Clustering students based on motivation-to-elearn: A Blended Learning Approach

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Abstract

Technological advances during the last decade have provided huge possibilities to support e-learning. However, there are still concerns at decision-making levels regarding the Return-of-Investment (ROI) of e-learning, their sustainability within organizational boundaries and their effectiveness across potential learner groups, since the "one-size-fits-all" design approach is still currently in use. Literature shows that research efforts have concentrated on defining more affective measures and proving that design has a significant effect on learners' motivation, satisfaction, and retention. This leaves room for further research to identify alternative and innovative ways to center design on students' concerns when learning online. Our work focuses on the design of workable courseware usability evaluation methods to differentiate students and contextualize the improvement of learning-support systems from pedagogical and system perspectives. Our results suggest that students can be grouped in a three-cluster structure based on their motivation-to-elearn data, so instructors could predict the membership of new students to these clusters at the very beginning of the technology-enhanced learning experience, making possible the anticipation of the usability issues that most affect student results. This also facilitates the definition of pedagogical interventions that could timely help at-risk learners, contributing to the retention rate.

Keywords:, Student clustering, Motivation-to-elearn, Usability-Evaluation method, Learning-centered framework

Introduction

E-learning bears the promise to deliver cost-effective education in an innovative way by improving pedagogy, resource-allocation, content development, student access practices, potential cost reduction and revenue growth. Though e-learning in recent years has grown significantly, organizational concerns prevent its adoption as a strategic component for either skill development or education, due to its disruptive impact on internal practices, culture and infrastructure. In addition, other relevant concerns, such as return-on-investment (ROI), the quality of learning content, the accreditation of results, student retention, the engagement of faculty in online learning and the integration of e-learning platforms with operational systems that support student registration or human-resource management practices. Thus, many organizations are still experimenting with e-learning even though there is no solid business model grounded on empirical evidence. Some organizations have implemented blended-learning initiatives to test the concept within their boundaries. This has been done in a fragmented manner without consistent monitoring, partial results and high start-up costs (O'Neill, Singh and O'Donoghue, 2004). More recently, organizations are learning to measure results, but creating and sustaining cost-effective learning supported by technology is still a obstacle for organizations, including Higher-Education institutions, their managers nand development teams (Bischel, 2013; Harris, 2010).

Cost-effective approaches are of specific relevance for organizations. This effectiveness is measured by both the achievement of learning, students' and teachers' attitudes and related cost-effectiveness. By definition, cost-effectiveness focuses on comparing different ways of achieving the same objective. The most effective choice is the least costly of the compared alternatives. Its organizational impact occurs in three levels. At an individual level, cost effectiveness comes mainly from each student learning at their own pace content delivered just-in-time in accordance to special needs and life-stage in education, professional development, and language training (Hjeltnes and Hansson, 2004). At a societal level, the development and delivery of high-quality and interactive learning content is better controlled when articulated with key players since that will add more value to skill development and foster economic growth. At the institutional level, cost-effectiveness comes from better and greater administrative flexibility, the reduction of geographical barriers, lower teacher/student ratios and economies of scale which lower the cost per student through re-use and modularization of learning content, by requiring less often specific instructor interactions. The critical point is not only to reach cost-effectiveness but also sustain it over time, which requires both investments to update and upgrade content and infrastructure and develop instructors' skills to produce high-quality, interactive and well suited content to students' needs and performance feedback. To achieve this, cost-effective approaches have to provide mechanisms to match their design with the needs of learners, teachers, society and institutions, since the outputs of a learning experience are relevant to the needs and demands of its users while requiring less resources than other institutions that meet these criteria (Hjeltnes and Hansson, 2004). That is why the main goal of this research is to identify predictive models for e-learning to support such cost-effectiveness.

Literature shows that most work so far has focused on developing courseware tailored to individual cognitive or learning styles and analyzing objective performance measures (Britain & Liber, 2004). Though both have benefited individual learning, on one hand, identifying learning styles is time-consuming for students and raises both ethical and governance concerns for institutions. On the other hand, using performance measures have provided inconclusive evidence on the effectiveness of online pedagogies, making it hard to extract from it sound theoretical foundations to define quantitative design guidelines. Also, there is a need to better understand the role of learning contexts on student results, covering its social, cultural and historical aspects (Blandin, 2003; Preece and Rogers, 2002; Pillay, Clarke and Taylor, 2006). Moreover, during the last decade there was an increasing research interest in defining new measures related to attitudes, motivation to learn, emotions, and satisfaction in Technology-Enhanced-Learning (TEL) scenarios (Pillay, Clarke, and Taylor, 2006; Šumak et al., 2011; Zaharias & Poulymenakou, 2009). To this end, research efforts indicated that the usability evaluation of TEL experiences should be performed in a more holistic and integrated manner to support the notion of learning-centered design (Costabile .et al, 2005; Mehlenbacher et al, 2005; Venkatesh et al, 2003) and must provide timely information to instructors for the early definition of pedagogical interventions.

Supporting learning-centered design, however, requires specific methods and tools. Furthermore, providing such integrated approaches has been fraught with difficulties. First, the prevalent view on e-learning is fragmentary, showing a lack of monitorization of results and little (or no) attention to the articulation between pedagogical and usability goals and IT investments within organizational contexts (Blandin, 2003; Duchastel, 2003: O'Neill, Singh, and O'Donoghue, 2004; Harris, 2010). Second, assessing the effectiveness of learning-support systems has proved to be a more complex undertaking than conventional usability evaluations (Ardito et al, 2006; Granic & Cukusic, 2011; Karoulis & Pombortsis, 2003). This is partly due to the added complexity introduced by pedagogical, organizational culture, social and process-related aspects affecting the learner experience

(Blandin, 2003; Duchastel, 2003). Indeed, the learner experience is considerably more complex than the user experience if we consider the additional requirements emerging from knowledge acquisition, task closure, and length of interactions (Rentroia-Bonito and Jorge, 2004). Third, the modelling of learners is complex. This has been addressed mainly cognitively, and is difficult to get sensitive and explicit user data (Bandura, 1997; Leong, Ho, and Saromines-Ganne, 2002, Lee & Mendjinger, 2011). Moreover, during the last decade researchers have been defining new attitudinal measures exploring the relationships with the usability of learning-support systems (Granic & Cukusic, 2011, Zaharias & Poulymenakou, 2009). In addition, the management of cognitive and psychological user data within development teams and organizations raises ethical and governance issues. Fourth, the complexity of collecting and combining large amounts of multi-source, qualitative and quantitative data coming from learners and systems during real and ongoing learning experiences is not an easy task (Dougiamas & Taylor, 2002; Leong, Ho, and Saromines-Ganne, 2002). Fifth, the difficulty to ascertain solid and agreed-upon theoretical foundations, and the difficulty to get evidence in real learning settings, with extra concerns regarding small sample sizes, interference in student learning, low response rates, unstructured working methodologies, and reliability and validity of measurement scales make it harder to obtain valid and generalizable results (Cook and Campbell, 1979).

These difficulties have prevented the identification of shortcomings beyond usability problems, reaching factors that may have an influence on the learning context where the student-system interaction takes place. This short-sighted view has translated into poor and ill-timed feedback to improve pedagogy and the learner experience and have made harder to control and cost-effectively improve TEL experiences (Britain & Liber, 2004). And also, this has impaired the role of e-learning as an effective organizational component to achieve expected organizational goals. Some researchers have contributed to this body of knowledge with integrated evaluation frameworks for specific TEL experiences to help better understand the socio-technical implications at strategic and operational levels (Ardito et .al, 2006; Costabile et al., 2005; Mehlenbacher and Lucas, 2005). However, these approaches focused on general principles for learning-centered design. Given the specificities of each experience, more operational approaches are required. More recent approaches were centered on mobile learning technology (Vavoula & Sharpes, 2009), while our endeavors strive to remain technology-agnostic. Indeed, e-learning is still a developing area. This requires both from learners and instructors a new mindset and roles in order to gain full user acceptance and organizational adoption, before it can provide the full benefits it promises (Battaglino et al, 2013; Bichsel, 2013). Due the complexity of this endeavor, we focus on the interaction between students and learning-support systems by exploring the people-system fit within instructional settings. To this end, we explored the relationship between the usability of a learning-support system and students' performance and satisfaction, more specifically on analyzing the role of motivation to e-learn in clustering students at the very beginning of the experience.

Our research results provide design guidelines for organizations to build cost-effective TEL experiences based on what students' valued most in an e-learning experience. This could contribute to better personalise courseware, setting up a basis for predictive modelling, which would help instructors to know more about students' most valued items at the very beginning of the course, thus supporting learner-cantered design while using simpler measures to gather student data. As a key contribution we were able to cluster students into groups according to their profile, which paves the way towards adapting content delivery to student characteristics from the onset of a course. In this sense, predictive modelling emerges as a potentially useful component to deliver a more personalized experience while helping instructors to focus on specific pedagogic interventions to improve student learning, satisfaction and retention.

CONCEPTUAL FRAMEWORK

Based upon previous work (Rentroia-Bonito & Jorge, 2003, 2004), we propose a Usability Evaluation conceptual framework for learning-support systems. This framework is a bidirectional relationship between structure and behavior that starts at the organizational vision and ends with the analysis of the strategy-results fit. Structure drives student behavior and, reciprocally, student behaviors gradually influence structure (Bandura, 1997). Figure 1 shows this conceptual framework.

Structure relates to the learning-design process and supporting system, which are influenced by institutional strategies. Within TEL experiences, student behavior is of both an online and offline nature. Online or resource-usage behavior is the set of student actions performed when using the system to access available learning or class-related information resources. Offline behavior is the set of student actions performed in face-to-face contacts with peers and instructors regarding class activities. Either behavior is influenced by internal student attitudes and beliefs and externally by learning contexts. Systems, as part of learning contexts, influence student perceptions during interactions, and are themselves influenced by students when the context allows learner agency (Bandura,1997; Pillay, Clarke, and Taylor, 2006; Lee and Mendjinger, 2011). In the former case, students update their mental models and skills to better deal with system functionalities. In the latter, context-related factors could be modified or improved (Chyung & Vachon 2005, 2013). For example, systems could get upgraded to better support the students' tasks, especially if student feedback is collected and acted upon by development teams and process managers.

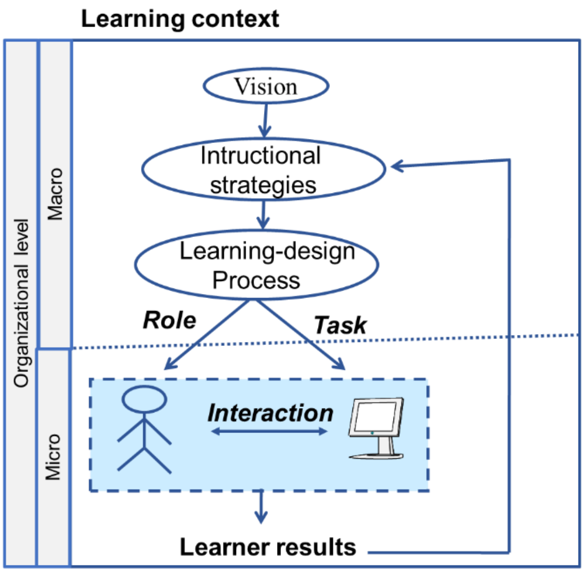

Figure 1: Conceptual framework

This conceptual framework comprises three basic entities. First and foremost, the learning-design process, which provides yardsticks to define educational goals, model learning tasks, define roles in learning contexts, and monitor results regarding stated learning strategies. Second, the learning-support system, whose ease-of-use and usefulness to support the performance of each learning task are evaluated by learners. Third the learners, whose needs are the main focus of design efforts and the source of quantitative and qualitative data in TEL experiences, tasks, roles and the people-system interaction are relationships in this conceptual framework. Learning task links the context's micro- and macro-organizational levels; thus, articulating operational actions with strategic choices of instructional processes and pedagogical goals. Interaction ensures the situated analysis within the learning scenario. Role relates to the set of responsibilities or duties students perform when interacting with the learning-support system.

As shown in Figure 1, learning-support systems reflect institutional decisions to implement specific organizational strategies for skill development. Examples of these are investments in technology, instructional approaches and methods, facilities, making expert staff available to produce content, instructor support and also setting goals for system usability. Additionally, instructor teaching style, context-specific organizational values and climate shape pedagogical methods, and contribute to set up the class' sub-culture, which foster or inhibit learners' expected behaviors and actions.

The integrated analysis of these three relationships within a specific learning context focuses the efforts of development teams on learning-centered design, since this framework takes into account usability and learning goals and also student results. In this manner, TEL designers iteratively analyze context-related design-oriented user feedback and perform inspection evaluation techniques, which progressively contribute to improve the student-task-system fit within the particular learning setting. Thus, development teams can holistically evaluate usability in a broader sense, feedback stakeholders and perform cost-effective improvements in TEL experiences at micro-organizational level by systematically using this research evaluation method and tools. Figure 2 shows its phases.

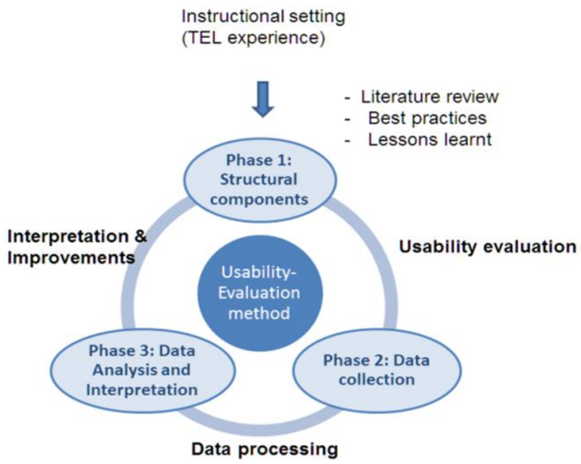

Figure 2: Usability Evaluation Method

The focus of the first phase (Structural components) is to adapt the system to pedagogical practice creating the learning context based on literature review, best practices and lessons learnt (Martins et al, 2007; Rentroia-Bonito, 2014). In the second phase (Data Collection), data was collected via questionnaires specifically developed to achieve this research goal and system logs (Rentroia-Bonito, 2014). These questionnaires collected student motives to e-learn, satisfaction and usability data throughout the TEL experience. They had closed and open questions thus facilitating the iterative identification of improvement areas in technical (e.g. usability of learning-support system) and non-technical (e.g. context-related) aspects of TEL experiences that affect student results (online and offline behaviours, satisfaction and performance). Synchronously, resource-usage data was extracted. In the third phase (Data Analysis and Interpretation), development teams analysed the collected data in an integrated manner by using statistical techniques, such as descriptive statistics, mean comparison, cluster and discriminant analyses (Johnson & Wichern, 1992; Brown & Wicker, 2000) and interpreted results.

RESEARCH METHODOLOGY

This was an exploratory research focusing on setting the basis to support predictive modeling and achieve TEL cost-effectiveness. Due to the topic's complexity, we chose a mixed-method research design that combines qualitative and quantitative research methods and several data-collection techniques (Dix et al, 1998; Nunnally, 1979). Each one of these methods and techniques are well-known and individually used by researchers from

Information-Sciences, Engineering and Education fields (Dix et al, 1998; Preece & Rogers, 2002; Venkatesh et al, 2003). To this end, we instantiated our conceptual framework in a specific real instructional setting, analyzing it as a case study. In this way, we deeply analyzed a TEL experience within its context, specially focusing on the aspects that could affect student results (performance, satisfaction and system usage).

Since Higher-Education institutions are no exception to the competitive pressure to improve learning effectiveness and their cost efficiency, we instantiated this framework in a real TEL situation: an Engineering course about Multimedia Content production (MCP). Our general hypothesis was: "*Students' perceived usability of a learning-support system and learning results might be influenced by their motivation-to-elearn*". Figure 3 shows the research model. To test this general hypothesis, we needed to have well-defined hypothetical variables and reliable measures to answer research questions. To this end, we develop a key construct to cluster students and tested the others to get some evidence for the following research questions:

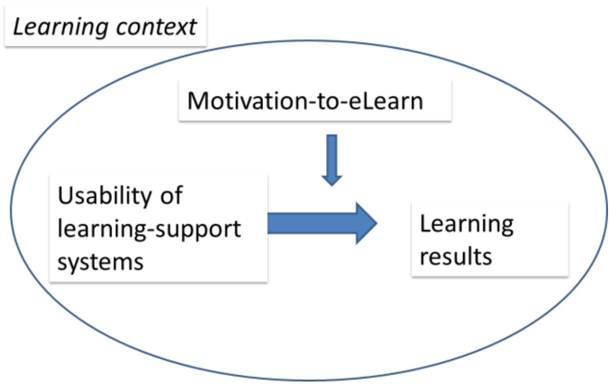

Figure 3: Research Model

RQ1: Do motivation-to-elearn differentiate groups of students?
RQ2: Can motivation-to-elearn be used to predict student membership?
RQ3: Are there differences in the perceived usability of learning-support systems and learning results by student clusters?

The research model has both input and output variables. Input variables relate to what activated the evaluation process within the Learner-System Interaction. Considering Norman's extended framework (Dix et al, 1098) and the theoretical foundations of the Technology Acceptance Model (Venkatesh et al, 2003), our input variable was perceived usability and its specific dimensions: ease-of-use and usefulness.

Usability is a software quality attribute that can be measured by using qualitative and quantitative variables (Dix et al, 2003). To measure usability, within Human-Computer Interaction, the system is taken as a stimulus to potential learners. This stimulus can motivate, or not, users to interact. Based on the Technology Acceptance Model, we proposed to measure the perceived ease-of-use and usefulness of each one of the system functionalities that support the performance of the defined learning tasks. Based on the Technology Acceptance Model, we proposed to measure the perceived easy-of-use and usefulness of each of the functionalities of the system that supports learning tasks. Table 1 relates Body of knowledge to evaluate usability items of the supporting e-learning system.

In this research model, students' motivation-to-elearn, acts as a control variable. In this sense, the role of motivation-to-elearn is crucial to differentiate students, support the definition of specific intervention strategies and improve learning results. Since we did not find a proper definition for this variable in the literature (Bandura, 1997; Chyung & Vachon 2005,2013; Dix et al, 1998; Gagne & Deci, 2005; Zaharias and Poulymenakou, 2009), we defined Motivation to e-learn as *an individual construct denoting an internal* *set of processes (both cognitive and behavioral) by which human energy becomes focused on learning particular work-related content (whether by actively interacting with courseware, participating in a virtual class, self-studying, doing e-homework alone or in group) to achieve specific learning goal* (Rentroia-Bonito & Jorge, 2004).

Table 1: Body of Knowledge and usability items

Body of knowledge	Item
Learning methodologies	1. Posting in class fora
	1. Uploading materials
	2. Downloading materials
Technology Acceptance Model	3. Participating in wiki
	4. Participating in Chat
	5. Consulting grades
	6. Searching for archived learning content (slides and videos)
e-Learning	7. Consulting Class news
	8. Consulting archived webcast videos

To identify motivation-to-elearn (MEL), the literature revealed key traits of TEL experiences related to system, context, and people. Table 2 shows the knowledge body, dimensions and items selected for building this construct. The first two dimensions are extrinsically related and the last one is of intrinsic nature. These items were identified not only in the literature but also validated in four user sessions to fine-tune their definition and user interpretation. From all proposed items, we selected a 22-item set to minimize sampling content error. Later the internal consistency and temporal stability of this construct was analyzed in order to optimize it for future applications (Daws, 2000; Nunnally, 1978).

Table 2: Knowledge body, Dimension and items

Knowledge body	Dimension	Motivation-to-elearn (MEL) items
Technology architecture	System-related	1. Accessibility to learning content from anywhere, anytime
Learning methodologies		2. Security in accessing learning contents and protection of my personal data
Usability Engineering		**3.** Personalized feedback associated to learning online
		4. Ease-of-use system interface of learning-support
		5. Flexible presentation of learning content in the way I prefer it
		6. Aesthetic presentation of learning content
Captology	Context-related	7. Author credibility of available learning content
Learning methodologies		8. Support from course instructors
		9. The adequacy between the learning content and objective
Management theories and processes		10. institutional support to promote, disseminate, and execute technology-enhanced learning initiatives
		11. Resources available to support learning online (e.g. equipment, physical space, contents, technical support, etc.)
Social cognitive theory	Individual-related	12. My previous experience during e-learning
		13. My relevant others' experience doing e-learning
Identity theory		14. Feeling that I am part of my learning group
Expectancy theory		15. The usefulness of contents to my learning objectives
		16. e-learning contributes to my competency development
		17. Using my personal computer when studying online
		18. The convenience of learning which is of my interest, where I want, when I want, at my pace
		19. Liking studying the subject matter of the course
		20. Believing that communication with instructors in this learning experience will be adequate
		21. Believing that this experience will really contribute to achieve my learning objectives
Self-efficacy		22. Believing that I can learn this subject online

Output variables include learning results, specifically student grades and satisfaction with the several elements of the learning experience. Table 3 shows the element used to measure student satisfaction, based on Herzberg's Hygiene theory (Chyung, 2005), and student feedback during this b-course.

Table 3: Satisfaction with the learning experience items

1	Learning task performed on the supporting system (ex. Watching videos, participating in forum and chat, tests)
2	Available learning content (videos, slides)
3	Used e-Leaning platform
4	Communication with instructors and peers,
5	Available archived contents,
6	Instructor support,
7	Acquired knowledge,
8	Grades achieved
9	Received feedback

The number of selected items of this scale was both smaller and more reliable than similar published measures (Roca, et al, 2006; Leong et al, 2002). Also, literature suggested that student online behaviors could be analyzed through their access patterns, namely the number of accesses to learning resources, among others (Dyer, 2003; Venkatesh et al, 2003). For the purpose of this research, we used it as a measure of student resource-usage behavior.

OUR FRAMEWORK PUT TO THE TEST

A research group from our university set up an instructional setting called, for the purpose of this research work, MCP (Multimedia Content Production) Online, and defined specific pedagogical and usability goals. This course was part of the Computer Graphics and Multimedia curricula of the Computer Science Engineering Degree at *Instituto Superior Técnico* in Lisbon. MCP Online was a blended-learning course combining all elements related to a conventional class scenario within our university setting, entailing all its interdependent organizational dynamics, with a Learning Management System (LMS) adapted to its internal teaching practice. This course had been taught during the spring semester at the two campii of our university.

Learning content was structured around theoretical concepts and related examples, and was made available to students through slides (.pdf and .ppt formats) and multimedia archives of past classes (video, audio synchronized with presentation slides) following the course syllabus. Learning tasks were defined and system functionalities were activated together with brief working instructions and rules. Learning tasks were: (i) Participation in scheduled classes, (ii) Studying learning contents made timely available on the system according to course syllabus; (iii) Doing a course project, elaboration of periodic reports, participation in its specific forum and weekly chat; (iv) Analysing hot multimedia topics and posting their summaries on specific thematic forum, and (v) Taking quizzes and exames. Students could perform: (a) individual tasks, such as consulting current and archived learning materials, participating in class, fora, project's support chat, and (b) group tasks, such as doing a project and respective report by using the system's integrated *wiki* component. In addition, students could receive feedback and consult class information resources, also online.

Out of the total of students registered for this course, we only used the responses of same students that participated in the first and third usability evaluation sessions. Thus, our sample was composed of 107 students, all Portuguese. Table 4 shows sample demographics.

Table 4: Student sample demographics

Student variable	Options	% sample
University campus	Campus A Campus B	55 % 45 %
Gender	Female Male	22 % 78 %
Age	20-24 years 25-30 years	82 % 18 %
Undergraduate year	3rd year 4th year 5th year	7 % 73 % 20 %
Specialization area	Intelligent & multimedia Systems Information Systems Others	29 % 52 % 19 %
Number of courses taken in this semester	Less than 3 courses 4 courses 5 courses 6 courses More than 7 courses	8 % 14 % 36 % 24 % 18 %
Student availability	Holding partial job Full-time student	21 % 79 %
Preferred locations to study online	Home IST Library IST	83 % 6 % 11 %
Hours using Internet	Less than 1 hr/day 2 hrs/day More than 2 hrs/day	7 % 14 % 79 %
Participation in e-Learning	Never participated in similar learning experience Participated just once Participated more than one time	80 % 13 % 7 %
Recommend the participating in online courses to relevant ones	Yes No	85 % 15 %

On a weekly basis, and based on instructor class records, 39% of students had more than one face-to-face contact with instructors. 15% of students had more than two face-to-face contacts with instructors per week. Based on system data, 82% of students accessed it between one to eight times per working day. Students' self-reported data also indicated that 63% of them stayed less than or equal to 10 minutes each access.

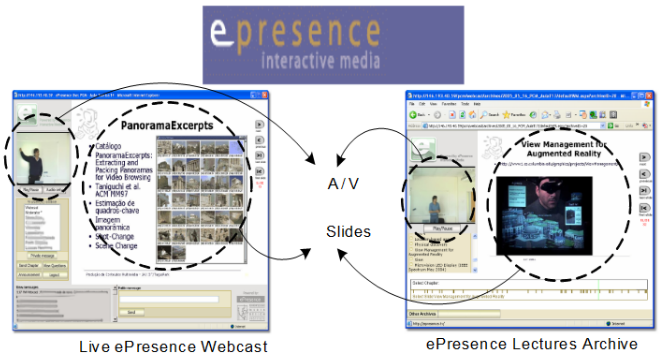

Figure 4: The supporting system's e-Presence component

Our research group selected and customized an open source Learning Management System (Dougiamas & Taylor, 2002), including a webcast and multimedia archiving functionality. Figure 4 displays a sample of the e-Presence component. The system prototype was tested within same course in the previous year and was improved according to user and technical feedback (Rentroia-Bonito, 2014). The system was designed to meet three main requirements: (i) learning content management: (ii) class webcast and archive, (iii) evaluation methods and collaborative work. Its main functionalities were identified based on the defined priorities; university's teaching process and analysis of strengths and weaknesses of available LMS platforms. In short, the supporting system was based on an open-source LMS, called Moodle (www.moodle.org) integrated with a streaming webcast and multimedia lesson recording system. The former allowed students to access many different contents, participate in online *fora*, take quizzes, check grades, etc. The latter allowed the webcast of lecture events in a course. In this way, students could attend classes remotely, viewing slides, which were synchronized with audio and video streams. They could also participate in classes via chat-room, as well as placing questions to teachers and other colleagues. The internal instructional process and its supporting system covered the structural component of the MCP course. After structuring the experience, the instructor team focused on the relationship management. Instructor and teaching assistant lectured in a traditional way while opening different communication channels (online and offline). Also, the teaching assistant moderated weekly chat sessions and coached students, in face-to-face meetings, about project assignments and system functionalities according to defined course deadlines and students' needs.

At the very beginning of the course, students were informed about class dynamics and course evaluation methods. This information was also online. Participating students used the supporting system as the sole tool to perform main learning tasks. Students used system functionalities according to planned learning tasks and were kept informed about their progress and class dynamics by consulting respective fora and grades. Anonymity and confidentiality were both stressed and ensured by the professor and the research team during online and offline interactions. Moreover, students also took a quiz and filled in the online questionnaire during the same week spending, on average, around ten minutes on each.

During the first week of the course, registered students filled in the Motivation-to-elearn questionnaire, indicating for each item shown in Table 2, their opinions regarding "How inportant was the item for them when learning online, on a rating scale ranging from *"Not important for me" to "Very important for me".* Usability evaluation was done in three specific moments: in the first week, at 6th and 11th weeks of the course. Students filled in an online questionnaire, indicating, for each item indicated in Table 1, their opinions about: (a) how easy it was to perform each task on the system, on a rating scale ranging from "*Very difficult" to "Very easy",* and (b) how useful were the tasks performed on the system for their learning, on a rating scale ranging from *"Not useful for me" to "Very useful for me".* During the 11th week of the course, students filled in the Satisfaction-with-the-learning-expereince (SEL) online questionnaire, indicating for each item shown in Table 3, their opinions regarding to what extent they were satisfied with each item of the learning experience, on a rating scale ranging from *"Totally dissatisfied with this element of the learning experience" to " Totally satisfied with this element of the learning experience".* It also had open questions regarding what they liked the most and the least about MCP online. These questionnaires was previously tested during a similar experience during earlier versions of the course and was improved based on student feedback (Rentroia-Bonito, 2014).

During analysis, questionnaire-based data were complemented by resource-usage data in order to detect usage patterns and also monitor course progress against its goals. Furthermore, student open feedback was asked and content-analyzed and as a course practice, results were discussed during project meetings to identify improvement areas and decide on their deployment or incorporation into the development process. Moreover, short reports on what was done after each evaluation session were published in the homepage of MCP Online, as static information for students to consult. This practice contributed to identify and clarify potential sources of student dissatisfaction and sustained a constructive class culture.

OUR RESULTS

To obtain evidence for our research questions, we first analyzed the reliabilities of MEL and SEL scales by calculating their respective Cronbach's Alpha coefficient. This coefficient is a measure of internal consistency, indicating how closely a set of items are related as a group, thus indicating the scale reliability: The closer the Alpha Coefficient is to "1", the more reliable the scale is. Afterwards, we performed cluster analysis followed by a discriminant analysis to predict new-student group membership. Lastly, we identified specific-cluster differences in usability evaluation.

The Alpha coefficient obtained for MEL was 0.86, and for SEL was 0.87. These are well-above the minimum required for exploratory studies (Nunnally, 1979). Also, we performed an item-to-item analysis to optimize both scales. After this analysis, just motivation-to-elearn changed the number of its items. It kept a 0,85 alpha coefficient but dropped 7 items, mostly individual-related (see Table 2, items 9, 12, 13, 15, 16, 17 and 18). We used this optimized scale in the validation test session. MEL was used to group students based on the homogeneity of their responses regarding to what students valued the most as reasons to e-learn.

To identify the cluster-structure, we used the Complete-Linkage method, and tested its stability by using the Ward Method, as suggested by (Johnson & Wichern, 1992; Daws, 2000). The number of clusters was chosen based on the partial R-square. This three-cluster structure accounted for half of the variance (52%). To identify which MEL items differentiated students' clusters, we analyzed the three-structure in a two-dimensional space defined by the two resulting factors from the clusters analysis, as shown in Figure 5.

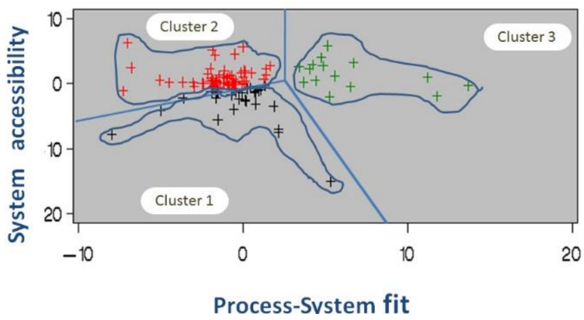

Figure 5: Resulting three cluster structure

The main MEL items with a high influence on the first factor were *Instructor support, Aesthetic content presentation, and Institutional support*. These three salient items resembled the macro and micro-organizational levels associated to any learning context: well-presented content presentation and instructor support within institutional contexts that promote, disseminate, and execute TEL initiatives. These relate to the basic elements of the learning-design process and supporting system in any TEL experience. Also, this factor particularly focused on the pedagogical-related heuristic "Match with 5curriculum" (Karoulis & Pombortsis, 2003). That is why we called this factor Learning *Process-System fit.* The main MEL items that highly affected the second factor were "*Accessibility to content from anywhere, anytime*", *"Easy-to-use interface", and "Personalized feedback"*. All three items were system-related. However, "*Accessibility to content from anywhere, anytime*" was twice as salient on this factor in comparison with the two other items. Indeed, student concerns on Accessibility to contents went beyond connectivity from anywhere, and anytime. It included system registration and getting adequate and fast helpdesk support. This was particularly critical at the beginning of the learning experience where system-related concerns dominated. This factor focused on the pedagogical-related heuristics "Match between designers' and learners' mental models", other usability-related items, and more operational heuristics suggested by the literature (Karoulis & Pombortsis, 2003). We called this second factor *System accessibility*. Table 5 shows identified clusters' size and Table 6 summarizes their main traits. Based on these traits, we named the clusters "Technology-driven (TD)", "Resource-driven (RD)" and "Organization-driven (OD)". For example, TD students valued system-related items higher than the others.

Table 5: Student clusters' size

Cluster	Number of students	% of students
Technology-driven students (TD)	28	26%
Organization-driven students (OD)	64	60%
Resource-driven students (RD)	15	14%

To identify significant differences regarding learning results across student clusters, we used the Kruskal-Wallis test with a significant level of 5%, a universal standard for this type of research.

Table 6: Student clusters' main traits

Student cluster	Main characteristics
Technology-driven (TD)	Students valued "Easy-to-use" interface and "Personalised feedback and undervalued "Accessibility to contents". They conistently rated system-related items high.
	Of those students majoring in Other specialization area, most were TD students. TD students were mainly registered in campus A. They were the most active group online that also meet regularly with instructors face-to-face. In terms of course workload, TD was the second busiest student group.
Organization-driven (OD)	Students rated high and allocated about the same importance to content, individual and system issues
	Of those students that were between 25-30 years years old, most were OD students. They were also mainly registered in campus A. This group met with with instructors face-to-face more frequently on a weekly basis that the other two clusters. In terms of course workload, OD students were the busiest.
Resource-driven (RD)	Students valued more "Instructor support", "Aesthetic content presentation", and valued less "Institutional support"
	RD students were mainly registered in Campus B, prefered to study at the University, held partial jobs, were majoring in Intelligent Multimedia Systems, and spent less than 1 hour/day on the Internet. A higher percentage of female students belonged to this cluster. This cluster was the least active in meeting with instructors face-to-face on a weekly basis. In terms of course worload, RD students were the least busy of the three clusters.

As shown in Figure 6, we found significant differences regarding usability of learning-support system and student satisfaction, specifically in the usefulness and ease-of-use of participating in wiki and in satisfaction with the available learning content. Indeed, TD students found participating in wiki of a little useful, whereas RD students found it moderately useful for their learning followed by OD students. RD students found participating in wiki easy-to-use followed by TD and OD students. Regarding satisfaction with the available learning content, OD students were the most satisfied followed by TD and RD students. These differences gave some indication for next improvements.

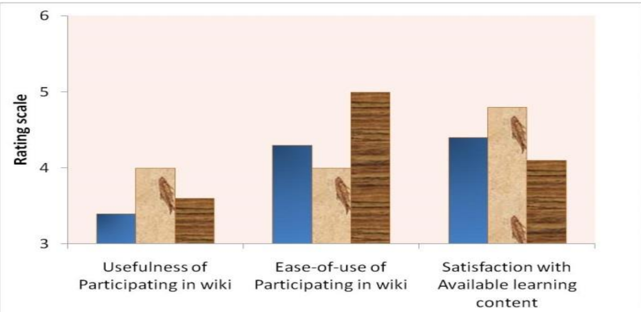

Figure 6: Significant cluster-specific differences in Usefulness of wiki and Student Satisfaction

After obtaining this three-cluster structure, we employed a discriminant procedure to derive a classification criterion. In our case, the overall misclassification rate is around 7%, mainly due to the misclassification of student observations of the OD cluster into the TD cluster. In order to evaluate the performance of this classification function, we ran a validation test using the data from the next edition of MCP Online. We used the same evaluation method. Since the reliability of the measures was established with the motivation-to-elearn data extracted from the previous MCP course, we collected student data twice during the semester: at the 1st and 3rd evaluation sessions. In the 1st evaluation session, 56 students participated (53% of the registered total) filling in the improved version of the online questionnaire. This version had fifteen motivation-to-elearn items reflecting the results of the performed item-to-item analysis. 41% of students from the validation sample were classified into the TD cluster, 46% were classified into the OD cluster and 13% were classified into the RD cluster. In the 3rd evaluation session, we just collected usability, student satisfaction data and resource-usage data.

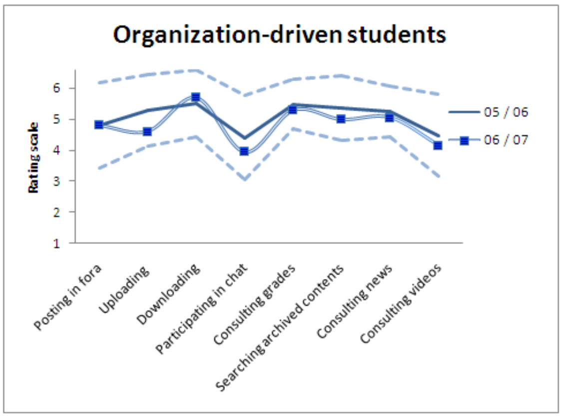

Figure 7: Comparing perceived usefulness across sessions for OD students

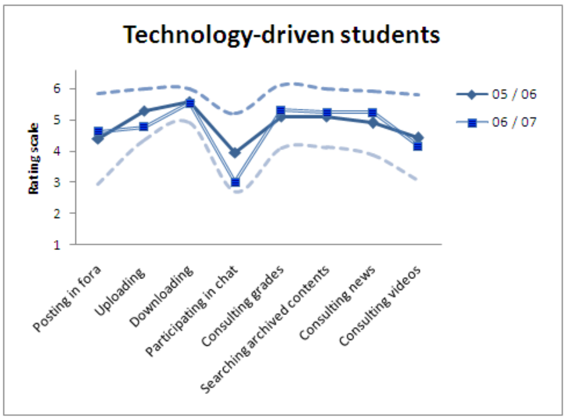

Figure 8: Comparing perceived usefulness across sessions for TD students

Since new students were allocated to known clusters, they were expected to show similar concerns regarding usability and learning results. Indeed, after analyzing student data across semesters, similar traits and average responses were observed in TD, OD and RD clusters of both samples. As an example, Figure 7 and 8 display the average response of OD and TD students of MCP course from the pilot project (05/06) and validation test (06/07) to assess the perceived usefulness of the learning-support system across b-courses. In both figures, the lighter line represents the usability evaluation performed in the validation test and the darker line represents that of the previous year. The upper and bottom dotted lines were obtained based on the means plus/minus one standard deviation of the evaluation for the first year. The impact of some improvements made in MCP online on the learning-support system, before the second year started, was reflected in student evaluations. Despite the difference in values that were sample- and time-specific, the response patterns of each student cluster showed similarities across semesters, since all responses of the validation test (second year) fell within the dotted lines. While our results appear to be solely based on questionnaire data, we did measure resource access patterns for all students throughout the semester. However, aggregate figures show a large variability, which made differences across clusters inconclusive. Clearly, further work is required to better analyze usage patterns across clusters.

The advanced knowledge given by this analysis to the instructors at the very beginning of the learning experience contribute to define class strategies based on its composition, because the composition of the cluster structure is expected to influence learning results. For instance, in our pilot project, the size of the OD cluster was almost twice of TD cluster and four times of RD cluster. The situation with the validation sample was different from that of the previous semester. The size of the TD cluster was about 14% bigger than that of pilot project, and the OD cluster was about 15% smaller than that of the pilot project. Both clusters were about the same size. The practical implication of this kind of cluster composition could be: (a) more demands to significantly improve this class aspects that caused dissatisfaction to TD students (e.g. available learning content), or (b) implementing changes that could motivate TD students (e.g. personalized feedback). These could have a bigger impact in the course dynamics of the second year than for TD students in the previous year. We thought this was because students belonging to the TD cluster were more active online than their colleagues and reported the lowest levels of student satisfaction and perceived usefulness with participating in wiki. Instructors must take into account these time-related and sample-specific differences when defining intervention strategies in the learning context to optimize resources and get expected results.

Regarding learning goals, we also looked at traditional class metrics such as approval rate, class attendance and drop-out rate. More than 90% of the students got a passing grade. This was well-above the results of the course in previous year. At the end of the course, on average class attendance was 69% per student, with a standard deviation of 23%. At the end of the course, drop-out rate was around 1,4%, half that of previous year. Every enrolled student used the learning-support system as a learning tool, though to different extents. Indeed, based on system data, students were high consumers of dynamic class information, but low contributors to its creation by means of adding new threads or posting to existing threads in class fora. We also noted that, TD students had the highest total number of accesses followed by OD and RD students.

Regarding the stated usability goals, the current situation reflected that six out of nine system functionalities were perceived by all students as useful to achieve their learning goals, and eight out of nine functionalities were perceived as easy to perform. In accordance, perceived usefulness of system functionalities was below 80% for TD and RD students. Based on cluster profiles, those students were likely to be distant students. The fit between learning task and system functionality must be improved, especially for them. Indeed, there was a need to improve the consulting of archived webcast videos and the participation in online communication tools (forum, chat and wiki). Perceived ease-of-use of system functionalities were above 80% for all three clusters. Improvement areas were just needed in the usage of wiki, which in fact had some technical problems with its in-built editor.

In relation to student satisfaction, this was below 80% for all three student clusters. Each cluster differed in their satisfaction levels. Overall, OD students had their needs more reinforced by the context than the other students. This indicated that student needs were not equally addressed when planning MCP online, and this is an area for future work (Rentroia-Bonito, 2014). To conclude, Table 7 summarizes these results regarding the formulated research questions.

Table 7: Research results

Research questions	Evidence
RQ1: Do motivation-to-elearn differentiate groups of students?	Yes (Figure 5, Table 2)
RQ2: Can motivation-to-elearn be used to predict student membership?	Yes (Table 5 and 6, Figure 7 and 8)
RQ3: Is there differences in the perceived usability of learning-support systems and learning results by student clusters?	There were a few significant differences in the perceived usability of learning-supporting system and student satisfaction by clusters (Figure 6)

Despite the limitations of this research, rooted in its sample size, the challenges of studying multidimensional TEL phenomena in a real instructional setting, and the lack of integration of system databases; these results shed some light on the formulated hypothesis and research questions. We found that: (a) Motivation-to-elearn and Student satisfaction-with-the learning-experience were reliable measures; (b) motivation-to-elearn could be used to cluster students; thus, predicting new-student membership, and (c) Student groups perceived differently the usefulness and ease-of-use of participating in wiki, and were differently satisfied with the available learning content; even though they had performed similarly. Based on these results, we could support the definition of more assertive intervention strategies, instead of the traditional "one-fits-all-approach", to better deal with usability and student results across clusters in technology-enhanced learning experiences.

IMPLICATIONS FOR DESIGN

We identified three major implications for the design of TEL experiences. First, though there is lot of work ahead to consolidate predictive models for e-learning, these results are promising to facilitate the anticipation of the impact of student membership to a known cluster. This is key to learning cost-effectiveness. In our pilot project, this let development teams to adjust the task-system fit through the identification of proper improvement areas. Also, this way, students contributed to validate the design and build a constructive class culture towards continuous improvement. Qualitatively speaking, our results indicated that there is a need to include institutional and class strategies in the deployment of TEL scenarios.

A second implication relates to system adaptability, specifically when designing interfaces of learning-support systems. Knowing in advance what usability items influence student performance the most helps development teams adjust what is useful for students taking into consideration its cluster-specific differences. Consequently, different types of interfaces can be designed. For instance, the most appreciated learning resources and class information for Technology-driven students could be differently organized in the interface than those most appreciated by Resource-driven or Organization-driven students. This initial orientation acted as operational design guidelines, thus, minimizing user confusion and frustration when interacting with learning-support systems.

A third implication relates to the evaluation of usability of learning-support systems. Development teams must focus their attention on several aspects when planning or improving TEL experiences. This covers basic pre-requisites to plan TEL experiences, the processing of multi-channel textual information, the management of student expectations to diminish the numbers of outliers, the deployment of improvement areas related to what matters the most to students and also what is aligned with organizational and constituency goals. Moreover, the acquisition of required instructor skills, for example conflict and people management, data-mining and statistical techniques and the like have an important role on student satisfaction.

CONCLUSIONS AND FUTURE WORK

The main objective of this research was to identify predictive models for e-learning to support TEL cost-effectiveness. To achieve this goal, we proposed a conceptual framework, developed supporting evaluation method and tools and empirically tested them within a real TEL experience with a relatively small student sample.

Results suggested that students can be grouped in a three-cluster structure based on their motivation-to-elearn. Furthermore, their evaluations contributed to identify cluster-specific technical and non-technical improvements. Moreover, we predicted the membership of new students to clusters based on their responses at the very beginning of the TEL experience, and anticipated what usability issues of performed tasks on the system had to improve. All these provided a workable way to obtain quantitative guidelines for system adaptability and also reinforced a culture of monitorization at formative evaluation level. By using this bottom-up, iterative and integrated usability evaluation framework, development teams can contribute to build friendlier contexts, and more satisfactory learning experiences in a cost-effective manner for institutions, instructors and students.

Future work should address several areas to better understand the context-dependent nature of TEL experiences and consolidate theoretical underpinnings, for instance (a) improving the generalizability of Motivation-to-elearn as a tool to differentiate students and to bridge the designer-user communication gap, (b) further analyzing the system data of TEL experiences in order to identify distinctive access patterns by clusters; (c) further studying the interactions between students and student-content by using social-analysis network techniques on system data to complement the profiles of each student cluster, and (d) exploring the role of affective states and persuasion in the different TEL scenarios and its impact on the retention of at-risk or low-performing students.

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