Je-LKS
Journal of e-Learning and Knowledge Society
The Italian e-Learning Association Journal
PEER REVIEWED PAPERS
EMEMITALIA CONFERENCE 2016
Vol. 13, n.3, 2017
ISSN: 1826-6223 | eISSN: 1971-8829

A LEARNING ANALYTICS TOOL FOR USABILITY ASSESSMENT IN MOODLE ENVIRONMENTS

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Keywords: Learning Analytics, Usability Evaluation, Learning Management Systems, Moodle.

Evaluating user experience is a challenging task, particularly in e-learning. Existing e-learning systems are limited in their ability of being evaluated based on the user interfaces because current evaluation approaches are usually expensive in time and organization and require active users' participation. Moreover, a usability assessment is needed whenever a new version of the "user interface tailored for a given type of device (e.g. laptop, tablet, smartphone) is developed". In this paper, we get around the problem leveraging on the increasing adoption of analytics tools in e-learning and on logs transparently tracked by e-learning platforms. We introduce an automated analytics approach aiming at assessing the usability of both desktop and mobile user interfaces of a Learning Management System through specific native indicators (e.g. efficiency and satisfaction). They are defined as comparable scores and calculated automatically based on the tracked log files. In order to put the proposed approach into practice,

for citations:
Fenu G., Marras M., Meles M. (2017), *A Learning Analytics Tool for Usability Assessment in Moodle Environments,* Journal of e-Learning and Knowledge Society, v.13, n.3, 23-34. ISSN: 1826-6223, e-ISSN:1971-8829
DOI: 10.20368/1971-8829/1388

we implemented it on the Moodle LMS. Our contribution promises to reduce both time and cost for usability assessment of user interfaces in e-learning, while ensuring adaptability to different devices and systems.

1 Introduction

Emerging technologies are greatly influencing how people approach daily educational experiences in both formal and informal contexts. The concept of e-learning is gaining increasing popularity since it promotes the adoption of multimedia technologies to improve education, including online and onlife access to content and services. This success has led to a wide range of Learning Management Systems (LMSs), each one of them with different features and learning approaches (Thakkar & Joshi, 2015). Some LMSs are able to improve learning capabilities via social and gaming tools; others have custom services developed to support adaptive mobile learning and ensure online exams integrity (Fenu *et al.*, 2017). Moreover, new data-mining methods embedded into LMSs extract information about the learning processes from raw data to allow teachers and content makers to improve their courses (Conde *et al.*, 2015). The good usability of LMS user interfaces used to provide such features is crucial to ensure positive learners' perception of material and services. Evaluating LMS user interfaces and improving the usability of their design is as essential as challenging.

Since the purpose of e-learning systems is not only to interact, but also to support knowledge dissemination and acquisition, traditional usability design guidelines and usability evaluation methods are not sufficient in e-learning. In general, traditional methods are categorized in analytical and empirical. The first ones are used for interface inspection by usability experts and perceived as a quick and low-cost alternative to the second ones, where testing with final users is performed. However, they require active users participation (e.g. experts or learners) which is usually expensive in cost and time. Moreover, LMS interfaces are firstly designed to allow access from web browsers in desktop devices. Styles and layouts are often responsive. Later, full support for mobile device access (i.e. hybrid or native applications) is provided. This design process has great impact on testing. Every time a new interface is designed or the support for a new type of device is added, a usability evaluation is needed.

In this paper, we get around the problem leveraging on the increasing adoption of analytics tools in e-learning and on logs transparently tracked by e-learning platforms. We introduce an automated analytics approach aiming at assessing the usability of both desktop and mobile user interfaces of a Learning Management System through native indicators (e.g. efficiency and satisfaction). They are defined as comparable scores and calculated based on the log-files tracked during normal learners' activities. It results in an efficient and transparent usability evaluation method. To put into practice the proposed approach, a Moodle LMS plugin was developed to compute and display the indicators. Our contribution can represent a quick and low-cost alternative for usability assessment of LMS interfaces, applied either in cooperation with the traditional usability evaluation methods or as an independent method.

The paper is organized as follows. Section 2 analyzes the existing usability evaluation methods and analytics tools in e-learning. Section 3 presents the proposed approach, including the description of the required log data and how such data are combined to compute and compare the indicators we defined. Section 4 describes the analytic tool developed into Moodle LMS as practical application. Finally, Section 5 draws analysis and outlines future research.

2 Background

In this section, we first provide an overview of how traditional usability evaluation methods play a significant role in external software quality. Then, we describe relevant analytics tools in e-learning and their contribution to acquire information from learners' data. Finally, we focus on works bridging analytics and usability, highlighting similarities and differences with our approach.

2.1 External Software Quality Evaluation

At the basis of software development, particularly of e-learning platforms, there is the engineering aspect. The aim is to create software which does what it is expected to do and does that in the right way. To achieve this challenging goal, software engineering includes tasks such as software quality validation and verification (Vasanthapriyan *et al.*, 2015). The term software quality generally refers to a measure of correctness of a software system, but there are several definitions of software quality and parameters used to model it.

One of the most popular classification is defined in ISO/IEC 9126 standard published by the International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC). This includes six quality features: efficiency, functionality, maintainability, portability, reliability and usability. In contrast, ISO/IEC25010 distinguishes internal (i.e. structural) and external (i.e. functional) quality features. The first ones refer to the perception that the user has of the system in terms of utility. On the other hand, the second ones refer to the development of the software product. In this paper, we consider the external ones. The main properties are: efficiency as the amount of resources expended in relation to the accuracy and completeness with which the users' achieve their goals; satisfaction as the degree to which users are satisfied with the experience of using a product in a specified context of use; learnability as a measure of how easy is for a user to learn to use a system; memorability as a measure of how a a user easily memorizes the way a task should be performed. The external quality classification proposed in (Rogers *et al.*, 2011) includes the parameters defined into the two standards and we use it to identify our indicators. Such indicators describe the quality of the user experience and greatly influence the success of LMSs.

Evaluation methods for external software quality are used for identifying problems and improving an interface design. In general, analytical methods are used for interface inspection by some usability experts and perceived as quick and low-cost alternative to the empirical methods where testing with final users is performed. Mainly, two analytical methods and two empirical methods exist: heuristic evaluation is a cheap and quick method where a small group of evaluators inspects a user interface to find problems using a set of usability principles; cognitive walkthrough requires that evaluators analyze a user interface by simulating step-by-step user behavior; thinking-aloud asks users to verbalize thoughts while interacting with the interface; questionnaires statistically measure opinions, preferences and satisfaction of users with the interface. The analytical methods identify interface problems cheaply and sooner than empirical one, which identifies more issues, but at a higher cost. The usability inspection should be accompanied by user testing for more reliable results. However, when only one method should be selected, cost-effective and easy-to-conduct analytical evaluation seems to have an advantage. Other researchers emphasize another aspect in the e-learning context, namely pedagogical usability. While general usability is concerned with usability of online environments, i.e. the user interface of the LMS, pedagogical usability is concerned with the tools, content, interface and tasks of learners to learn in various learning contexts according to the selected pedagogical objectives. The main assumption that lies behind pedagogical usability is how the functions of the system facilitate the learning of the material. Evaluating the usability of LMSs includes the e-learning platform and the provided educational content, but the latter is non-frequently studied.

2.2 Analytics Tools in E-Learning

E-learning has led to the increasing availability of data about learners. In this direction, analytics and data mining techniques analyze such data to improve and refine learning through LMSs (Nespereira *et al.*, 2015). We consider analytics techniques for the measurement, collection, analysis and reporting of data about learners to optimize learning and where it occurs.

The goals of analytics in e-learning (i.e. descriptive, diagnostic, predictive, prescriptive) have been largely analyzed. More precisely, descriptive ones provide information about the current state of the learning environment, then diagnostic ones process values to identify reasons. In addition, if pre-defined patterns are available, future trends can be forecasted with predictive techniques. Furthermore, prescriptive ones can be used to set action plans. These analytics goals are still under research. In (Tempelaara *et al.*, 2015), between the main objectives, the follows are mentioned: predict students' performance; model learning styles; suggest learning material; enhance learning environments. These objectives are achieved through activities and computations which allow to capture students' interactions with resources and other students, providing different overviews and peer comparison (Lukarov *et al.*, 2015).

Multiple learning analytics tools and plugins driven by reference models, data sources and indicators have been developed. In (Del Blanco *et al.*, 2013), the authors underline how the use of standard formats for learning material provides greater support for analytics. Moving the focus to standards suitable for track and store users' interaction, different sources of users' data and correlated type of data exist: demographic data (sign-in on platform), previous knowledge data (entry tests), academic performance data (historical records), learning disposition data (questionnaires) and platform utilization data (system logs). In our approach, we integrate the latter ones.

2.3 Analytics Tools in External Software Quality Evaluation

The increasing adoption of analytics in e-learning has led to several tools defined to evaluate the external LMS quality. In (Nanduri *et al.*, 2012), the authors proposed an analytical framework to evaluate the effectiveness of LMSs. It considers quality characteristics such as accessibility, reusability, performance, security, usability. The focus in (Rohini & Chabbra, 2014) is on the quality component related to navigation and tracking. Using analytical methodologies, the authors created the user interaction pattern and checked parameters on navigation, orientation and learning tracking. The process consists of four steps: prediction (selection of the parameters to be evaluated), monitoring (data patterns are stored during fixed periods), analysis (score computation from raw data) and reporting (visualization of results in a clear way). In (Scheffel *et al.*, 2015), an evaluation framework based on a set of quality indicators (i.e. learning support, learning measures, data aspects, and organizational aspects) is proposed and compared with other frameworks to check correctness and applicability. The results highlight that the framework has issues on concept definition, differentiation, and questionnaire adaption.

In LMS development, its evaluation is essential since the main objective is the good interaction between the users and the offered services. During the development of platforms intended for desktop usage, effective evaluation methods are usually those in which active intervention of users or experts is required. Although the evaluation results are highly accurate, this evaluation requires a large amount of resources and staff. In addition, managing test users and users' collaboration is not always guaranteed. In (Liaw *et al.*, 2008), they investigated the reasons why users' satisfaction in LMSs was influenced by users' collaboration. In the case of a LMS in which a web portal already exists, at a later stage, developers often provide a responsive version for mobile devices, or even a native application supported by the same backend, but with an entirely-new interface. In such case, performing again an evaluation step is expensive. This is the reason behind our approach, which compares the quality of a desktop interface and a mobile interface to verify that the latter is equally solid from the usability viewpoint.

3 The Proposed Approach

In this section, we describe the proposed approach designed for automated interface evaluation, including the description of the required log data tracked by the LMS, how such data are combined to compute the indicators we define, and the comparison process between desktop and mobile interfaces (Fig. 1).

3.1 Environment Setup

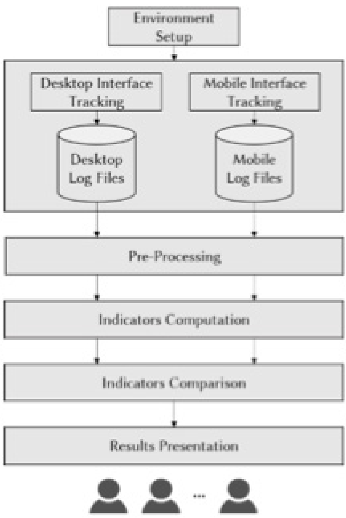

Fig. 1 - The proposed approach

The main goal is to compute a relevant set of usability indicators modelled as numerical scores to make possible the evaluation and the comparison of desktop and mobile user interfaces for the same LMS. For that purpose, it is required a set of test users (e.g. learners) and a time length for the test period. The number of test users can largely range; a value around 30 can usually ensure statistical validity (Sauro & Lewis, 2012). All the users should use both desktop and mobile interfaces based on their learning context during the test period. Consequently, the comparison will be within-subjects (i.e. all the users use both the interfaces). This setting has been selected since it reduces the variability on how users interact, making the scores comparable. The test period should be long enough to track a relevant amount of data.

During the test period, the LMS tracks the data needed to compute the usability indicators. Section 3.2 describes the format of the tracked data and how the data coming from users' interactions on desktop and mobile interfaces is pre-processed and partitioned. Section 3.3 details how the scores associated to the proposed indicators are computed and Section 3.4 discusses how the scores for both interfaces are compared and presented to human evaluators.

3.2 Data Tracking and Pre-Processing

In the proposed approach, the LMS is instructed to track temporal records related with the time a user performed an interaction on the interface. Each record is associated to an individual interaction and a single type of device. More precisely, the LMS captures the following temporal data for each user:

- **Session Starting Time (SST)** is the time when a new session between the user and the LMS starts, i.e. the timestamp related to the login action.
- **Session Ending Time (SET)** is the time when the current session between the user and the LMS ends, i.e. the timestamp related to the logout action.
- **Activity Starting Time (AST)** is the time when the user opens a resource. The resource is considered consulted if the user spends a minimum amount of time on it. This verification is done through the comparison between the timestamp of access to that resource and the timestamp of exit from it.
- **Activity Ending Time (AET)** is the time when the user closes a resource. If it has been occurred that the user has opened a resource at the time AST, the timestamp of the exit action from such resource represents the AET and it is associated to the last AST for that resource.

Timestamps are formatted in ISO8601, have millisecond resolution, and are partitioned in two sets based on their source device (i.e. desktop or mobile).

3.3 Indicators Computation

The approach defines a list of quality parameters and how the associated scores are computed. These scores do not represent an absolute evaluation of the quality, but allow to quantitatively compare two interfaces. Four quality indicators are included: efficiency, satisfaction, learnability, memorability.

Efficiency. It aims to evaluate the navigation to the desired resource and the navigation among pages (e.g. statistics, syllabuses). It includes the *Navigation Time* (NT) defined as the amount of time needed to reach and open a page or a learning resource and the *Utilization Time* (UT) defined as the time needed to consult the content of the desired resource. The first one is represented by the difference between AST and SST, while the second one by the difference between AET and AST. Then, the resulting efficiency scores are computed: *Score of Efficiency for Resources* (SER) is defined as the average of all NTs referred to a specific type of interaction in the case the task requires only navigation activity, while *Score of Efficiency for Information* (SEI) as the average of the sums between NTs and UTs for a specific interaction type and a task consisting of navigation and fruition (e.g. watching a video-lesson).

Satisfaction. It is an indicator of the amount of time the user spends on the LMS. The parameter is certainly affected by the quality of learning material, but it can be assumed that users do not spend a lot of time on a LMS if they are not satisfied from the user interface. The *Single Session Duration* (SSU) for a given user is defined as the amount of time spent by the user on the LMS during a single session and computed as difference between two consecutive SET and SST. The *Total Session Time* (TSD) for a user is the total amount of time that the user has spent on the LMS and is calculated by adding all the SSU for that user. The *Average Time per Session* (ATS) for a user is obtained by dividing TSD by the number of sessions for that user. Finally, the *Score of Satisfaction* (SS) is the average of the ATS values for all the test users.

Learnability. It measures how easy is for the user to execute a task for the first time. The timestamp when the task is executed for the first time and the timestamps of subsequent interactions are compared. If the learnability is low, it will be a significant NT change between the first interaction and subsequent ones; contrary, if the learnability is high, the first interaction is executed in a time near to that of subsequent ones. Low values of the difference between NT of first interaction and NT of *n-th* interaction (*n* is a free parameter) reflect a high learnability. User Learnability Time (ULT) is defined as the difference between NT of the first interaction and NT of *n-th* interaction. *Score of Learnability* (SL) is defined as an inversely-proportional function associating increasing values to decreasing values of the average of ULTs for all users.

Memorability. It is assumed that a user interface is easy to be memorized if an interaction happened after a period of inactivity is similar to the one happened before the period. Low values of the difference between NT of last interaction before the inactivity period and the NT of the first interaction after that correspond to a high memorability. The User Memorability Time (UMT) is defined as the difference between the NT of last interaction before the inactivity period and the NT of the first interaction after that period. The *Score of Memorability* (SM) is calculated with an inversely-proportional function which associates increasing values to decreasing values of the average of all the UMT for all the users, considering the UMTs for a given interaction type.

3.4 Indicators Comparison and Results Presentation

The five mentioned scores are computed for each couple of user interface and interaction type. For instance, if N user interfaces and M interaction types are evaluated, then N*M scores will be calculated. For instance, to compare two interfaces on a specific interaction type considering a given indicator, the desktop interface score and the mobile interface score associated to that indicator are evaluated. However, observing which score is greater than the other is not sufficient since the difference between such scores could not be statistically significant. Therefore, the approach requires to run a statistical test (e.g. Paired t-Test) for each couple of indicators scores and compute the confidence intervals related to the difference. For instance, we consider the couple of scores associated to the SL for the interaction of accessing a video lesson in both a desktop interface and a mobile interface, supposing that the first score is greater than the second one. To establish whether the SL is statistically better for the desktop interface rather than the mobile interface, the statistical test is run to obtain a confidence interval. Considering such interval, it is possible to confirm or discard the initial hypothesis. The scores and the statistical analysis are presented to human evaluators to be evaluated.

4 Practical Application

In this section, we describe the analytics tool, underlining the transition from the theoretical approach to the Moodle LMS plugin. This tool puts the approach into practice, providing insights about users' interactions and information on usability comparison between desktop and mobile interfaces.

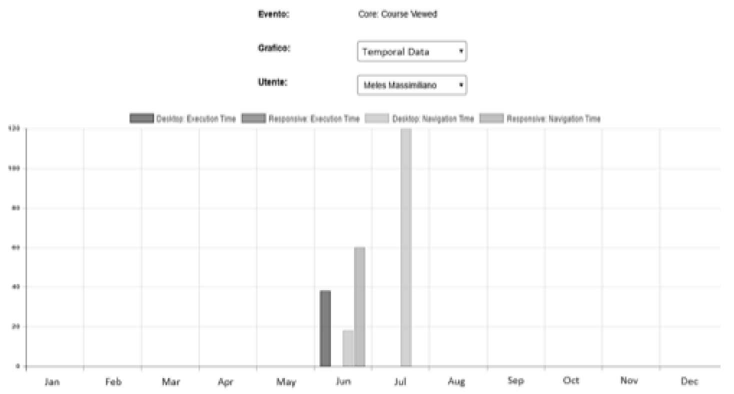

Fig. 2 - Temporal data bar chart

One of the main Moodle characteristics is the modular structure which allows developers to extend the LMS with new features and functionalities. The proposed tool is developed as a report plugin which provides useful views of data in a Moodle site, using several web technologies: HTML and CSS for structure and styling, PHP as server-side language, JavaScript as client-side language, Chart.js as JavaScript library for graph drawing, JQuery as JavaScript library for ensuring cross-browser compatibility, and AJAX as asynchronous method to exchange data between server and clients.

Each step of our approach is associated to a software module in the Moodle plugin. In back-end, the Data Tracking software module exploits the standard log generation in Moodle. Each interaction with an LMS interface component throws an event notification when a user performs an action for which that component has an event observer. Using Moodle APIs, the module filters the events to be directly read from the logging subsystem, avoiding import/export operations. Then, the Data Pre-Processing, the Indicators Computation and the Indicators Comparison software modules implement the operations and calculations defined by our approach. In front-end, the tool is available on the Moodle main menu with the following pages and functionalities:

- **Usability Score Visualization**. The user can select a reference interaction type and a time period. Based on them, it is displayed a table containing scores for the indicators we proposed. More than one type of interface can be selected and they can be compared considering such scores.
- **Graph Visualization**. Three graph types are available for visualization of aggregated data: a bar chart showing values for the selected indicator for each type of device during a selected period, providing information about the usability changes on the LMS; a pie chart comparing the

number of users' interaction on each type of device; a bar chart displaying data for each user and type of device during a given period (Fig. 2).

- **Temporal Data Visualization**. The user can select a reference interaction type and a period for monitoring the given interaction type. Based on them, it is shown a table with a row for each LMS user. The table contains the average navigation time, the average execution time and the number of interactions on the LMS for each user interface (e.g. desktop or mobile).

Human evaluators firstly setup the test environment, selecting the test users and the test period. Then, they continuously compare the user interfaces under evaluation through the analytics tool available into the Moodle main menu.

Conclusion

In this paper, we proposed a novel approach based on the use of analytics tools for the evaluation of interface usability using specific native indicators. A proof-of-concept plugin is implemented on Moodle LMS. The proposed approach has several positive aspects. In fact, standard usability evaluation needs active users' collaboration, while our approach transparently collects data during normal learning activities. It promises to reduce time and cost for usability evaluation in e-learning, ensuring adaptability to devices and LMSs.

In future research, we plan to apply the approach in real learning contexts and compare subsequent versions of the same interface or different versions of the same interface for different devices. Moreover, the approach will be tested in other contexts outside e-learning (e.g. e-commerce).

The proposed approach can be an alternative for user interface evaluation in e-learning when it is preferable to avoid no cost-efficient standard methods.

Acknowledgments

Mirko Marras gratefully acknowledges Sardinia Regional Government for the financial support of his PhD scholarship (P.O.R. Sardegna F.S.E. Operational Programme of the Autonomous Region of Sardinia, European Social Fund 2014-2020 - Axis III "Education and Training", Thematic Goal 10, Priority of Investment 10ii, Specific Goal 10.5).

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