduAdapt

the connection: network signal strength and type of connection (3G, 4G, WiFi, etc.). Finally, there is a group of data related to the user, including whether the user is stationary or in movement and the current location.

The server receives these data from the client and stores in the ontology. Previous stored is the learner profile are the following data: courses in which the student is currently engaged; keywords related to the subject being discussed at this time in the course; student's learning style; native language and additional languages that the student speaks; needs/doubts identified in the LMS; student basic registered data (name, area, semester, etc).

With these informations, a reasoner is used along with some predefined rules, as will be exemplified in the first evaluation (Sect. 5.2), to find the appropriate subject in the ontology that the LO should cover. This result is then used to find an appropriate learning object in the LOs repositories using the Learning Object Metadata (LOM). Requests in HTTTP format using the OAI-PMH[5] protocol allow metadata harvesting in this repositories. The return is a XML document containing metadata of LOs that match the query.

Once a LO is chosen, two types of adaptations can occur: scale and format. Scale adaptation consists in altering the resolution of the learning object that has been processed. This technique is used in adapting videos and images to suit them to devices characteristics. Furthermore, some HTML 5 LOs need some adaptation in the size of their content for a better visualization according to the device's screen size. The HTML 5 meta tag viewport allows the device to know how content should fit on its screen. This property is used by the browser to optimize the object to the device's screen.

On the other hand, format adaptation occurs when the LO has a document not supported by the device or not compatible with the learning style or the current situation. This consists in a conversion of formats. Among the possible conversions provided we can highlight:

- Text converter: from one format to another, including TXT, HTML, RTF, RTFD, DOC, DOCX, WORDML, ODT, WEBARCHIVE and PDF;
- Text to audio: use of text to speech tools, converting an text file to an audio file (MP3 format);
- Diagram converter: conversion from text file to a diagram;[6]
- Video to audio: this conversion consisting in extracting the audio track of a video, generating an audio file in MP3 format;
- Wiki converter: converts documents to Wiki format. Currently the supported formats are HTML, Plain Text, DOC and DOCX;

After choosing and adapting the LO, the server sends it to the client for presentation to the learner. The next subsection covers the prototype implementation, describing the tools used and presenting some screenshots of the developed application.

4.2 Implementation

We developed a prototype to evaluate EduAdapt. The ontology was modeled in Protégé and exported in OWL format. We then stored this ontology in a semantic database named *StardDog*.[7] The server was implemented in C#

[5] https://www.openarchives.org/pmh/.

[6] At the moment the only conversion of this type possible uses the tool available at https://github.com/weidagang/text-diagram.

[7] http://stardog.com.

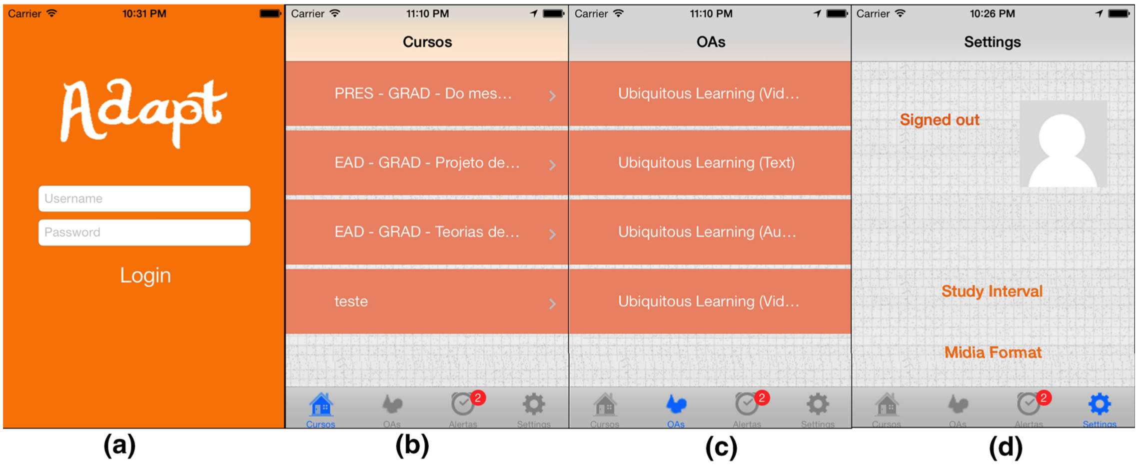


Fig. 10 Screenshots of the iPhone Adapt application

using Visual Studio 2012. Both server and semantic database were hosted in Amazon Web Services (AWS). The server uses SPARQL (SPARQL Query Language for RDF) queries and applies the reasoner Pellet in the ontology. We also defined rules using SWRL (Semantic Web Rule Language). As described before, we used OAI-PMH to integrate or server with LOs repositories such as *Ariadne*,[8] *Merlot*[9] and *BIOE*.[10]

We initially developed the prototype of the client App, named Adapt, for the Apple iOS. For this, we used the Objective C language and the Apple XCode 5. Figure 10 shows some screenshots of Adapt running on an iPhone. In Fig. 10a we can see the login screen for authenticating in the system. The credentials are validated with the server using OAuth 2.0 protocol.[11] The next screenshot, Fig. 10b, displays courses that the student is engaged in Moodle. The connection with Moodle is done at server side. Additionally, from this screen on, in the bottom, are the main options in Adapt app: Courses (this screen), LOs, Alerts and Configuration.

Once selected the course, Fig. 10c shows preselected LOs as determined by the server. These LOs are chosen following the adaptation process described in the previous section. Finally, Fig. 10d presents the configuration screen. In this screen users can set some preferences, such as study interval (for generating alerts) and options regarding media format. Finally, there is a screen that exhibits current alerts, consisting of notifications generated by EduAdapt to remember the learner to take a look at pending contents.

In the future, we plan to create an Android version too. In Fig. 11 we show some learning objects as viewed in the Adapt application. These objects use the following media, respectively: a presentation (in PPT format), a document (in PDF format), a video (in AVI format), and an audio (in MP3 format). These objects displayed in Fig. 11 are examples of the results obtained by the system in generating adapted material to student learning style.

5 Evaluation and results

We carried out some experiments in order to evaluate EduAdapt model. Particularly, we tried to answer the problem statement proposed in Sect. 1. To accomplish this, we employed two approaches. The first evaluated the OntoAdapt ontology, demonstrating the use of this resource with some scenarios as well as some metrics and comparison with other similar ontology. After that, we evaluated EduAdapt model in a second moment. We used the developed mobile application and applied a survey in a course with 20 learners (convenience sample [35]), during one semester, to analyze their perception regarding our proposal. The results will be shown in the next subsections. The process used in the evaluation follows the flowchart presented in Fig. 12.

5.1 Ontology evaluation

Ontology evaluation is an important step in a building of a reusable ontology [29]. Although there are many ontology evaluation propositions, we do not have an agreed and straightforward method for evaluation and comparing ontologies [25]. In our proposal, we evaluated OntoAdapt based on two main strategies. The first is based in scenarios in order to illustrate the use of ontology by the application. The second strategy consists of analyzing the quality and

8 http://www.ariadne-eu.org.
9 http://www.merlot.org.
10 http://objetoseducacionais2.mec.gov.br.
11 http://oauth.net/2/.

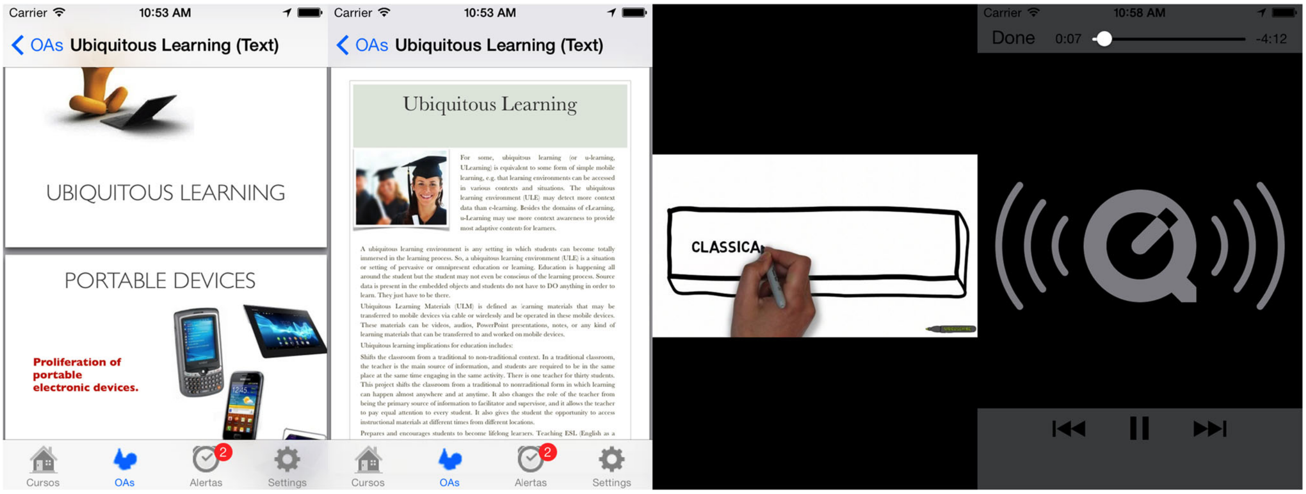
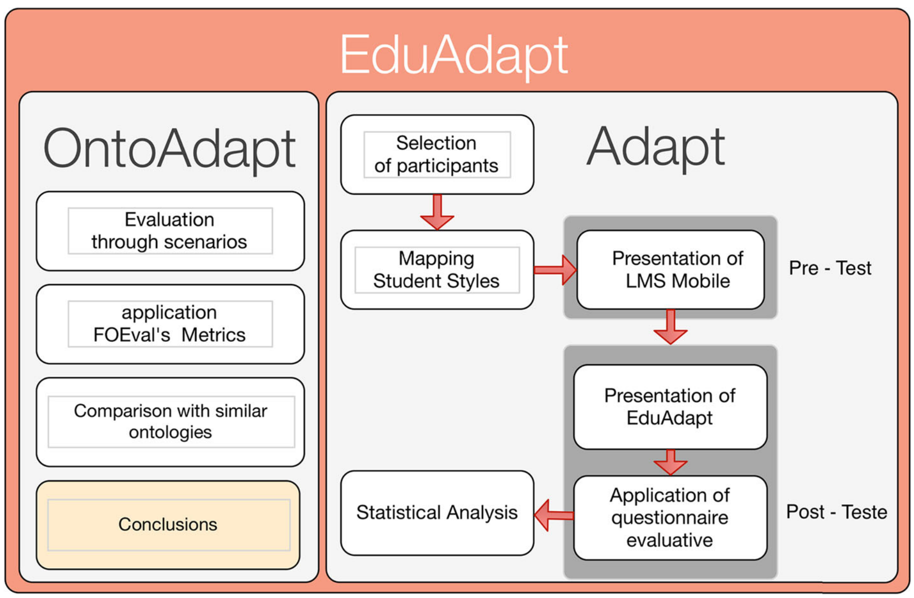


Fig. 11 Learning objects shown in Adapt application

Fig. 12 Methodology used to evaluate EduAdapt



the fidelity that the OntoAdapt ontology provides to cover concepts related to the associated subjects. We achieve this by comparing the results with another ontology with similar concepts, i.e., a golden standard. The following subsections show both evaluations.

5.2 Scenarios

The scientific community has used scenarios to evaluate context awareness [10, 31]. Using this concept was proposed 3 scenarios to illustrate and evaluate the behavior of OntoAdapt ontology. For each scenario we developed a rule that could be used in EduAdapt Model to identify the situation and suggest the most appropriate LO. The first scenario shows the use of the Adapt application and explains the way in which the application adapts the Learning Object.

> John is sitting on a park bench with his smartphone. The device has a good level of battery and a good connection to a WiFi network. His learning style was previously detected as Visual and Verbal, with the use of Felder and Silverman questionnaire. In the Adapt application in his smartphone, John marked his preference as "Videos." In analysis of an LMS test revealed that John has difficulties in a specific content in one of the courses that he attends. By detecting that situation, the system sends an appropriate learning object, in this case a video, according to John context

Fig. 13 *SWRL* rule for the first scenario, representing a learner using his mobile device

```
Learner LearningObject(?OBJ), Student(?Learner), hasActivity(?Learner, ?Act), hasDevice(?Learner, "smartphone"), hasDificultyKeyword(?Learner, ?KW), hasKeyword(?OBJ, ?KW), hasLOMediaType(?OBJ, ?Media), hasLearningStyle(?Learner, ?Style), hasLearningStyle(?OBJ, ?Style), hasMediaType(?Act, ?Media), hasStudentMidiaPreference(?Learner, ?Media), CanSendHighBattery(?Media, "True"), CanSendHighConnections(?Media, "True"), CanSendToSmartphone(?Media, "True"), DeviceNetConnection(?Device, "WiFi"), DeviceType(?Device, "smartphone") -> ChosenObject(?OBJ), hasObjectChosenToStudent(?Learner, ?OBJ)
```

Fig. 14 *SPARQL* query to obtain the learning object

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX onto: <http://www.owl-ontologies.com/OntoAdapt2.owl#>
SELECT ?Title ?Link     WHERE {onto:ID
                     onto:hasObjectChosenToStudent  ?obj.
                    ?obj onto:LO_Link ?Link.
                    ?obj onto:LO_Title ?Title.}
```

Fig. 15 *SWRL* rule for the second scenario, depicting a user in movement

```
LearningObject(?OBJ), Student(?Learner), hasActivity(?Learner, ?Act), hasDevice(?Learner, ?Device), hasDificultyKeyword(?Learner, ?KW), hasKeyword(?OBJ, ?KW), hasLOMediaType(?OBJ, ?Media), hasLearningStyle(?Learner, ?Style), hasLearningStyle(?OBJ, ?Style), hasMediaType(?Act, ?Media), hasStudentMidiaPreference(?Learner, ?Media), CanSendLowConnections(?Media, "True"), CanSendToSmartphone(?Media, "True"), DeviceNetConnection(?Device, "3G"), DeviceType(?Device, " smartphone") -> ChosenObject(?OBJ), hasObjectChosenToStudent(?Learner, ?OBJ)
```

(including learning style, device and bandwidth capacity).

To implement this scenario we developed a rule, detailing aspects that could be used to identify the most suited LO to the learner's context. The rule for this situation is shown in Fig. 13. With this rule, the system sent objects that would assist the learning process tailored to the specific mobile device. The property *hasActivity* defines the activity type that the learner is doing at the moment. In this case, the learner is *stationary*. This information is obtained from the device sensors (accelerometer in this case). The property *hasDificultyKeyword* has the needs that the learners have, such as difficulties or doubts. With this knowledge, the system will seek LOs that attend to these keywords. If a LO has a keyword and is compatible with media and device, then the properties *ChosenObject* and *hasObjectChosenToStudent* will have the LO reference and location. Using this SPARQL query, the object is obtained. Before send the LO to the learner, the Adapt application shows a push notification to learner, indicating that it exists a new object to download. The LO starts downloading when the learner clicks in the notification. We are using a SPARQL query to get the object location, as illustrated in Fig. 14. This query is used in all other scenarios.

The aforementioned scenario considered an user who has a mobile device but he is not moving. So, we developed a another scenario in order to demonstrate a situation in that the user is in movement. Below we present scenario 2 with this perspective:

> Felipe is running with his smartphone. The device has a full charged battery and the network connection is 3G. Felipe learning Style was previously detected as Visual–Verbal. In LMS Moodle, Felipe has shown difficulty in a specific content. Therefore, the Adapt system sends an object adapted to Felipe learning style and suited to his device. Since Felipe is in movement, the LO is converted to an audible file, from the original video format.

The rule that describes this scenario is shown in Fig. 15. In this rule, the property *CanSendLowConnections* runs with a function of evaluating if the selected media is

Fig. 16 *SWRL* rule for the third scenario, in which the learner is using a stationary device

```
LearningObject(?OBJ), Student(?Learner),hasDevice(?Learner,"Desktop"), hasDifficultyKeyword(?Learner, "Algorithms"), hasKeyword(?OBJ,"Algorithms"), hasLOMediaType(?OBJ, ?Media), hasLearningStyle(?Learner, "Sensitivo_Intuitivo"), hasLearningStyle(?OBJ, ?Style), hasMediaType(?Act, ?Media), DeviceNetConnection(?Device, "WiFi"), DeviceType(?Device, "Desktop") -> ChosenObject(?OBJ), hasObjectChosenToStudent(?Learner, ?OBJ)
```

adequate to learner's connection, in this case 3G. The property *CanSendToSmartphone* is triggered using *DeviceType*, which indicates that it is a smartphone. With this, the classes *ChosenObject* and *hasObjectChosenToStudent* receive learning objects that match the characteristics imposed by this rule. Using a SPARQL query (see Fig. 14) the object is selected and sent to the user device.

Finally, the third scenario differs from the others because the learner is using a stationary device:

> Amanda is at the University in a Computer Lab. She is using a desktop computer and her learning style is Sensitive–Intuitive. Amanda has difficulty in Algorithms. Detecting this, the Adapt system sent a learning object adapted to her style and device.

We presented the rule for the third scenario in Fig. 16. In this case, an inference will be applied and will indicate LOs that match the learning style "sensitive–intuitive," WiFi connection and the learner difficulties. In this rule, the device is a Desktop and the connection is WiFi. With this set of information, the reasoner will search for LOs that contain this description, keywords with "algorithm" and that are appropriate for this scenario. With these combinations, the chosen object is stored in the properties *hasObjectChosenToStudent* and *ChosenObject*.

These scenarios show basically applications that can be developed using OntoAdapt. The benefits of employing an ontology, instead of a traditional database, are mainly the capacity of executing rules, the possibility of inferring information and the representation of semantic among the concepts modeled. In the next subsection we will evaluate some metrics of OntoAdapt.

5.3 Metric-based evaluation

We used the methodology described in *FOEval* [4] to evaluate OntoAdapt ontology. *FOEval* consists in a group of metrics that assist the evaluation of local or remote ontologies. To evaluate OntoAdapt, we employed the metrics *coverage*, *richness* and *level of detail*, as proposed in FOEval. These metrics provide weights that help to choose the better ontology for a specific application. As a golden standard, we used the ontology described in the work [27]. We selected this ontology because it has many similarities with OntoAdapt in conceptual terms. The ontology described in [27] aims at adapting Web Systems, using the learner context in order to respond to the needs in a particular situation. Another reason for comparing with this work refers to the possibility to have access to the OWL files, visualizing it on Protégé. Other works that we considered did not provide access to the developed ontology.

Table 1 Metrics of OntoAdapt ontology and of the golden standard

Metrics Description logic	OntoAdapt SHOIN(D)	[27] SHOIN(D)
Annotations	7	7
Object property	15	71
Data property	25	39
Properties to the specific domain	18	98
Properties with specific range	7	59
Total number of classes	28	52
Total number of subclass	2	31

Table 1 shows some metrics of OntoAdapt and the ontology described in [27], extracted from the software Protégé. We complemented these metrics using a tool called *Manchester—OWL Ontology Metric*[12] which is used to validate and display statistics about an ontology described in OWL [14]. This tool calculates metrics as counters and statistics about expressiveness of the ontology.

Table 1 shows some characteristics of the ontologies. The metric *Description Logic* (DL) consists of a formalism to represent the knowledge in a domain. There are many DLs that are defined by classes, properties and construction of axioms that they support. In both ontologies the DL has the same *SHOIN*(*D*), indicating that the ontologies have transitive rules, hierarchies (with the use of the sub-property rdfs:subPropertyOf), nominal, inverse properties, cardinal restrictions and the use of data properties [19]. The annotations are free semantic elements used to describe any feature or axiom in an ontology. The object properties indicate the relationships between instances of two classes, while the data properties indicate relations between instances of classes and RDF or XML literals data types. The properties that have either a specific domain or a particular range are those not be used in other areas other

[12] http://owl.cs.manchester.ac.uk/metrics.

than initially determined. The metrics *Number of classes* and *Number of subclasses* represent the quantity of elements found in the two considered ontologies.

The metrics in Table 1 were used to calculate the *Attribute Richness* (AR) and the *Relation Richness* (RR) as proposed in [4]. After that, these two metrics were used to estimate the *Ontology Richness* (OR) [4]. The RR metric reflects the diversity of relationships and placements of relations in the ontology. The ontology that has more relationships (composition), instead of inheritances (specializations), is considered richer than the taxonomy with the opposite characteristic. The calculation of RR is defined as the ratio between the number of no hierarchical relationships and the number of all relationships of the ontology. The metric AR is used to denote the amount of information stored by an ontology. This metric determines that the more attributes are defined in ontology, the better will be the knowledge that the ontology represents. The calculation determines that the AR is defined as the ratio between the number of attributes defined for all classes and the number of classes that the ontology features.

The results for the ontology OntoAdapt were 0.88 points for RR and 0.89 points for AR. These two results indicate that OntoAdapt is richer in attributes than relations. Adding both metrics we can obtain the OR which is 1.77 points. This metric can be used in comparison with other ontologies, in order to determine how the value of OR is significant. Another metric serves to demonstrate how the proposed ontology is divided, i.e., the distribution of OntoAdapt. The Subclass Richness (SR) or Inheritance Richness (IR) reflects the distribution of information across different levels of the ontology [4]. This is a good indication of how well knowledge is grouped into different categories and subcategories in the ontology. The calculation of the SR is the ratio between the number of subclass by the sum of the number of classes and subclass. This resulted in 0.06 points. This value indicates that OntoAdapt tends to be vertical, because the value of SR is not very high. Moreover, it indicates that the ontology represents detailed knowledge.

Table 2 summarizes the metric in concordance with the FOEval model comparing the values of OntoAdapt and the ontology described in [27]. The values obtained in the ontology describes in [27] were better if compared to OntoAdapt. The amount of relationships of OntoAdapt is greater than the other ontology, but the RR value is not the most relevant factor to chose between them. In contrast, the OR value is determinant to affirm that the compared ontology is richer and has more information (contains more attributes and relationships) than the ontology proposed in this work. This is because the scope of the golden standard is wider than the scope of OntoAdapt, which focuses mainly on adaptation LO to the student context and learner style. This also influences the SR metric.

Table 2 Comparisons between the two ontologies

Metrics	OntoAdapt	[27]
RR	0.88	0.69
AR	0.89	3.0
OR	1.77	3.69
SR	0.06	0.37

Finally, we evaluated the OntoAdapt coverage. This consists in evaluating if a set of common and varied terms in a specific field is present in the proposed ontology. The coverage can be assessed through the use of specific keyword related to the main subject. For this evaluation, we selected ten keywords (Learning Style, Learning Object, Location, Time, Learner Performance, Device, Activity, Context, Student, Connection), obtained from closed related works in the area of educational content adaptation. The selected articles [3, 17, 38] involve adapting or recommendation of learning objects. With the chose keywords we performed a comparison with existing classes in the ontology. The results indicate that OntoAdapt corresponds fully with all terms selected. With this result, we can state that OntoAdapt has a good coverage of domain in terms of elements.

Regarding the structure of the ontology, according to [36], the metrics are not yet well defined. Some methods consist in searching to verify the depth of the class hierarchy, but because of the properties related to specific domains and relationships this is a complex task [36]. The expressiveness of the language used for modeling the ontology defines an upper limit on the complexities that are applied in the reasoner tasks. Using Protégé, we can evaluate the complexity of an ontology. Both cases match the description $\mathcal{SHOIN}(\mathcal{D})$, which allows the verification of the reasoner in a satisfactory time and with exponential complexity [36].

5.4 Evaluation of the EduAdapt behavior

Aiming at performing the experiments of EduAdapt model, we have used the data gathered in an experiment in a course entitle *Ubiquitous and Mobile Computing* with 20 learners who used the Adapt application during 1 month. All the learners had previous experience with e-learning and are enrolled as undergraduate students in the Computer Science area. Firstly, we collected students' learning style using the Felder and Silverman [12] questions. In Moodle, we provided a link to that survey. The results demonstrated that learners were preferentially, reflective, intuitive, visual and global. This conclusion can be seen in Fig. 17. The confidence interval for the data referring to the learning

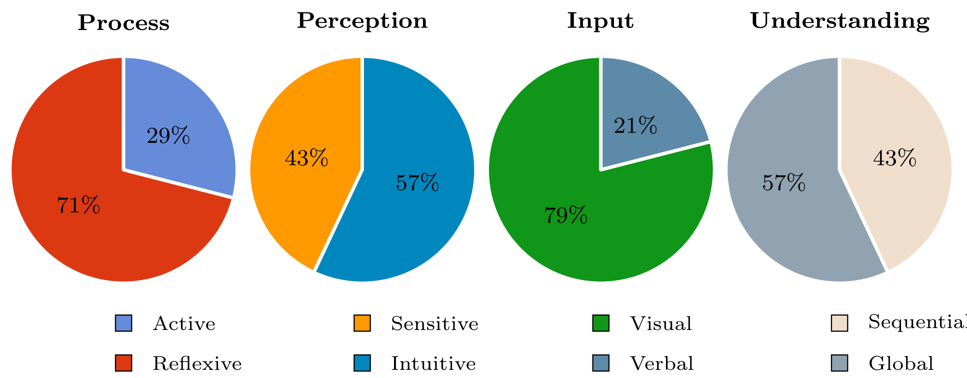


Fig. 17 Distribution of learners in relation to the dimensions of the Felder and Silverman questionnaire

Table 3 Results of application of the questionnaire of Felder and Silverman

Dimension	Confidence interval	Margin of error
Processing	[2.35; 0.098]	1.07
Perception	[2.34; −0.009]	1.18
Input type	[1.8; −0.52]	0.64
Comprehension	[2.29; −0.009]	1.15

style of students is 95 %. This range is detailed in Table 3. After the definition of learning style according to the methodology presented in Sect. 2, we performed the experiments, divided into pretest and posttest.

In the pretest, the students were presented to the mobile application Adapt after the identification of their learning styles. To do this, we used devices (*Apple iPad*, *Apple iPhone* e *Apple iPod*) with Internet access (WiFi or 3G) with the application installed. We also built 20 LOs related to the subject of the course and capable of adaptation for different formats and media. These objects were available in five media, according to each learning style, as given in Table 4. The learning objects were stored in a repository to be accessed via Web Services from the mobile devices.

At the moment that learners opened Adapt and logged in, using their Moodle credentials, they immediately received an LO adapted to their context, including device characteristics and learning style. This changed during the course, according to different subjects, important keywords and learners' doubts detected. Each class, a new subject was the topic of discussion in the course. Accordingly, LOs suggestions were sent to users' devices considering the current discussion, learning style and user preferences.

As a posttest, at the end of the month, all learners were invited to answer a survey regarding *Adapt* application. The developed survey was based on the work of [9] and [32]. Compound of 10 statements, the students had to rate using the Likert [21] scale. This scale provides five alternatives in an interval ranging from 1 point (completely agree) to 5 point (completely disagree).

To identify the reliability of this survey we employed the Cronbach alpha [15], allowing to estimate the correlation between the answers given by respondents. The Cronbach alfa to this survey resulted in 0.8, indicating that the evaluation is reliable. Results above 0.7 indicate a minimum of acceptable reliability [15, 16]. The statements that compose the applied survey are depicted in Table 5.

Table 6 presents the results obtained with the survey. The first column in the table represents the formulated statements. Following columns indicate the percentage of answers to each item, considering *Likert* scale. To better analyze the answers, we calculated the WAV—weight average value of the items. This value indicates that the closer to 5 the value, the greater the level of satisfaction of students in relation to the application. In contrast, the closer to 1 indicates the lowest satisfaction. All the values of WAV obtained were >3. This indicates that the learners believe that the EduAdapt model can become a tool to improve the learning process.

An analysis of the results allows us to conclude that the statements regarding "adaptation," "presentation" and

Table 4 Relationship among different media and learning objects [13]

	Sensitive	Intuitive	Visual	Verbal	Active	Reflexive	Sequential	Global
Media								
Audio	–	–	–	✔	–	–	✔	–
Wiki	✔	–	✔	–	✔	–	–	✔
Diagram	✔	✔	✔	–	–	–	–	–
Text	–	–	–	–	–	✔	✔	–
Video	–	–	✔	✔	–	–	–	–

Table 5 Statements used in the evaluative survey

1.	The educational content is properly adapted to the device
2.	The presentation of the subject is suitable to me
3.	The content availability in the device is appropriate
4.	Considering the current model of distance education, this application can help in my learning
5.	This application can promote greater interest in learning
6.	I can easily understand the content displayed on the screen
7.	The application enables to study independently of the location and surroundings
8.	I found the system easy to use
9.	The application is fast
10.	The application eased my learning

Table 6 Answers obtained with the evaluative survey

Response	Strongly agree (%)	Agree (%)	Indifferent (%)	Disagree (%)	Strongly disagree (%)	WAV[a]
S1.	8	75	8	8	0	3.83
S2.	8	50	17	17	8	3.33
S3.	25	67	8	0	0	4.17
S4.	58	25	8	0	8	4.25
S5.	50	50	0	0	0	4.50
S6.	50	25	25	0	0	4.25
S7.	42	33	17	8	0	4.08
S8.	17	67	17	0	0	4.00
S9.	8	33	58	0	0	3.50
S10.	42	42	8	0	8	4.08

[a] WAV—weight average value = $(5P + 4Q + 3R + 2S + 1X)/12$ where P, Q, R, S and X are the numbers of answers in Likert scale and 12 is the number of interviewers [39]

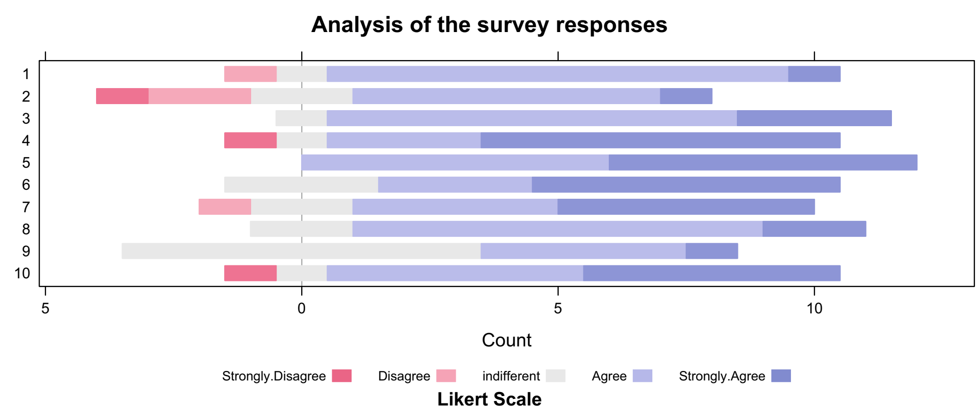


Fig. 18 Frequencies of survey's answers

"performance" (statements 1, 2 and 9) showed the lowest scores. However, the values in the range 3.33–3.83 are consider satisfactory to this work, being above mean and therefore closer to 5 than 1. Figure 18 shows the number of positive responses from students regarding EduAdapt model. The high incidence of agree and strongly agree are obtained in statements related to personal interest and understanding (statements 5 and 6). Considering usability (statements 8 and 9), there were a general agreement, although in terms of performance we obtained the highest indifference of users, since most considered that this experimental use was not enough to evaluate this characteristic. Finally, considering statement 10, we got an intermediate grade in comparison with all the others, although the majority of the responses were in the agree portion of the survey. In fact, this was a ambitious statement, generating some indifference and one strong disagreement. Despite this result showed some encouraging

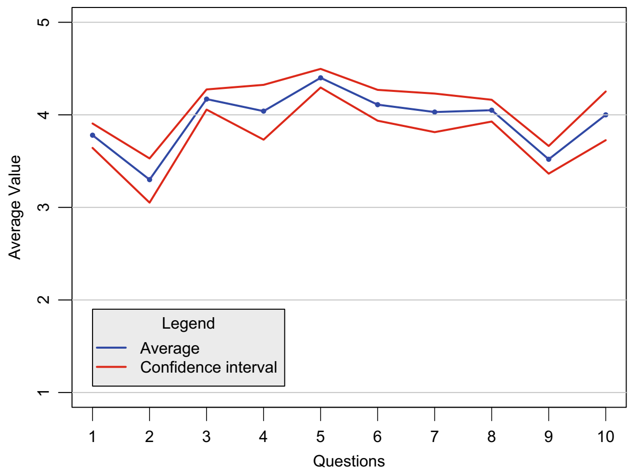


Fig. 19 Mean value between the answers group and confidence interval

results in the process of exploring more the used of adapted LOs, considering learning styles, for educational process, it does not constitute a definitive or generalizable result.

Figure 19 presents a graphic with the confidence interval together with the means regarding the statements in the answers. To estimate the normality of the data presented, we made calculations that indicate how much the value is close to average in a population, using the standard deviation to scale. In Fig. 20 we show the mean values, z-score and coefficient of variation. The value that represents the mean is ranging between 3.3 and 4.5, as mentioned above. The coefficient of variation, indicating the homogeneity of the sets of values, was bellow 25 % for the majority of values obtained (70 %), signalizing that the answers are consistent. As for the z-score value, evaluating the possibility of a normal distribution showed that this was not the case. In this evaluation, three questions demonstrate value above 50 %. In others words, the obtained answers do not follow a normal distribution.

We applied the Wilcoxon–Mann–Whitney test [1] in order to check whether the samples have the same distribution. This adoption is justified because we used the Likert scale, which is not classified as a parametric scale, and we employed a relative small sample. To carry on the test, the samples were divided into two groups. The first included the concordant answers (strongly agree and agree) and the second consisted of answers that disagree (strongly disagree and disagree). With this, we applied the test using 0.05 as the value significance level that the two sets follow the same distribution. In addition, the test results in a negative value when using the statistic software named R,[13] The two groups do not follow the same distribution model, thus indicating the independence of values composing the sample. In other words, from the result of an element we cannot infer any conclusion about the other.

[13] http://www.r-project.org.

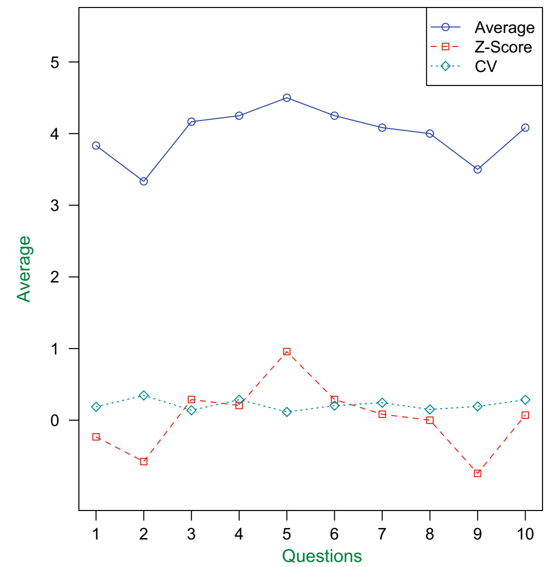


Fig. 20 Means, z-score and coefficient of variation

6 Related work

This section presents a review of the works that use ontologies for educational purposes and points out the differences with our proposal. Ontology Organizational Learning Objects (OOLOs) were proposed for helping to organize the content created in a company, specifically a software house [3]. The OOLO ontology makes the content reuse easier and improves the organizational learning. To address organizational needs, ontology OOLO was based on the LOM model [11] to consolidate individual knowledge as part of the organization knowledge. This knowledge can be organized in LOs, facilitating reuse and better availability of content. Structurally the OOLO has five categories that describe the content of the object, the object lifetime, the technical format, educational characteristics and distribution rights [3].

The work proposed by [17] takes into consideration the learner cognitive structure, the content of learning objects and their semantic relationships. The main objective is to recommend objects adapted to the reality of the learner and making use of ontology to represent semantic. This proposal initially obtains the learner difficulties and then combines with concepts available in the repositories of knowledge ontology [17]. From the use of SWRL rules, the prerequisites are evaluated and the recommendation of learning objects is performed. In their approach, ontology is also used to represent the structure of the content LO, together with the semantic relationships and concepts.

Another work [30] presents an ontological structure corresponding to the standard LOM. The proposal adds a conceptual framework of learning object metadata and implements the relationships between them, emphasizing the pedagogical significance. The proposed ontology is based on software agents that interpret the learner needs finding appropriate Learning Objects, incorporating some descriptive properties. Furthermore, the ontology implements the relationships between components and establishes restrictions that allow defining the cardinality of the model, including instances that represent specific members of each class. With this approach, the ontology allows to transform the standard semantic definition in formal machine triable, making LO interoperable [30].

Specifically considering educational ontologies, a reference work, which we used as a gold standard in the evaluation, is described in [27]. This ontology works with a model developed through the context ontology in a network. This ontology works by means of contextualizing the location, student profile, student device and learning domain. The goal is developing a more flexible and expressive system. Although this work has a different goal than OntoAdapt, it has the ontology closest related to this proposition.

Finally, the last work considered proposes an ontology used to classify language learning materials, describing the profile of the users and providing an adaptive learning environment [38]. The architecture is composed of three modules: User Interface Manager (UIM), Test Evaluation Manager (TEM) and the Course Recommendation Mediator (CRM). The UIM module provides an adaptive and friendly interface, responsible for storing the characteristics of the learner in an ontology. The UIM is in charge of applying periodic testing via module TEM, to evaluate the learner abilities. The CRM module selects teaching materials according to pedagogical rules and learner profile. The courseware and all educational materials are annotated using ontology terms extracted from the *Adaptive Language Learning Course* (ALLC) and *Language Learning Ontology* (LLO) [38]. These ontologies are used to store learner information, content and provide content adaptation for the learner.

Generally, the related works use ontology to standardize learning objects incorporating aspects that would ease the choice of educational content for a particular subject and student. Similar to our work, related works are focused on the sharing of educational materials through the use of ontology. Differently from works mentioned, we present an ontology that uses patterns of ontologies already conceptualized trying to modulate the user context and device with intent to indicate a suitable learning object.

The last two works presented have the greatest similarities to this proposal. However, different from our approach in the work [38] the term adaptation means only to adapt content according to the user profile. Furthermore, although their proposal is targeted at mobile devices, they do not consider context data or characteristics of the device itself. Besides, in the case of the latter work, it was not possible to evaluate its ontology. In our work, we incorporate concepts similar to those presented in this section, but we focused on incorporating information regarding devices and context. OntoAdapt aims specifically at better adapting learning objects to users, considering their context and learning styles.

7 Conclusion

In this article we described EduAdapt, a model for adaptation of learning objects in learning environments. This model is based on an ontology including the representation of learner, context, profile, learning style and mobile device. The main objective is to find the most appropriate learning object to students need according to their current context and learning style. Considering the results, the first evaluation regarded the ontology. The scenarios showed the possibility of representing different situations applying rules to OntoAdapt. Additionally, the metrics (coverage, richness and detail level) allowed a comparison of the proposed ontology with a golden standard, a reference for our proposal. In terms of coverage, OntoAdapt employs the main terms considered in the area, becoming an alternative for use in adaptive systems for mobile and ubiquitous learning environments. However, in terms of richness the golden standard presented better results, because it covers a greater range of concepts and has a wider scope.

The second evaluation consisted in employing EduAdapt in an one semester course. The results showed a mean acceptance of 77.5 %, with a coefficient of variation bellow 20 % for the majority of the answers (precisely 70 % of responses). We also obtained the Weight Average Value (WAV) >3, signalizing a positive answer to the aforementioned problem statement of this research. In other words, the students believe that the proposed model could in fact help in their learning process.

This work presented a model that considers students' contexts, and particularly their learning styles, to adapt and to present learning objects tailored to mobile devices and the surroundings. In this process we can highlight as the main scientific contribution the proposal of a model for learning objects adaptation that employs inferences and rules in an ontology considering various contexts, including the student's learning style. For allowing these adaptations of LOs, we proposed an ontology, considering four group of information related to the adaptation process: Student, Learning Object, Device and Context. Comparing to the related works considered in this article, a considerable fact is the number of context information used by EduAdapt. Regarding context acquisition, EduAdapt combines implicit and explicit gathering. The use of location and movement contexts, by means of the GPS and accelerometer sensors, constitutes a explicit and automatic acquisition. These data are used together with implicit information inferred in the proposed ontologies.

The study and development of adapting learning objects are not new; many works try to adapt LOs according to context and devices. Regarding the EduAdapt model, one differential is the capacity of obtaining objects from pre-existent repositories and tailoring it to the learner. Another contribution is the integration with a LMS allowing the student to visualize LOs and contents related to the courses they are engaged, helping the application to better know their needs.

Finally, we highlight that the adaptation of the resource selected to the student is done at the specific time in which the student context is received. This makes the adaptation in EduAdapt dynamic, only converting the object in the specific moment that the user access it and according to their context. Comparing to the static approach, the main drawback is the delay that could occur between the user access and the provisioning of the adapted LO. However, an advantage is that there is no need to store the adapted object in the server. Besides, this solution potentially makes LOs more suited to learners' needs.

In the scope of EduAdapt we have some opportunities for future works. We can further integrate with different learning environments and also employ many available repositories of learning objects. Another possibility is to allow students to evaluate the provided learning objects. In this way we could investigate methods to assess the quality of the adaptation provided. Furthermore, we could conduct a profiling, evaluating the performance of EduAdapt in terms of response time, scalability and bottlenecks.

What is more, we did not exhaust the possibility of considering other context information, albeit believing that we consider some important aspects in the area of ubiquitous and mobile learning. Regarding the Adapt prototype, we are in the process of developing a product, which will be commercialized by the partner company. An Android and a Web version of the client are also under development.

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