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Thème

Models and Tools for Usage-based e-Learning Documents Reengineering

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To my parents,
for their constant support and unceasing love

To my precious wife Saliha,
for her affection, devotion and patience

To our wonderful kids Ilyas, Malek and Maya
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1 Introduction

1.1 Background

We are living a sustainable technological revolution, whose waves are reshaping different aspects of our lives. Digitization and online publishing have probably made the greatest difference to the production and dissemination of knowledge than any other technological innovation since the invention of the press. Digital documents are omnipresent in modern life, turning digital reading as a mainstream phenomenon. Current trends in the literature reveal that readers, particularly digital natives, are more inclined to read in digital format (Singer and Alexander, 2017). This is possibly due to the high availability of digital documents and to their innovative features such as the integration of rich contents (graphics, images, speech, videos, etc.) in an interactive way (possibility of interaction and non-linear navigation). These specific features of digital reading can also affect reading performance, as they require more attention from the reader and demand a higher cognitive load (Jeong, 2012).

Education is one of the areas most impacted by technological change: learning approaches and settings are rapidly evolving towards high integration of information technologies, making them increasingly present in the classroom and beyond. This has prompted the widespread adoption of distance or blended learning, the emergence of online educational portals and an increase in the number of registrations for online courses. As a result, more and more educational resources are being put online by thousands of course authors and consulted by millions of learners every day, both for quick reference and for in-depth and focused study.

1.2 Rationale and problem statement

A primary concern of the creators of contents, be it paper or digital, is to best convey knowledge by sustaining document reading, understanding and appropriation. However, designing documents that are received the way the author wishes has always been difficult, partly because of the intrinsic difficulty of structuring ideas and writing, partly because the readership and its reactions are not known at the time of writing. In general, authors "*know comparatively little about the abilities, purposes, opinions, prior knowledge and circumstances of their readers*"(Waller, 1979). The digital world increases this difficulty by multiplying the possibilities related to mixed media and interactivity, hence increasing the complexity of documents with the use of multimedia, more and more interactivity, etc. While such documents promote innovative uses, their usages are neither totally known nor easily predictable.

Today, an important part of learning is done online, becoming distant and increasingly self-directed. The intrinsically sensitive nature of the world of education adds another level of complexity to the challenge of creating digital contents tailored to the needs of learners. This is particularly pronounced and is most noticeable in the context of informal learning where the educational environments allow a great diversity of profiles (ages, origins, needs) and very distinctive learners' behaviors (in terms of usages, time, preferences, etc.). Because of this diversity, learners are expected to take primary responsibility for their learning process. However, many studies have shown that a significant proportion of learners still need support and guidance, and that otherwise, they may be disoriented, frustrated or confused (Hara, 2000). Therefore, course authors and instructors need to be the leaders and helpers of learners, and their role should also encompass that of a facilitator who mentors learners throughout the course and delivers meaningful, learner-focused experiences (García-Solórzano et al., 2012). One way for authors to achieve this is to ensure that learners can understand the content provided, ensuring that it is continuously tailored to best meet the expectations and needs of these learners.

Reading a document implies processing and analyzing its content in the perspective of comprehension (Oh, 2013). Previous research has shown that "course quality" is a crucial factor that shapes readers' level of comprehension (Dascalu et al., 2014; McNamara and Magliano, 2009). This compels course authors to continually review their contents to continuously address quality improvements that support learners' understanding. They are, however, challenged to identify which obstacles learners encounter during their reading, and to design the necessary corrective actions accordingly. As a result, many authors not only review their courses infrequently and superficially, but do so very little, unless they receive effective support, such as informative feedback on learners' reading experiences, comprehension difficulties and possible remedial solutions (Patchan and Schunn, 2015).

1.3 Research goal, questions and objectives

1.3.1 Research goal

The educational settings are cyclic, each arrival of new learners gives time to authors to improve their learning material: the documents of their courses evolve and hopefully get better (e.g. more precise, more comprehensible, more adapted to their students need, etc.). With logging capabilities afforded by the learning platforms, interaction traces (or logs) are automatically captured and made available for analysis. This enables course authors to consider learners' traces as a valuable *source of knowledge* that provides them hints and guidance on how to evolve their courses.

Using data to act, solve a problem or facilitate decision-making is not new in education. However, in recent years, a significant increase in the amount of data available has transformed the way in which it is collected and used. This is largely due to the "big data" generated by learning platforms, as well as the emergence of advanced computing facilities with high capacities to analyze and transform data into knowledge. The correct capture, analysis, and communication of learner data would open infinite perspectives for optimizing learning outcomes and performance. In this context, the analysis of learning based upon educational data to extract useful knowledge emerged as an area of research, known as *learning analytics*, with the aim to understand and optimize learning (Siemens and Gasevic, 2012). According to Gunn (2014), one of the most important research question for learning analytics at present is: *how can available raw data be converted into actionable knowledge for teachers and learning designers who are not technical experts?*

The main hypothesis of this research is that the application of learning analytics methods to learners' traces of course reading could reveal the learners' difficulties in understanding from their behaviors, and thus how to make these courses evolve in order to meet their requirements and needs. As content creators, course authors are in the best position to update their documents and we strongly believe that they should be supported during the analysis and revision phases. When presented timely and appropriately, the discovered knowledge can be used by authors to make sound decisions in improving the quality of the courses according to learners' needs. Consequently, our main research goal can be formulated as follows:

Research aim

To investigate the use of reading analysis on learners' traces in order to identify their comprehension issues and to assist authors in improving their contents accordingly.

1.3.2 Research questions, objectives and methodology

In relation to the research goal, this thesis addresses a set of research questions (*RQ*); for each research question, research objectives (*RO*) are mentioned.

*RQ*1: "*What is the general conceptual framework for supporting authors to improve their courses and solve learners' understanding issues?*". To answer this question, we provide a usage-based reengineering framework. The objective that relates to answering this question is:

- *RO*1.1: To define a methodology for analyzing reading usages in order to identify understanding problems and support authors in solving those problems.

*RQ*2: "*What are those understanding issues?*". To answer this question, we build on background related to document engineering, digital reading and comprehension, and document revision. The related objectives are:

- *RO*2.1: Identify the most important document properties that contribute to the level of ease of understanding afforded by these documents.
- *RO*2.2: To identify the reading issues that may arise from these properties.

*RQ*3: "*According to those understanding issues, what remediation can be proposed to authors?*". To answer this question, we consider the use of computational and analytical tools derived from the fields of educational data mining and learning analysis. The objectives that relate to answering this question are:

*RO*3.1: To design appropriate suggestions for solving these understanding issues.

*RQ*4 : *"How is it possible to detect those issues and associate suitable remediation actions?"* The answer to this question requires the study of methods of analyzing learning traces. The objectives that relate to answering this question are:

*RO*4.1: To elaborate a reading analytics approach for reengineering courses based on learners' usages.

*RO*4.2: To conceive a reading activity model allowing the analysis of learners' traces.

*RO*4.3: To build an informed synthesis of reading activities using indicators.

*RO*4.4: To build a strategy based on these indicators to detect the reading issues and to suggest remediation actions.

*RQ*5 : *"What kind of systems and tools can effectively support authors for course improvement?"* This question is answered on the basis of research in *learning analytics* and the use of visualization for presenting the results of the analysis. The objectives that relate to answering this question are:

*RO*5.1: To identify functional and design requirements for implementing assistive systems that present the information timely and appropriately.

*RO*5.2: To implement these requirements through a functional prototype for course reading analysis, comprehension issues detection and remediation actions taking.

*RO*5.3: To validate the support methods and tools, and to evaluate a functional prototype for analyzing course readings, detecting comprehension problems and taking corrective action.

1.4 Research contributions

This research makes a set of contributions associated to our objectives. Table 1.1 summarizes these contributions and provides the related research questions and objectives according to the chapter where they are addressed.

Research Question	RQ1	RQ2		RQ3	RQ4				RQ5		
Research Objective	1.1	2.1	2.2	3.1	4.1	4.2	4.3	4.4	5.1	5.2	5.3
Contributions	1	2		3	4	5	6	7	8		9
Chapters	5				6				7		8

Table 1.1 Research questions, objectives and contributions in each chapter

The contributions of this thesis are the following:

1. A general framework for usage-based document reengineering. This framework uses readers' usage feedback to generate reengineering actions that change the structures and the content of the document. The results are presented to the author in order for him to assess possible document rewriting(s) that correspond to readers' needs.

2. Factors of comprehension related to document structures, and the associated issues. In order to identify the comprehension problems that can arise from the design of a document, we first propose a document model and its associated structures. For each of these structures, we identify the factors that can influence the learner's level of understanding. Each factor is examined to identify the reading problems with which it may be related.
3. Taxonomy of document reengineering actions. From the document model, we identify the edition actions that can be performed by the author to update a document at the surface or in depth. We use these actions to generate revisions. To associate revision actions to the different types of reading issues, we first elaborated a taxonomy of primitives (atomic reengineering actions) that reflects the most common edition actions used in digital content production.
4. A reading analytics approach for course revision. Instantiating the reengineering framework, we propose an approach for course revision that is based on the analysis of learners' traces of reading. It is a non-intrusive approach that provides authors with insight into their course consumption at different levels of assistance, each level exploiting data from the previous one. These range from *computing reading indicators* to reflect documents consumption, *detecting reading issues* to highlight possible comprehension difficulties, to *providing revision suggestions* to guide authors in improving their courses.
5. "Reading sessions" concept and algorithm. In order to study reading activity using the traces collected on learning platforms, we define the concept of "*reading session*" to denote the active period during which this activity takes place. We propose a new session identification approach where sessions are delimited more efficiently by: (1) considering solely reading activity; (2) using actual learners' data that represent their interactions within the learning system; and (3) computing page per page stay time and threshold values. This approach defines a dynamic process that allows updating the detected sessions at each arrival of new traces (each page has its own values fixed until the arrival of new data).
6. Taxonomy of reading session-based indicators. Several indicators computed using learners' reading sessions are proposed, originated from widely used metrics in navigation analysis. Organized into four classes (stickiness, rereading, navigation, and stop & resume), they are intended to help characterize reading behavior from the following perspectives: (1) learners' interest and their reading pace; (2) learners' rereading usages; (3) learners' navigation within the course; and (4) learners' reading interruptions, stops and resumes.
7. Generating course suggestion according to the reading issues. We use the taxonomy of revision actions that formulate appropriate revision actions to the different types of reading issues we have identified. These actions are finally rewritten into sentences, understandable by course authors.
8. CoReaDa: a reading analytics dashboard. CoReaDa is an implementation of the approach for online courses reading analysis and revision, instantiated for courses delivered on a major European e-learning platform.

9. A SET OF EVALUATION AND VALIDATION STUDIES. We validated our different proposals (i.e. analyzing course reading, detecting reading issues, suggesting revision actions, and using CoReaDa for these tasks) through a series of studies that involved online course authors and learners. In these studies, the items under scrutiny were:
   - The capabilities of the session identification approach and algorithm for detecting sessions that are compliant with learners' real ones (*Study 1*).
   - The perceived relevance of the set of indicators for course revision, from the authors' perspective (*Study 2*).
   - The capabilities of the issues detection approach in enhancing authors' awareness about learners' comprehension issues, and the usefulness of the provided suggestions (and thus relevance of the revision primitives) for giving authors guidance in performing revisions (*Study 3*).
   - The conformance of the detected issues with actual learners' reading difficulties, according to learners' opinion (*Study 4*).
   - The usability of the dashboard, and the author's level of acceptance and attitude towards adopting the dashboard in their revision tasks (*Study 5*).

List of publications

- "A framework for usage-based document reengineering" (2013) in *Proceedings of the 2013 ACM Symposium on Document Engineering* (DocEng'13), Florence, Italy, pages 99–102. ACM.
- "Towards reading session-based indicators in educational reading analytics" (2015) in *Design for Teaching and Learning in a Networked World. Lecture Notes in Computer Science*, vol 9307, pages 297–310. Springer, Cham.
- "Leveraging Learners' Activity Logs for Course Reading Analytics Using Session-Based Indicators" (in press) in *International Journal of Technology Enhanced Learning* (IJ-TEL). Inderscience.
- "Towards fine-grained reading dashboards for online course revision" (2^{nd} revision under review) submitted to *Educational Technology Research and Development* (ETR&D). Springer.

1.5 Thesis outline

The remainder of this thesis is structured into two parts as follows:

PART I: BACKGROUND & RELATED RESEARCH – introduces the concepts and previous research related to the subject of this thesis. It consists of two chapters.

CHAPTER 2: ENGINEERING AND REENGINEERING EDUCATIONAL DIGITAL DOCUMENTS – highlights the impact of technology on reading and learning. It then discusses the factors influencing learners' level of comprehension in the context of online reading. Course quality being a decisive factor in the success of learning, the chapter establishes a logical connection between course reading, learners' level of comprehension, course content quality and authors' tasks of revision. Finally, the complexity of the course revision process for online course author is discussed.

Chapter 3: Usage analytics and knowledge discovery in educational documents – is related to methods of collecting reading usages, analyzing them, and presenting the results in a meaningful way. It introduces the fields of learning analytics and educational data mining. It then discusses the potential use of learning analytics dashboards by course authors for revising their educational contents.

Chapter 4: Summary and discussion of the related research – concludes the first part of the thesis by discussing the presented related research.

Part II: Contributions – is dedicated to the development of all our proposals, their implementation and their evaluation. It consists of the following chapters:

Chapter 5: Usage-based document reengineering for sustaining reading and comprehension – introduces a generic framework for usage-based document reengineering. The different structures that compose digital documents and that impact comprehension are investigated. This allows elaborating a taxonomy of comprehension issues and associated reengineering actions.

Chapter 6: Usage-based Course Reading Analytics – presents an instantiation of the reengineering approach for course revision. It introduces the concept of "reading sessions" computed for learners' traces in order to model the reading activity and to define and compute a set of reading indicators. It then describes a methodology for assessing comprehension issues by the analysis of the values of the reading indicators. It finally presents a methodology for associating revision actions to the different types of reading issues.

Chapter 7: CoReaDa: The COurse READing DAshboard – presents an implementation of the theoretical proposals after discussing the functional and design requirements. CoReaDa is the name of the developed prototype, instantiated for courses delivered on a major e-learning platform.

Chapter 8: Evaluation and validation of the proposals – It presents the methodology for evaluating and validating the different contributions presented in this thesis. It consists of several studies, each evaluating a particular aspect of our proposals. The chapter also presents the results, comments on them and discusses them.

Chapter 9: General conclusion – summarizes and discusses the research and its results. The contributions are reviewed, and reflections on the results are given. The thesis concludes with an outline of future work.

Part I

Background & Related Research

2

Engineering and reengineering educational digital documents

Modern technology is transforming education and is profoundly reshaping how teachers offer their courses and how students learn from them. In this chapter, we begin by discussing some of the major paradigm shifts in educational practice that have followed the rise of the new digital age (§2.1). Reading is one of the most important learning activities that have been significantly influenced by technology (§2.2). We therefore review the impact of this transition to digital reading on learning behavior, reading performance and learning outcomes (§2.3). One measure of learners' reading performance is their level of understanding, and an effective strategy to improve this level is to provide good quality contents. To fit learners' need, these contents need to be maintained through updates and revisions. This chapter thus concludes with a review of the requirements and challenges related to identifying and fulfilling learners' revision needs (§2.4).

2.1 Learning in the digital age

2.1.1 Learning

Definition 2.1 (Learning)

"Learning is a process by which an individual assimilates information, ideas and values and thus acquires knowledge, know-how, skills and/or competences. Learning occurs through personal reflection, reconstruction and social interaction. Learning may take place in formal, non-formal or informal settings. " (Cedefop, 2014)[a]

[a] European Centre for the Development of Vocational Training (Centre européen pour le développement de la formation professionnelle)

Learning is the process of acquiring new or modifying existing knowledge, behaviors, skills, values, or preferences (Gross, 2015). According to definition 2.1.1, learning may take place in formal, non-formal, or informal settings. Table 2.1 provides the official definitions adopted by several European educational policies as formulated by the European-Commission (2011) and Singh (2012).

	Formal learning	Non-formal learning	Informal learning
Location	Organized and structured environment dedicated to learning (e.g. general education, vocational training, higher education)	Not provided by an institution; learning takes place through planned activities (e.g. workplace training, structured online learning)	Daily activities related to work, family, or leisure and interests
Degree of structure	Highly structured objectives, time and support (e.g. requirements)	Can be structured but more flexible learning	No structure
Intentionality	Intentional from the learner's perspective	Intentional from the learner's perspective	Can be intentional but mostly unintentional or incidental
Certification	Leads to a qualification, certificate or diploma	Not usually certificated	No certificate
Facilitator	Teacher/trainer	Trainer, coach, mentor	-

Table 2.1 Comparison between the different types of learning contexts

A. Formal learning

Formal learning takes place within an organized learning environment such as universities, institutions or the workplace. Its learning objectives are well structured and precisely defined. Usually, this form of learning is designed in such a way that time, objectives, tasks and resources are clearly communicated and learning leads to certification. Formal learning is intentional from the learners' point of view.

B. Non-formal learning

Non-formal learning is not conducted by an education or training institution, and generally does not lead to certification. However, it is structured in terms of learning objectives, time and/or support. Non-formal learning is intentional from the learner's point of view, it is part of other planned activities without being explicitly structured in terms of precise deadlines, listed objectives and the support provided. Non-formal learning can still be validated, which can then lead to certification or recognition of prior learning, as non-formal learning is also sometimes described as semi-structured learning.

C. Informal learning

Informal learning takes place outside the curricula offered by formal and non-formal education institutions and programs. It results from activities of daily living related to work, family or leisure. It is not structured (in terms of learning objectives, learning time or learning support) and generally does not lead to certification. Cross (2011) claims that more than 80% of learning is informal, which corresponds to the unplanned and non-traditional method that most people learn to achieve, both professionally and personally. Unlike formal and non-formal learning, both of which are considered planned learning, informal learning is not planned.

2.1.2 Learning in the digital age

2.1.2.1 Distance learning

Distance education has a history spanning almost two centuries and with roots dating back several centuries[1]. The historical evolution of distance learning can be divided into three main periods corresponding to the media used: printed materials, television, and the Internet, respectively. For Kaplan and Haenlein (2016), distance learning can be defined as providing education to students who are separated by distance (i.e., who are not physically present in the same space) or by time (they may learn at their own pace, in accordance with their schedules). It can be facilitated by a wide range of media, including letter correspondence, radio, TV and telephone.

Some of the most important developments in education have occurred with the invention and popularization of the Internet. The interest to use the Web as a learning medium is driven by the strong belief of teachers and education policy experts that this can foster new approaches to learning, such as the sharing of instructional materials between educators and learners. New and innovative methods of teaching and learning are being developed and exploited, bringing a new generation of distance learning modes, known as electronic learning, online learning or e-learning. Online learning can therefore be viewed as a modern version of distance learning that improves the learners' access to educational opportunities.

2.1.2.2 e-Learning

The origin of the term e-learning is not certain. It is often suggested that the term originated most likely in the 1980s, which coincided with the emergence of another delivery mode known as *online learning*. Although the distinction between these two concepts is still subject to debate (Guri-Rosenblit, 2005; Moore et al., 2011), they are often taken as synonyms.

While the principles of e-learning have been well documented since the 1980s (and even before), the term "e-learning" only emerged in 1999. E-learning can be defined as follows:

Definition 2.2 (e-Learning)

The concept of e-learning relates to "*the use of electronic media for a variety of learning purposes that range from add-on functions in conventional classrooms to full substitution for the face-to-face meetings by online encounters*" (Guri-Rosenblit, 2005)

For Rosenberg and Foshay (2002), e-learning refers to using Internet technologies to deliver a wide spectrum of solutions that improve knowledge and performance. For the authors, e-learning is based on the following fundamental criteria:

[1]The first documented example of correspondence training (as distance education was called for many years) dates back to 1828, when Professor C. Phillips published an advertisement in the Boston Gazette offering educational materials and tutorials by correspondence. In 1843, the Society of Phonographic Correspondence was founded, which could be considered the first official distance learning institution because it received, corrected and returned shorthand exercises performed by students taking a correspondence course.

1. It is networked: consequently, instant updating, storage and retrieval, distribution and sharing of information is possible.
2. It is delivered to the end-user using standard internet technologies.
3. It focuses on the broadest view of learning, going beyond the traditional paradigms of training.
4. It involves the use of electronic device (e.g. computer, mobile phone) in some way to provide training, educational or any other learning resources.

2.1.2.3 Implications of e-learning on education

An important part of today learning is done online, becoming increasingly self-directed, open and informal. Many education institutions are now fully based on online courses. For years, e-learning has been trying to complement the way we learn to make it more effective and measurable. It creates new opportunities for personalized learning both at home and at work, reduces the need for costly classroom training and reconciles traditional and new forms of knowledge transfer (Meinel et al., 2003). E-learning has emerged as mainstream learning and teaching mode both in distance learning institutions and in traditional universities, continuing education institutions and workplace training, and has recently been extended to primary and secondary schools.

E-learning has shifted from an instructor-centered approach (traditional classroom) to one that is more student-centered and where the students have a greater degree of responsibility for their learning. (Gros and García-Peñalvo, 2016). This has contributed to the growth of personalized learning where individuals are expected to take more responsibility for guiding their own learning. Knowles (1975) defines *self-directed learning* as a process in which individuals take the initiative, with or without the help from others, in diagnosing their learning needs, formulating goals, identifying human and material resources, choosing and implementing appropriate learning strategies, and evaluating outcomes. By emphasizing the freedom to choose one' s learning path, self-determination, autonomy and the ability to learn independently are now important skills in education. Many students, even in academic settings, appreciate the self-determination of informal learning over teacher-led supervision in their formal learning (Lai and Smith, 2017). Nevertheless, the success of this learning form demands that learners be empowered to make their own learning decisions, which is probably not always the case.

2.1.3 Educational technologies

Educational technology is an inclusive term for both learning tools and the theoretical foundations for supporting learning and teaching. It encompasses a very wide range of computer-related technologies that support teaching or learning, like e-learning, Educational technology (EdTech), Computer-Based Training (CBT), Information and Communication Technology (ICT), Computer Aided Learning (CAL), and Virtual Learning Environments (VLE). Learning technology encompasses several domains including learning theory, computer-based training, online learning, and m-learning (the use of mobile technologies for educational purposes).

One of the innovative results of the opening of education is the availability of courses with a very large number of students, open to all and available online. These types of courses are called “Massive Open Online Courses” or “MOOCs”[2]. A MOOC is mainly an open-access online course (without specific participation restrictions) that allows for unlimited (massive) participations (Kaplan and Haenlein, 2016).

2.1.4 Learning management systems

A *Learning Management System* (LMS)[3] is an environment intended for automating the management of teaching and learning, and facilitating the organization and provision of educational resources to students. Guy (2009) defines LMS as a form of software that is created to provide, track and supervise training and learning. An LMS implements tools for creating and structuring rich and possibly multimedia courses, publishing tests and/or surveys, and sharing various multimedia tools, services and resources to support the learning process.

Many education institutions use LMS solutions for the administration and organization of their courses. Not only these systems are not only deployed in conventional learning contexts, but also in vocational training and by companies. They are being used to support face to face, collocated and traditional classrooms as well as distance learning. Popular commercial platforms include Blackboard Learn[4], WBTmanager[5] , Intralearn[6], Fronter[7] and Desire2Learn[8]. Popular open source platforms include: Moodle[9], Canvas[10], dotLRN[11] , ATutor[12], Claroline[13], and Sakai[14].

Different stakeholders may have different objectives for using an LMS. According to the survey of Romero and Ventura (2010) (of 304 studies): (1) students in general use these systems to customize their learning, to revise specific content and to engage in discussions related to exam preparation; (2) teachers and instructors use them to give and receive prompt feedback about their instruction, as well as to provide timely support to students; and (3) administrators use LMS to inform their allocation of institutional resources, and other decision-making processes.

[2]The term MOOC was first coined in 2008 by David Cormier and George Siemens, describing a twelve-week course on *Connectivism and Connected Knowledge* at the University of Manitoba, Canada (Cormier and Siemens, 2010)

[3]LMS is also known as: Computer Learning Content Information Management System (CLCIMS), Course Management System (CMS), Learning Content Management System (LCMS), Learning Management System (LMS), Learning Platform (LP), Learning Support System (LSS), and Managed Learning Environment (MLE).

[4]http://www.blackboard.com (accessed on November 23th, 2018)

[5]http://www.xperteam.net/produit/wbt-manager-lms (accessed on November 23th, 2018)

[6]http://www.intralearn.com (accessed on November 23th, 2018)

[7]http://www.itslearning.com/global/fronter (accessed on November 23th, 2018)

[8]http://www.d2l.com (accessed on November 23th, 2018)

[9]http://www.moodle.com (accessed on November 23th, 2018)

[10]http://www.instructure.com (accessed on November 23th, 2018)

[11]http://www.dotlrn.org (accessed on November 23th, 2018)

[12]http://www.atutor.ca (accessed on November 23th, 2018)

[13]http://www.claroline.net (accessed on November 23th, 2018)

[14]http://www.sakaiproject.org (accessed on November 23th, 2018)

2.2 Digital document and their usages in e-learning

2.2.1 "Document" as a concept

The word document was in antiquity not just something that stood in hand or a piece of written evidence, but also related to teaching and instruction. The Latin *doceo* means 'teach'; *documentum* is thus the act of teaching. The first serious reflection on the term 'document' is probably that of Otlet (1934) who noted that objects such as sculptures, artifacts and other works of art could also be considered documents since they are an "expression of human thought". Pushing the reflection even further, Briet (1951) defined a document as "any physical or symbolic sign, preserved or recorded, intended to represent, to reconstruct, or to demonstrate a physical or conceptual phenomenon"[15]. She remarked that an antelope can also be qualified as a document once it had become an object of study or physical evidence of specific events (e.g. a capture and placement in a zoo).

In the broad sense, a document can be any means (instrument or media) capable of transmitting knowledge or information in a more or less sustainable form. This traditionally amounts to using a record carrying written or graphical information. This concept of document has undergone a progressive "dematerialization" during the last century with digitization. In this vein, for Buckland (1997), "... whatever is displayed on the screen or printed out is a document. One might say that the algorithm is functioning as a document, as a dynamic kind of document,... it would be consistent with the trend, ... towards a defining document in terms of function rather than physical format".

2.2.2 Digital documents

2.2.2.1 Definition

With digitization, documents have shifted from being only textual to becoming evidence of something and everything that has been observed or expressed. Their storage has shifted from paper to electronic, which increased their interactivity and their richness. For Pédauque (2006), these documents should be studied according to their three dimensions at the same time: (1) the document as a *form* (digital structure, i.e. a container assembling data content and structure in order to make it readable both by its designer and its readers), (2) the document as a *sign* (content, i.e. the text that should be processable by a knowledge system), and (3) the document as a *medium* (communication tool, i.e a means of information distribution even in the future). These dimensions relate to modalities that determine the degree of "maturity" of a document: anthropological (for legibility), intellectual (for assimilation) and social (for diffusion scope) (Yahiaoui et al., 2011).

A digital document can theoretically include any *digital composition* of content created on a computer. The existence of the electronic document is more of a logical matter than physical: they are fundamentally strings of bits rendered through a

[15]"[un document est] tout indice concret ou symbolique, conservé ou enregistré, aux fins de représenter, de reconstituer ou de prouver un phénomène ou physique ou intellectuel" (Briet, 1951)

computer system, with no humanly discernible physical reality (Laha, 2010). While (Buckland, 1997) argued that the answer to the question of what actually constitutes a document is not obvious, Levy (2016) offered an open view by considering a document as simply "a way to delegate the ability to speak to inanimate objects".

Definition 2.3 (Digital document)

"A digital text may be a linear text in digital format [...], a nonlinear text with hyperlinks [...], a text with integrated media [...]; and a text with response options [...]. In some cases, text represents a single text, but more often text includes multiple texts, and can be a Web site, a collection of Web sites, etc. The digital text may be client--side and closed (e.g., a CD--ROM Living Books story), or networked and either constrained or open (e.g., accessed via a server, which may or may not provide access to the Internet). Text is not restricted to written prose; text can be primarily visual, such as an animated graphic, video clip, photo slide show, or image with little accompanying verbal information, and verbal information may be presented in auditory rather than written format." (Dalton and Proctor, 2008)

Digital documents are often thought of as digitized versions of physical documents (paper-based or print documents). As a result, they are often described by comparing their properties with those of their physical counterparts. Paper documents are tangible objects with an explicitly defined beginning and end and are supposed to be read as a linear sequence of texts, from top to bottom (although some sections may be omitted as a result of readers' cognitive reading strategies) (Putro and Lee, 2017). They are therefore very distinct from the intangible, unlimited and intertextual nature of interactive digital documents. While paper documents have indivisible content and presentation, digital documents have a separate presentation and storage, and it is only through the rendering device that the content gets a visual output. This makes it possible for digital documents to have different representations on different supports. Moreover, some types of documents, mainly web-based, have a more conditional, not permanent existence; they become unstable because of this possibility to their content to be updated and to their design features to be changed: therefore, each time a reader returns to a document, he may find it modified (Crystal, 2010, pp. 240). As they are generally displayed online, they allow additional features such as new means of access, easy handling and updating, new means of dissemination and a wider audience (Thompson, 2005, pp. 318-320).

2.2.2.2 Hypertext

The history of hypertext goes back to 1945 when Vannevar Bush published his article "As We May Think"[16] to describe a hypertext system called Memex, which would use microfilm technology to store a cohesive record of all human knowledge. (Bush et al., 1945). The term "hypertext" was first coined by Nelson (1965) when presenting his Xanadu system: "Let me introduce the word 'hypertext' to mean a body of written or pictorial material interconnected in such a complex way that it could not

[16]https://www.theatlantic.com/magazine/archive/1945/07/as-we-may-think/303881/

conveniently be presented or represented on paper". He defined *hypertext* in the following words:

Definition 2.4 (Hypertext)

"'Hypertext' is a recent coinage. 'Hyper-' is used in the mathematical sense of extension and generality (as in 'hyperspace,' 'hypercube') rather than the medical sense of 'excessive' ('hyperactivity'). There is no implication about size– a hypertext could contain only 500 words or so. 'Hyper-' refers to structure and not size."
***Theodor H. Nelson**, Brief Words on the Hypertext*[a]*, 23 January 1967*

[a] https://archive.org/details/SelectedPapers1977

Hypertext enables readers to navigate within and between documents (*hyperspace*) in a non-linear way, and thus to read the texts in whatever order they deem most appropriate. Hyperlinks (hypertext links, or simply links) are the basis for creating and managing relationships and associations within and between documents. The actual sequence of the visited text is determined by the user's choices at the time of navigation. Unlike the author's historical full control over the reading order, in hypertext he can only suggest an order that he defines via the document plan and navigation links. Hypertext, therefore, frees the author from the obligation to create sequential text (Nielsen et al., 1990) and offers readers an autonomy over the text as they are free to decide whilst reading where to proceed in the text. With hypertext, the distinction between the active author and passive reader is totally blurred (van Ossenbruggen, 2001).

2.2.2.3 Multimedia

Multimedia documents are digital documents that include rich content of various types, such as text, audio, images, animations, video and interactive content. These objects are called *media* and their compositions constitute *multimedia documents*. They contrast with media that use only rudimentary computer displays such as text-only or traditional forms of printed or hand-produced material.

For Jourdan et al. (1998), a multimedia document is organized spatially and temporally, and has an integrated navigation structure. It is thus the interactive and heterogeneous arrangement, in time and in space, of data coming from several types of media. Multimedia documents share the non linear structure of the hypertext with the difference that the linearity is along a single temporal dimension, and not along a single text-flow dimension (van Ossenbruggen, 2001). In his thesis, Geurts (2010) characterized multimedia documents with two main properties:

– *Heterogeneous media types* such as image, text, audio, and video. The author of a multimedia document uses media items that are, either specifically created or (re)used from existing resources, to represent the message he intends to convey.
– *Spatio-Temporal dimensions*, besides the spatial and temporal ones. Consequently, the author of a multimedia document should, in addition to the spatial layout, synchronize media items in a meaningful way.

2.2.2.4 Hypermedia

Hypermedia is a concept that combines "hypertext" and "multimedia". This designation contrasts with the broader term *multimedia*, which may include non-interactive linear presentations as well as hypermedia. It hence extends the notion of the hypertext link to include links among any set of multimedia objects, like graphics, audio and video file, and virtual reality. In addition to the logical (organizational), spatial and hypertextual (the links between parts) dimensions of hypertext document, the temporal dimension introduces time and synchronization into digital documents.

The hypermedia is based on the node/link model of hypertext, with the nodes possibly containing media types other than text. As point out by (Hardman et al., 1994), many hypermedia systems employ hierarchically structured document formats but offer support for dynamic media types only in the leaf nodes of the document tree structure. Because the addition of multimedia in these documents does not change the underlying data and process models, the terms "hypertext" and "hypermedia" are often used interchangeably.

The integration of richmedia content into hypermedia has enabled the advent of innovative tools for the delivery of knowledge. For instance, hypervideos resulted from the integration within hypermedia of audiovisual content augmented with several kinds of data in a time synchronized way (Aubert et al., 2008; Sadallah et al., 2011). The integration of content-enriched video offers additional interaction and navigation alternatives and additional information levels.

2.2.3 Document structures

The evolution of the concept of *document* has led to an increased complexity of the document landscape associated with the sophistication of writing and dissemination processes. As a result, new technical challenges have emerged, both in providing proper document templates and in designing effective systems and tools to manage and produce these documents in a timely and efficient manner. The study and solving of the aforementioned problems are one of the main goals of the discipline of "document engineering", related to the design, development, testing, and maintenance of electronic documents.

Describing the composition, rendering and storage of a specific type of document requires the development of a suitable data model that discloses its different structures. Such a data model defines the entities that can be included in the document and the relationships that may exist between them. It specifies the structuring rules for the different elements of the document in the information space, as well as the mechanisms allowing the user to perform the various possible manipulations.

Völkel (2007) proposed a generic data model where the document is seen as a knowledge artifact that consists of several structures or layers built on the top of its atomic objects. Those layers determine the characteristics of a document ranging from its structure to the semantics of the content. According to Christophides (1998), a digital document can be described through four levels, each level being characterized by a data structure can be defined:

– The *semantic structure* defines the organization of the document's meaning (for instance, the narrative structure).
– The *logical structure* defines the organization of the document syntactic structure (titles, chapters, paragraphs, etc.).
– The *physical structure* or layout defines the document's appearance (typography, functionalities, etc.). It corresponds to the rules for presenting the document on a particular medium.

2.2.4 Digital documents in education

2.2.4.1 Digital reading

Reading is about the interaction between a human and a support, regardless of the nature of that support (paper or digital). According to Grabe (2009, p.14), reading can be seen as a complex combination of processes that are rapid, efficient, interactive, strategic, flexible, evaluative, purposeful, comprehending, learning, and linguistic. It involves the "activation of prior knowledge, the evaluation of the text, and a monitoring of the reader's own comprehension" (Alderson, 2000, p. 3). This process uses lower-level skills, such as the ability to recognize, decode and understand the meaning of words, and higher-level skills, such as the ability to make inferences that link information in a text, to understand the general context in which words are read (Duran, 2013; McNamara and Magliano, 2009).

Digital reading (also called online reading when done on the web) is the process of reading content that is in a digital format. Online reading was not considered an alternative reading method until the early nineties (Bawden et al., 2008). It has since grown at an increasingly rapid pace, becoming today a prominent mode of reading, especially for younger generations (Liu, 2005).

Digital reading has yielded numerous benefits that were absent on paper, including interactivity, non-linearity, immediacy of access to information, and richmedia use (text, images, audio and video) (Liu, 2005). With digital documents, cross-document referencing becomes a significant part of the entire reading process (Adler et al., 1998), allowing readers to leave one resource and explore a range of alternative ones. Whereas offline meaning construction is primarily invisible and internal, hypertext reading demonstrates more external manifestations of meaning making through the choices of links followed (DeSchryver, 2015). Mangen et al. (2013) suggested that the navigation mode could affect the reading process. For instance, scrolling may lead to spatial instability and thus hamper the reader's level of comprehension.

The digital reading typical characteristics of skimming and non-linearity are quite different from the deep and linear reading of print contents. Liu (2005, p. 705) argued that the digital reading mode results on "more time on browsing and scanning, keyword spotting, one-time reading, nonlinear reading, and more reading selectively; while less time is spent on in-depth reading and concentrated reading, and sustained attention is decreasing". Also noted was the potential for slow navigation and scrolling speeds, which hindered the reading of digital documents. The study presented by Chou (2012) revealed that readers of online contents tend to first scan for hyperlinked headings and that the link within text are used to access some in-depth information.

2.2.4.2 Digital reading and learning

Although learning oriented reading is still supported by the conventional way of reading printed materials (e. g. books, newspapers and magazines), it is increasingly moving towards the use of electronic, computerized and on-screen media (Coiro, 2012). This is partially the result of e-learning that drives students to massively integrate digital documents into their activities (Walsh, 2016).

Among learners, there is a consensus on the benefits of being able to access educational resources from anywhere at any time (Staiger, 2012). Digital documents are found to better convey data- and fact-based education material, compared to print documents more suitable to contents that required cognitive reasoning (Stoop et al., 2013a) and where readers are required to form a coherent cognitive map of the text (Jabr, 2013). Although some studies suggest that differences in speed and recall between media are insignificant (Eden and Eshet-Alkalai, 2013), they have also found that digital documents that optimize hypertext and multimedia engage learners better in an active reading form that can lead to improved learning outcomes (Rockinson-Szapkiw et al., 2013; Stoop et al., 2013a; Adler and Van Doren, 2014).

Active reading

A seamless and advantageous property of digital documents is their ability to engage learners in an interactive experience with contents be infused with richmedia contents to facilitate learning (Rockinson-Szapkiw et al., 2013; Stoop et al., 2013a). Reading activities where readers are actively engaged and have an interactive relationship with the text are known as "*active reading*" (Adler and Van Doren, 1972). According to (Schilit et al., 1999, p. 65), "Active reading combines reading with critical thinking, learning, and decision making, whereas passive reading is less careful and requires less effort". Significant learning occurs when learners engage in active reading by selecting, organizing, and integrating relevant words and pictures into mental models embedded in working memory (Mayer, 2002). As a basic metacognitive function, active reading allows content to leave strong memory traces and thus helps learners to understand a text for a specific purpose, such as a future reminder (Adler and Van Doren, 2014). This may explain the effectiveness of digital reading environments in enhancing learning and comprehension (Ortlieb et al., 2014).

During active reading, the learner acquires an understanding of the reading material by applying specific strategies, such as searching, highlighting, annotating, summarizing, comparing, cross-referencing, and revisiting portions of a larger work (Palilonis and Bolchini, 2015). One possible reason for some learners to prefer printed contents is this ability to easily markup paper documents (Stoop et al., 2013b). Annotation has been long recognized as a fundamental component of active reading strategies and a crucial aspect of engaged reading activities. They can be reused in conjunction with the document for research, navigation, repurposing, and richmedia content generation(Aubert and Prié, 2005; Aubert et al., 2008). Annotations can range from simple highlighting of key words and phrases to more elaborated data structures (Sadallah et al., 2014), seeking to place core concepts within the greater context of the subject. Annotations can provide benefits to students' learning both as a process and an artifact. As a process, they offer the opportunity to promote the in-depth reading of a textual resource (Marshall, 1998): it stimulates readers to reflect on the content they are about to annotate and to ensure the relevance and merit of their reflections before putting them on paper. As an artifact, annotations can provide alternative interpretations of the content (Agosti et al., 2004): this may incite the reader to update his knowledge about the current topic with the content of the annotation or the underlying content of the resource.

2.2.4.3 Learners' reading mode preference

The concept of reading mode (also called format, form, context, environment, or setting) is related to the nature of the container medium on which reading is performed (Liu, 2005). Readers' choices and preferences for one of the two modes of reading (paper-based versus digital) are diverse and vary according to the reading context and purpose (Liu and Ram, 2011). As opposed to reading the document in its linear form, readers tend more to dip into electronic documents seeking for particular information. The survey conducted by Gartner Inc. (2011) on consumers' experiences with on-screen and paper reading in six countries concluded that "the time spent reading on a digital screen is now almost equal to the time spent reading a printed text". Levine-Clark (2015) conducted three surveys on user preference between print and electronic books with five-year intervals (2005, 2010, and 2015). While there has been a shift of user preference toward e-books over a 15-year period, the choice between print and electronic format ultimately depends on type of use and category of users. A similar survey described by Carroll et al. (2016) and carried in 2012 and again in 2014 showed that by 2014, 32.9% of students across different disciplines noted they had 'no preference' when questioned on a preferred reading mode. In education, Millar and Schrier (2015)'s survey of 190 students revealed that 57.4% of them preferred paper format while only 25% preferred electronic format. Two main reasons motivate students' preference for digital documents: (1) that all the content (e.g., many books) is within the same media, and (2) that digital documents provide much convenience than paper ones. Other reasons reported include affordability, paper saving, and easy portability.

Generally speaking, information provided from printed contents are considered to be more trustworthy (Asim Qayyum and Williamson, 2014). This partly explains why learners prefer print media, especially when it comes to longer reading activities or when documents contain complex information (Stoop et al., 2013b; Tuncer and Bahadir, 2014). Another reason stated by Mangen et al. (2013) is that paper can provide the reader with location and time-related stimuli: touching the paper, and turning the pages makes it easier to recall things, in contrary of digital reading where reading is achieved by moving upwards and bottom. Despite students prefer to print online documents that require in-depth reading (Chou, 2012; Tuncer and Bahadir, 2014), they also want to learn via a digital realm with content that is integrated and interactive (Rockinson-Szapkiw et al., 2013; Stoop et al., 2013a). Summarizing many previous studies, Kurata et al. (2017) concluded that, overall, digital reading is becoming more widespread in education, and that traditional paper-based media are still very popular.

2.3 Comprehension in reading for learning

2.3.1 Comprehension as a measure of reading outcome

Reading is a process of interpreting and giving meaning to the written contents (Bulut, 2015). Most research evaluates the success of reading using outcome measures of efficiency and effectiveness (Oh, 2013). Reading *efficiency* includes speed and accuracy. Reading speed is primarily considered as an outcome or a performance measure. Accuracy usually refers to an individual's capability to identify errors in proofreading tasks. Reading *effectiveness* is often considered in terms of level of comprehension, which is of particular interest to us in the context of this research.

The reader understands a text when he manages to correctly extract the knowledge conveyed, using different skills. The result is then a mental representation that combines the extracted knowledge with the existing one. Two levels of comprehension can be distinguished: a literal level and an inferential level (McNamara, 2012; Chen et al., 2014).

– *Literal or shallow comprehension* is a minimally coherent mental representation which is achieved by readers from the meaning of the explicit knowledge in the text. Closed-end questions, such as multiple choice questions, allow in general to exam this level.

– *Inferential or deep comprehension* represents a highly coherent, richly integrated, plausible presentation. The readers can use the explicit knowledge in the text and their own prior knowledge to build deeper understanding from the text. Open-end questions are in general used to assess this level of comprehension.

While scholars have long debated an appropriate means for quantifying or measuring comprehension, the number of correct answers on a reading test is typically used to measure comprehension (Dillon, 1992).

2.3.2 Digital reading and comprehension

2.3.2.1 Effect of digital reading on its outcomes

Intensive research has been carried out in recent years on the difference in the level of understanding between the two reading modes (digital or paper). The objective is often to determine the effect of each mode on reading performance, using different measures: level of comprehension, reading rate, reading accuracy, deep reading, long-term critical thinking, and knowledge development (Margolin et al., 2013).

Early research focused primarily on the process and efficacy of reading from computers, rather than in terms of outcomes. For instance, Dillon (1992), by weighing the reading processes (eye movement, manipulation and navigation) and the results (speed, accuracy, fatigue, comprehension and preference), concluded that digital reading had its limitations, but that it was possible to eliminate this performance deficit (e. g., slower reading speed) using proper reading strategies. Studies conducted later by several researchers (e.g., (Farinosi et al., 2016; Porion et al., 2016)) have found no difference in terms of comprehension, both in educational or non-educational context. At the same time, other researchers have claimed the opposite by arguing that changing the reading mode would certainly lead to a difference in understanding.

The incorporation of richmedia contents into documents can make these latter easier to understand and faster to read than the same information in plain text (Green et al., 2010). This is because visual representation enables complicated data to be easily comprehended. Information retention may also be improved when using animations, diagrams, and hyperlinks and visual displays that enhance user experiences (Duran, 2013; Tuncer and Bahadir, 2014). In the same vein, (Ortlieb et al., 2014) argued that the use of multimedia content can be a valuable supplemental aid in reading and learning as the information is encoded through multiple channels or senses. It also improves recall rates with its entertaining way of presenting information (Walsh, 2016; Green et al., 2010). Puchalski et al. (1992) showed that the combination of different media modalities results in a greater depth of understanding particularly for struggling readers who tend to over-rely upon pictures to aid in decoding words and comprehending the text. In general, interactive hypermedia courses are perceived as having a positive effect on learners' comprehension level thanks to multimedia and the active reading possibilities (Ortlieb et al., 2014).

Despite the advantages of digital documents in terms of rich content and interaction, many recent studies (Delgado et al., 2018; Kong et al., 2018) showed a clear picture of screen inferiority, with lower reading comprehension outcomes for digital texts compared to printed texts. This is mainly due to the additional cognitive processes induced by hypertext and non-linear digital reading (Salmerón et al., 2006), reflected by two major and well-studied problems: disorientation and cognitive overload (Conklin, 1987).

A. Disorientation

Disorientation is due to the inherent nature of hypertext making it possible for readers to become lost in the text and fail to obtain an overview of the whole–they do not know where they are within the network. This may also drive readers to roam around the information without knowing what to do next; readers, therefore, need high meta-cognitive abilities, and those with less adequate linguistic skills may become confused more easily. Many authors note that readers are likely to experience difficulties when organizing the different parts of the hypertext into a global structure, whereas to read a linear text, it is sufficient to follow the reading order as defined by the author (Britton, 1994). Moreover, with a hypertext, the reader must use other features, such as graphical overviews or prior knowledge, in order to form a coherent representation of the text (Baccino et al., 2008).

B. Cognitive overload

Cognitive overload results from the amount and quality of decisions that readers must make when navigating through a hypertext document using navigation links. This requires additional thought and attention to decide which browsing path to take, whether to follow up on a subtopic or to return to the previous topic and how to deal with complex information choices. Studies (e.g., (Mangen et al., 2013; Mizrachi, 2014)) found that the level of comprehension with paper reading is higher, compared with digital reading. In an effort to explain this, Dündar and Akçayır (2017) indicated that digital texts make greater use of the learner's mental resources than printed texts and that this drainage reduces their retention abilities. Excessive information may also cause readers to forget what they have read. Moreover, decreased concentration may be induced by eye fatigue (Jabr, 2013). In general, memory and performance capacity improved after using paper and pencil while eye fatigue increases when using electronic reading device (Lin et al., 2015).

2.3.3 Factors of comprehension

Comprehension is ultimately the result sought in reading. It depends on both of the level of strategic or active reading expected by the reader and the ease of processing afforded by the content (McNamara and Magliano, 2009). From early research (Gray, 1935), two principal sets of factors were found to influence the understandability of a reading material: reader intrinsic factors (e.g. levels of intellectual capacity, reading skills, attitudes, and goals) and the readability of the material.

2.3.3.1 Factors related to the readers

The individual characteristics of readers have an important effect on the reading experience and on its outcomes. Many studies have investigated how prior knowledge (Calisir and Gurel, 2003; Calisir et al., 2008), working memory span (Lee and Tedder, 2003), and age (Lin, 2003) affect reading and navigation performance in different reading contexts.

Hyperlinks are the cause of non-linearity, which often leads to learner distraction, disorientation, and shallow reading (Akyel and Erçetin, 2009; Liu, 2005). Consequently, proper navigation skills are pivotal for on-screen reading. Coiro (2007) proposed a recursive cycle of online reading pattern with four elements: plan, prediction, monitor and evaluation. Readers should have a goal and build a mental model at first, predict where the link will lead, monitor after an action is taken and evaluate the pertinence of the decision. Although this four-part reading cycle is similar to that used when reading paper-based materials, the predicting, monitoring and evaluating parts focus on the uncertainty of what readers will end up with when they make a decision rather than where the author will lead them.

The two modes of reading share several reading strategies, such as planning/goal setting, rereading, monitoring, evaluating and correcting (Akyel and Erçetin, 2009; Coiro, 2007). However, how these strategies should be implemented depends on the reading mode (Murphy et al., 2003). Digital (and online) reading capitalizes on individual differences in navigational skills, which involve constantly making a decision on how to proceed while reading, and monitoring of this process (Akyel and Erçetin, 2009, p. 145), and are a reflection of metacognitive strategies specific to online reading. Highly skilled readers tend to use diverse comprehension strategies during the reading process (Stanovich, 2000). These readers are better at integrating prior knowledge with the information in the text in order to improve their comprehension (Haenggi and Perfetti, 1992). Low-skilled readers in general lack relevant background knowledge and vocabulary and do not know how to use strategies correctly or how to choose and employ appropriate strategies in an efficient way (León and Carretero, 1995). According to Sung et al. (2015), a good reader adopts these strategies in response to his reading objectives and according to his reading mode in order to optimally capture the meaning of the text. Coiro (2007) reported that skilled sixth-grade readers reading online texts have to deal with more complex processes and choices than if they obtained the same information offline or in print format. Although digital document can be browsed in a non-linear way, many readers still read them in a more or less linear fashion. This allows them to transfer the skills and strategies used in paper reading to digital reading, rather than using specific strategies, although the latter may be more effective.

2.3.3.2 Factors related to the document

The comprehension factors associated with the document properties are related to its readability. Consequently, a part of research on comprehension focuses on the study of content readability, expressed as the ease of processing afforded by the content (e.g. layout, organization, linguistic properties, etc.).

Readability is often evaluated using the characteristics of the document (François and Miltsakaki, 2012; Nelson et al., 2012; McNamara et al., 2014): content format (page layout, appearance, etc.), organization (headings, indexes, etc.), style (linguistic structural elements, tone of the writer, etc.), and theme (nature of the subject matter, etc.) (Gray, 1935). Its assessment aims to provide a quantifiable yet objective prediction of the level of difficulty to read and understand a given text. The readability reflects the ease for a reader to understand it. It is to not be confused with *legibility*, which is a measure of how easily a reader can distinguish individual letters or characters from each other. According to the early research of Dale and Chall (1949), the readability of a text is determined by the combination of all text aspects that affects the reader's understanding, reading speed, and level of interest in the text. For Richard et al. (1992), readability means: "how easily written materials can be read and understood. This depends on several factors including the average length of sentences, the number of new words contained, and the grammatical complexity of the language used in a passage". Mc Laughlin (1969) defined readability as, "the degree to which a given class of people find certain reading matter compelling and comprehensible". Dale and Chall (1949) provided a comprehensive definition of readability:

Definition 2.5 (Readability)

(Readability is) "*the sum total (including all the interactions) of all those elements within a given piece of printed material that affect the success a group of reader have with it. The success is the extent to which they understand it, read it at an optimal speed, and find it interesting." (Dale and Chall, 1949)*

2.3.4 Document readability assessment

2.3.4.1 Readability formulas

The earliest investigations of readability were conducted by asking students, librarians, and teachers what seemed to make texts readable. More sophisticated and automated methods were later introduced to predict readability in an analytical way, using *readability formula*.

Readability formulas are basically mathematical equations that compute certain constants and parameters taken from the text, in order to yield a readability score for that text. These formulas are mostly based on two factors related to text difficulty: lexical sophistication and syntactic complexity, generally measured by word and sentence length, respectively (Crossley et al., 2017).

In general, the formula for assessing readability take into account the number of sentences in a given paragraph, length of sentence (words count), number of syllables per sentence/ per word, and the nature of the sentence (active/passive). More than 200 readability formulas have been produced since 1970, in the hope of providing tools to measure text difficulty more accurately and efficaciously.

– The *Flesch Reading Ease formula* is an early readability formula (Flesch, 1943), among the most accurate formulas to have a widespread impact on text development and selection. It is based on sentence length and number of syllables per word. The use of this measure is so popular that it is included with popular word processing software such as Microsoft Word, Lotus WordPro, and Google Docs for English documents.

– The *Flesch-Kincaid* formula Kincaid et al. (1975) is another popular and heavily tested formulas, implemented in common word processing programs such as Microsoft Word. It is a linear combination of the mean number of syllables per word and the mean number of words per sentence. As such, it uses the same assumptions as the Fog Index and SMOG measure but calculates a finer grain measure of word length.

– The *Fog Index* Gunning (1969) measure uses average sentence length as measure of grammatical difficulty and the number of words with more than two syllables as an indicator of grammatical difficulty.

– The *SMOG* formula, proposed by Mc Laughlin (1969), consider that the word length and sentence length should be multiplied rather than added. It estimates readability using the square root of the number of polysyllabic words (words with three or more syllables).

– The *Dale-Chall* formula considers he reading difficulty as a linear combination of the mean sentence length and the percentage of rare words. In the revision version (Chall and Dale, 1995), the measure of lexical difficulty depends on the hypothesis that the percentage of words in a text increases linearly with the readability level.

Limits of the readability formulas

Document creators can calculate the readability of their contents in order to assess their quality and identify any problems that need to be corrected. In most cases, there are appropriate readability formulas that can be used. However, these formulas have been criticized for different reasons:

– because readability formulas are composed of the variables of words and sentence length, they correspond to the surface structure rather than the deep syntactic and semantic structure;

– their poor proven validity from the point of view of psycholinguistic theories (Bruce et al., 1981);

– they use of empirical correlations without being linked to any particular theory of reading or comprehension;

– their poor performance in predicting readers' judgments of text comprehension (Crossley et al., 2017).

2.3.4.2 Modern readability assessment methods

Although traditional readability formulas are still widely used, the above limitations combined with the increasing sophistication of NLP (*Natural Language Processing*) have accelerated the emergence of new approaches to assessing readability (Collins-Thompson, 2014). Their objective is to upgrade the readability formulas using more innovative and conceptually valid linguistic techniques (Benjamin, 2012). They generally involve a rich representation of the evaluated text, based on a variety of linguistic characteristics and using highly sophisticated prediction models based on machine learning. Different features were explored for the evaluation of readability, which Collins-Thompson (2014) classified into a set of categories (shown in Figure 2.1) identified as affecting readability. A readability measurement is thus a function that associates the text with a numerical output value corresponding to a readability level or a score. For instance, Crossley et al. (2007) used Coh-Metrix (Graesser et al., 2004), a NLP tool that produces indices of the linguistic and discourse representations of a text, to develop readability formulas for L1 and L2 readers. These formulas included measures of syntactic complexity, word frequency, and text cohesion. The results of the evaluation showed that these formulas outperform traditional readability formulas with some groups of readers. In a similar fashion, Pitler and Nenkova (2008) combined lexical, syntactic, and discourse features to predict judgments of readability. They found that linguistic characteristics related to syntax, semantics and discourse were good predictors of readability, which was not the case with traditional readability formulas.

Recent approaches for automatic readability assessment can be subdivided into two classes, according to whether it is carried out as a classification task or in terms of ranking (Dell'Orletta et al., 2014). Methods following a classification approach assign documents to specific readability classes. This is the approach followed in most part of the cases. For instance, Petersen and Ostendorf (2009) used Support Vector Machines (SVM) to combine the features of language models with classic readability indices in order to automate the task of selecting appropriate material for second-language learners. Text classification and feature selection were used by the SVM models which were trained on texts for children with labeled reading levels. Feng et al. (2010) measured how accurately the features used to train these classifiers can predict the suitability of a given text for a particular age group. On similar lines, Vajjala and Meurers (2014) apply readability features and machine learning to classify a corpus of subtitles in terms of target audience age group. Schwarm and Ostendorf (2005) designed a formula that included traditional measures along with syntactical complexity measures. The formula was successfully used to predict text reading level (second through fifth grades). Heilman et al. (2006) used the frequency

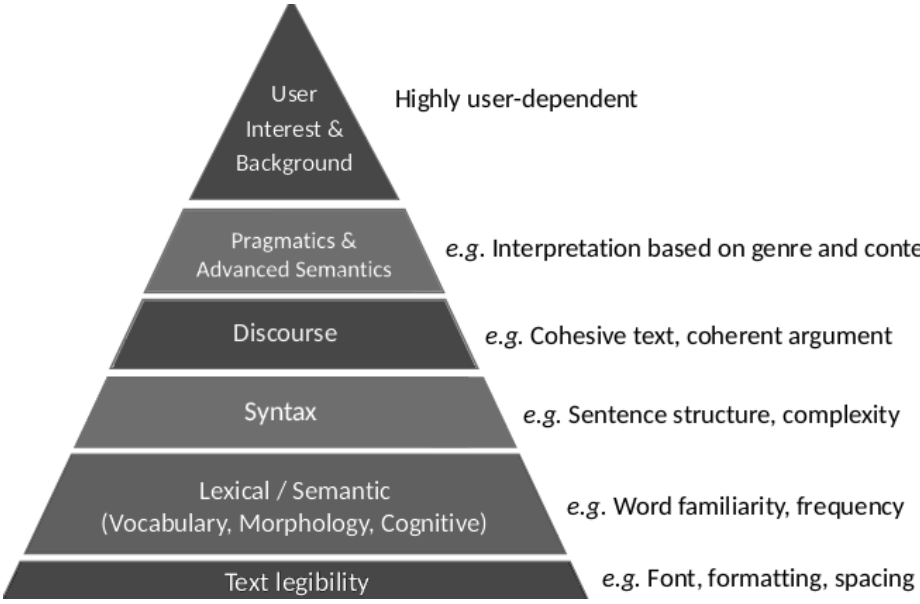


Fig. 2.1 Key aspects of text readability, ordered from lowest level (*text legibility*) to highest level (*user interest and background*) (Collins-Thompson, 2014)

of common grammatical constructions as a measure of grammatical difficulty to predict the grade level of texts and found that the inclusion of grammatical features lowered the error rate in level classification. The frequency of common grammatical constructions as a measure of text difficulty was also used by Heilman et al. (2006) for the same purpose.

Ranking-based methods assign the document a score positioning it within a readability ranking scale. They emerged as an alternative to classification-based methods, for dealing with less resourced languages or to meet specific needs, e.g. identifying finer-grained and customized readability classes. For instance, Tanaka-Ishii et al. (2010) combined pairwise assessments of texts to produce a document ordering by reading ease into a scale ranging from easy to difficult. Ma et al. (2012) also used a ranking methodology to predict reading level of books by considering visually-oriented features (such as the average font size and ratio of annotated image rectangle area to page area). Inui et al. (2001) computed the readability of sentences on a scale for deaf people using a comparator generated by an SVM. Scarton et al. (2010) tried different machine learning algorithms and selection strategies to label Portuguese texts as simple or complex.

2.3.4.3 Readability of Web-based documents

With the increasing availability of document reading on the Web, it is important to be able to assess their readability in order to determine how they can be better leveraged (Filho et al., 2016). Yet, very few efforts target the Web context. Among the limited amount of work that has targeted the application of readability models to web document, Vajjala and Meurers (2013) achieve good classification performance across different corpora, consisting of different genres of texts and different targeted age groups. Gyllstrom and Moens (2010) proposed *AgeRank*, a graph walk algorithm inspired by the PageRank algorithm that Google introduced to estimate the importance of Web pages. The algorithm provides a binary labeling of Web documents according to its appropriateness for children versus adults. The AgeRank approach also uses features such as page color and font size to help determine the page label. Akamatsu et al. (2011) proposed a method to predict the comprehensibility of web pages that uses hyperlink information in addition to textual features. The authors showed reasonably high positive correlation between the link structure and readability levels of pages on the Web.

2.3.4.4 Limits of automatic readability assessment

An automatic readability assessment can be useful for both human-oriented and machine-oriented applications. This includes the selection of suitable reading materials according to the desired literacy levels, the classification of documents by reading difficulty, and various NLP tasks such as automatic document summary, automatic translation and text simplification. However, as stated by Bailin and Grafstein (2001), there is no simple measure of readability since how easy a text is for an individual to read is the result of the interaction of a number of different factors, reflecting properties both of texts and readers and the interaction between them. Moreover, automatic readability assessment often fails to tell about text comprehension. This is even true in the Web context where, as sustained by (Collins-Thompson, 2014), little is currently known about basic readability properties of the Web, or the influence of readability on user interactions with Web content. According to Jones and Shoemaker (1994), the sole focus of automatic readability assessment is on the factors associated with that readability, and that they measure neither understandability nor comprehension per se. The readability assessment based on content feature appears to not be sufficient as a valuable tool for producing, revising, and selecting written materials, in particular when they are online. A major problem with readability assessment methods is that they do not determine whether the target audience understands the text well. Dascalu et al. (2014) argued that to date, little effort has been made to assess what learners actually understand from reading.

2.4 Document revision

Document quality depends on the factors related to its design and its writing and that determine the ease of reading afforded by the document. This quality is essential to maintain the level of comprehension, which is ultimately the result sought in reading. One way to enhance this quality is to continually improve the structure and content of the document and evolve it as needed, through document revisions.

2.4.1 Revision in the writing process

From a communicative perspective, writing is a goal-directed activity where the author tries to satisfy his need to inform and/or the need of his audience to be informed (Couzijn and Rijlaarsdam, 2005). The process of document composing is complex and requires high order thinking and disciplinary understanding. It is a time-consuming, non-linear process that involves multiple drafts even for those who do it for a living (Olmanson et al., 2016). It can include engaging content, outlining, writing, re-reading, evaluating, revisiting sources, re-organizing, adding content, and addressing editorial issues of flow, typos, and unconventional spelling.

Revision is one important step of the edition process, that has a direct impact on the authorship success. Traditionally, revision has been considered as a mere copy-editing writing task (Faigley and Witte, 1981). When the attention shifted towards a more process-oriented vision of writing (Fitzgerald, 1987), educators started to teach and train revision to their students. Consequently, the writing process now includes revision as a core component. According to Faigley and Witte (1981), revision results from evaluating the content through reading, comprehending, and criticizing in order to detect problems with it and, when a problem is found, selecting and applying a strategy to deal with the problem. Fitzgerald (1987, p. 484) proposed the following definition:

Definition 2.6 (Document revision)

"Revision means making any changes at any point in the writing process. It involves identifying discrepancies between intended and instantiated text, deciding what could or should be changed in the text and how to make the desired changes. Changes may or may not affect the meaning of the text, and they may be major or minor. Also, changes may be made in the writer's mind before being instantiated in written text, at the time the text is first written, and/or after the text is first written." (Fitzgerald, 1987)

This definition includes thinking, comparing, deciding, and choosing, then taking action. From a process-oriented viewpoint, Fitzgerald (1987) identified three important aspects of revision:

1. revision may occur at any time in the writing process, i.e. "before, while and after putting the pen to paper" or typing;
2. revision can be meaning-based (affecting the text-based) or surface-based (not meaning-changing); and
3. revision is directly connected to what happens in the mind of the revising author during the revision (revision as a mental process, learning through revision).

2.4.2 The revision process

Since the 1980s, several researchers have investigated the nature of revision, trying to determine how, how many times and when to revise (Sommers, 1980; Fitzgerald, 1987; Faigley and Witte, 1981). Revision was conceived primarily as a problem-solving process triggered by the identification of "discrepancies between intended text and instantiated text" (Fitzgerald, 1987). This perspective is a key element of the models developed by many researchers. The pervasiveness of this perspective is evidenced by the fact that expressions like "problem detection", "problem diagnosis", "problem resolution" have often been treated as synonymous with revision (Allal et al., 2004). These three expressions are the constructs of the "Reviewing" process which is defined in the model of writing proposed by Flower and Hayes (1981) and known as the *Cognitive Process Theory*. According to this model, writing involves three cognitive processes: planning, translating, and reviewing. The reviewing process was further elaborated as comprising several cognitive processes, including problem detection, problem diagnosis, and strategy selection (Hayes et al., 1987).

A. Problem detection

Revision often results from the need for improvement or correction. Problem detection is the process by which the author identifies the differences between the text produced or being produced and the intended text (Hayes et al., 1987). It is essential and must occur before any revisions can be made (Patchan and Schunn, 2015).

B. Problem diagnosis

Once a problem is detected, the author should have a clear idea of how to react to the problem in order to solve it. Problem diagnosis, as defined by Flower et al. (1986), refers to the ability to describe the problem, explain why it is problematic and suggest how to resolve it. It is therefore a question of creating a representation of the detected problems in order to provide the author with sufficient information to trigger an appropriate response (Hayes et al., 1987). A diagnosis can vary in terms of quantity and level of explicitness from well-defined representations (i.e. knowledge of the problem, including location and cause, which often leads to a specific solution to the problem), to poorly defined representations (ie only knowing that something does not sound right).

C. Revision strategy selection

Strategy selection consists in reacting to a detected problem (Hayes et al., 1987). This process requires both the ability to make decisions and the ability to solve problems. First, the author must decide which problems to solve and which strategy would be the most effective. When a problem is ill-defined or the most appropriate strategy is not obvious, the author must use a search strategy to find better solutions. Consequently, the quality of the solutions applied can vary according to the writing ability of the author.

2.4.3 Taxonomy of revision

The work of Faigley and Witte (1981) presents the first elaborated taxonomy capturing the intentions behind a textual change (Figure 2.2). Revisions are categorized on whether they change the information of the document (text-based changes) or not (surface changes).

- *Surface changes*. These changes do not affect the meaning. This class is further divided into:
  - *formal changes*: mostly copy-edits like spelling corrections etc.
  - *meaning-preserving changes* are changes that do not change the overall meaning, such as adding a word.
- *Text-base changes*. These are the changes that affect meaning. This class is further divide into:

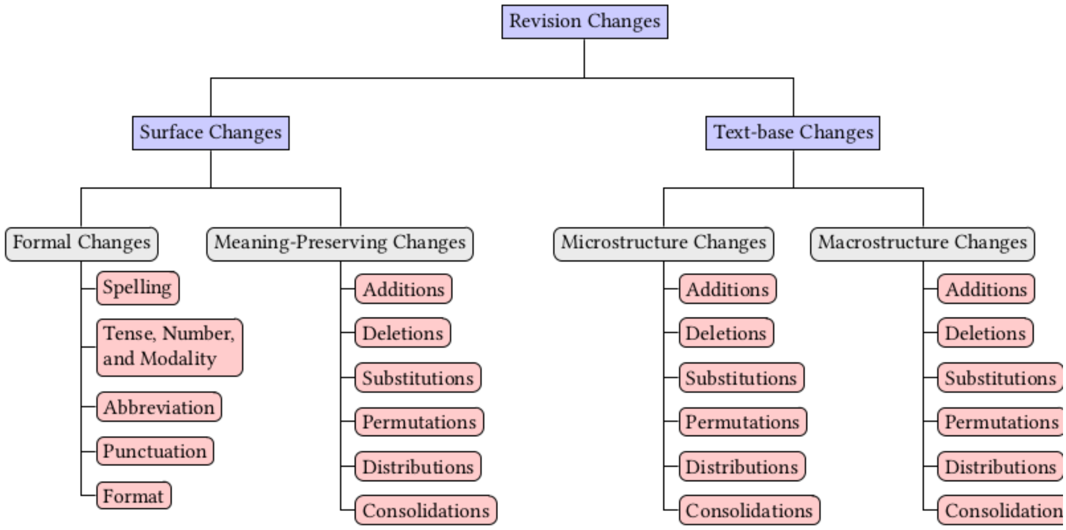


Fig. 2.2 Taxonomy of revision changes (Faigley and Witte, 1981)

- *Microstructure changes* are meaning changes that would not change a summary, but would still change the meaning of part of the text.
- *Macrostructure changes* are meaning changes that are so important that a summary of the text should be modified from one draft to the next.

Meaning-preserving, microstructure, and macrostructure changes can be additions, deletions, substitutions, permutations, distributions, or consolidations.

Many researchers reused the categorization as the coarse level revision categorization in their own schema (Cho and MacArthur, 2010; Early and Saidy, 2014; Daxenberger and Gurevych, 2012). More fine-grain classification was also proposed: *vandalism*, *paraphrase*, *markup*, *spelling/grammar*, *reference*, *information*, *template*, *file* etc. (Liu and Ram, 2011; Daxenberger and Gurevych, 2012). For instance, a taxonomy is elaborated in (Zhang and Litman, 2015) for *Surface changes* purposes (e.g. Fluency, Reordering and Errors) and *Content changes* purposes (e.g Claim, Rebuttal, Evidence). Early and Saidy (2014) used the Faigley and Witte taxonomy and further categorized revisions to *Main Idea*, *Developing Argument*, *Textual Evidence*, *Rhetorical Strategies*, and *Language Choice* for the analysis of the students' revision strategies. Other specific revision categories are typically defined according to the researchers' task. Pfeil et al. (2006) defined revision categories according to the action performed (*add information*, *reversion*, *vandalism*, etc.) in an attempt to identify differences in collaboration between different cultures. To analyze the revision model in Wikipedia, Jones (2008) designed a categorization of revision actions based on the characteristics of the Wikipedia dataset (*policy violation*, *add image*, *add link*, etc.). In the same context, Bronner and Monz (2012) classified revision edits in Wikipedia into factual (text-based) and fluency (surface) changes.

A general classification compliant to the taxonomy of Faigley and Witte (1981) is proposed by Allal et al. (2004). The revision strategies are divided into two classes:

- *Editing* includes correcting errors and making changes to improve the adequacy of the text without changing its general meaning;

– *Re-writing* entails transforming the content of the text (adding or removing segments), rearranging the organization of the text (segment sequence) and modifying the meaning transmitted by a segment.

These two categories can be combined in a revision process that would allow both errors to be corrected and content to be transformed.

2.4.4 Issues in document revision

Revision is a cognitively and procedurally challenging part of writing (Flower et al., 1986; Hayes and Chenoweth, 2006) that involves reconsidering ideas, organization, wording, and detecting problems (Hayes and Chenoweth, 2006; Olmanson et al., 2016). Whether it happens during outlining, composition, or rereading, revision is ideally a form of "re-mediation" which helps authors see their texts in new ways (Prior and Hengst, 2010). According to Scardamalia and Bereiter (1991), becoming an expert author means acquiring an ability to efficiently and frequently activate the writing processes of both planning and revising during a composition.

From early research, expert authors are found to revise in ways different from inexperienced ones (Faigley and Witte, 1981). Expert writers consider this step as an opportunity to enhance their skills and to discover better ways to express those meanings (Hayes and Chenoweth, 2006; MacArthur and Graham, 2016). They also review their documents to identify any discrepancies between the intended meaning and the meaning they express (Bereiter, 2013; Hayes et al., 1987). When writing, they typically take this knowledge into account, as well as the genre, purpose, and audience of the text (Berkenkotter, 1981). Experts know why they are writing and what the writing is meant to accomplish in the world, and this knowledge helps them to map their tasks and ideas (Flower and Hayes, 1981). For novice authors, the revision step is often difficult, and thus they approach it as an editing task (Fitzgerald, 1987). Low ability authors are especially likely to struggle with three components of the revision task: (1) detecting possible existing problems; (2) making a correct diagnosis of the detected problem; and (3) selecting a strategy of remediation.

2.4.4.1 Problem detection

In general, higher-ability authors succeed to detect more problems compared to lower-ability ones. Furthermore, they are much more likely to detect more problems related to global meaning (Fitzgerald, 1987; Hayes et al., 1987). According to Patchan and Schunn (2015), there are two possible factors that explain the difficulties in detecting problems. The first is the lack of knowledge about the problems that may occur in writing. The second is related to the fact that some authors can operate with an imprecise representation of their content: in general, authors tend to have difficulty perceiving errors in their own writing compared to other authors' texts, because when they read their own text, the errors are often automatically corrected in their minds (Flower et al., 1986).

2.4.4.2 Problem diagnosis

Similar to problem diagnosis, strategy selection also depends on problem detection. Expert authors make more revisions than novices, and in particular, they make much more global revisions. Consequently, they have more existing schemas for particular types of writing problems (Hayes, 2000). These authors not only have a broader understanding of more problems, but they also have more solutions adapted to these problems. This more sophisticated repository of knowledge (of problems and solutions) helps expert authors choose more effective solutions to the writing problems they detect.

Problem diagnosis is usually perceived as challenging, in particular when the issue is ill-defined or when the appropriate revision strategy is not obvious. This leads many authors to just undertake generic actions such as deletion or total rewriting. By avoiding in-depth analysis of the problems detected, the author often ends up with only limited knowledge of the types of obstacles that may exist in his content, making it more difficult to detect and solve these problems.

2.4.4.3 Strategy selection

To revise the content, authors must first determine the existing problems and then choose the appropriate strategy to apply. Problem detection and diagnosis are both crucial for an author to decide to revise them. If only detection occurs, the author is not likely to understand the nature of the problem or how to solve it. In such cases, the sole option available to the author to address the problem is to rewrite the text hoping that the new text will no longer necessary contain the problem originally detected. Because such a solution occurs when the author does not really understand the problem when trying to solve it, the initial problem may continue to exist. On the other hand, if an author is capable of both detecting and identifying the problem, the additional information could inform him on how to revise the issue text. Since revision occurs when the author understands where the problem occurred and how to solve it, the problem is more likely to be successfully solved.

2.5 Summary

This chapter provided an overview of the evolution of learning in the digital age. It focused on reading for learning and what it refers to in terms of tools, practices, with reading being the main learning activity and the basis for many other activities. Reading patterns have become increasingly diverse since the emergence of online learning environments. The latter are a source of a multitude of educational contents that exploit the innovative properties of digital documents such as hypertext, interactivity and multimedia.

An important measure of learning success through reading is the learner's level of understanding. This chapter addressed reading and comprehension, with a particular focus on elearning context. It thus examined the transformations that the transition to the digital age has had on both of them. It also discussed the different factors that have an impact on the level of understanding, including the quality of the course content. Revision being one effective strategy to improve course quality, a review of research in content revision, is presented. The chapter ended with a discussion of revision in terms of challenges it poses for authors in capturing and responding to readers' needs.

3

Usage analytics and knowledge discovery in educational documents

Most e-learning platforms include logging features that allow the use of automated methods for monitoring learners' behavior. This has fostered the emergence of the fields of learning analytics (LA) and educational data mining (EDM) which aim to leverage the data collected by these platforms in order to optimize the learning experience and outcomes. In this chapter, we first review the current trends in tracing and interpreting learners interaction within educational platforms (§3.1). We then describe the main methods and the application objectives of learning analytics and educational data mining (§3.2). One of the most active areas of learning analysis is the development of visual interfaces for presenting data to analytics stakeholders to help them make relevant pedagogical decisions. We thus conclude by diving into the state of the art in *learning analytics dashboards*, which are probably the most popular information visualizations used to present the results of the analytics process (§3.3).

3.1 Tracing reading usages in e-learning

3.1.1 Monitoring learning

Whether in traditional education, workplace training or lifelong learning, monitoring is a common practice that consists in tracking learner's activities and outcomes, commonly used to evaluate the effectiveness of the teaching and the learning. Learning monitoring can be defined as follows.

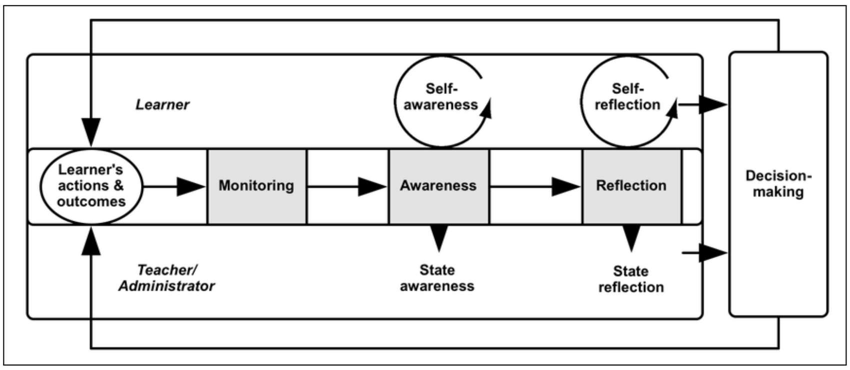


Fig. 3.1 Monitoring, awareness and reflection (Rodríguez-Triana et al., 2017)

Definition 3.1 (Learning monitoring)

Learning monitoring is "*an ongoing function that relies on the systematic collection of data on specific indicators to provide the various participants in a learning activity with indications of the progress and results of that activity*" (Marriott and Goyder, 2009)

Monitoring is a strategy used in different aspects of learning orchestration. Learners can monitor themselves (self-monitoring) which help them in promoting self-regulation (Tabuenca et al., 2014). They can also be supervised by a third person, usually a teacher or administrator (Rodríguez-Triana et al., 2017). This can help teachers and instructors regularly evaluate the effectiveness of their teaching methods and material to make subsequent instructional decisions and interventions (Chatti et al., 2012). In other words, monitoring is a straightforward strategy for promoting self and/or state awareness and reflection, which play a crucial role in evaluating and regulating the learning process (Figure 3.1).

Awareness.

Awareness, according to Dourish and Bellotti (1992), is an understanding of the activities of others, which provides a context for the activity of the observer. It is a subsequent step from monitoring and deals with inferring the current state of learner understanding or learning artifacts (Rodríguez-Triana et al., 2017). From the learner's perspective, awareness refers to the metacognitive process of being aware of his own state of understanding and progress (*self-awareness*) as well as teachers' awareness of the state of their students and classes (*state awareness*).

Reflection.

Reflection builds on awareness of one's experiences and requires critical thinking to examine the information presented, reflect on these experiences, question their validity and draw critical conclusions. It can be *self-reflection* (by the learner) which allows learners to gain insight into their experiences that can foster further learning. It can also be *state-reflection* when it deals with the learner's state of understanding and conducted by others (such as teachers or administrators). Both self- and state reflection lead to decision making that influences further learning activities (Rodríguez-Triana et al., 2017). For example, learners can identify the activities needed to improve their understanding, or a teacher can design activities to support some specific needs of learners.

3.1.2 Monitoring approaches

Monitoring and evaluating what is taught and what is being learned requires effective and trustworthy methods. Until recently, monitoring has been achieved through student assessment, grade analysis, attendance and graduation rates. They are based on human-centric approaches like direct observations, interviews, focus groups, and surveys. However, when learning takes place on online platforms, this form of monitoring is often not effective because it is too intrusive and costly (Thomas, 2014). In addition, it does not adapt well to the heterogeneity of learners' profiles and fails to quickly reflect possible changes that may occur in the learning context. Importantly, the data produced are limited, so the results of their analysis are rather inconclusive and it takes time to implement the ensuing recommendations.

The integration of options to record user activities with and within learning environments has enabled the development of automated approaches to monitoring and analyzing learning, supported by data related to learners, their preferences, their behavior, and their performance. They are based on tracking learners activities (the learning process) or their results and outcomes (product of learning) (Florian-Gaviria et al., 2013). These methods represent an opportunity to explore learning from new and multiple angles. For this purpose, it is first necessary to analyze the data using appropriate tools. This would then make it possible to identify patterns of learning behavior that can raise (state and self) awareness and reflection, and that provide more insight into the learning experience (Gašević et al., 2015).

3.1.3 Computer-mediated activity traces

The user's behavior within a digital environment results from the sum of his activities which often involve action and interaction with or through that environment. Mathern (2012) defines the concept of activity as a *set of processes more or less observable, immersed in a situation that aims to achieve a unified global goal*. An activity results from the set of *actions* related to that process. The traces of this activity are the marks that it leaves on the environment (but which are not necessarily the purpose of the activity and are not necessarily left intentionally). These traces can be interpreted in a particular way to give meaning to what happened.

The monitoring of an activity consists in deliberately manipulating the environment in which it takes place so that it is recorded, and so that the resulted trace is as appropriate as possible for the person who intends to use it. Different definitions are associated to the concept of "*digital trace*" (or "*interaction trace*", "*digital footprints*", or simply "*log*" and "*trace*" in this thesis), depending on its role and its utilization. For Settouti et al. (2009), "The trace is defined as a temporal sequence of observed elements recorded from a user's interaction and navigation". For Champin et al. (2012a), it is "a mark left by an activity", with the activity being related to a process (i.e to a series of actions): traces are thus what remains, what can be observed in this process or these actions. For Lund and Mille (2009), a digital trace is a sequence of temporally observed elements, which is either human interactions mediated and inscribed in the digital environment by itself on the base of the user activity, or a sequence of actions and reactions between a human and a computer. Champin et al. (2012b) specialized this general definition for the digital context as follows:

Definition 3.2 (Digital trace)

"*A digital trace is made from digital imprints left voluntarily (or not) by the digital environment in the digital environment itself during the digital process* (Champin et al., 2012b).

3.1.4 Trace-based interaction indicators

Digital traces left by users have attracted researchers' interest for their ability to reflect the mutual influence between users and the environment. Their high availability and the need to draw knowledge from them have led to the advent of sophisticated analytical methods that rely on automatic or semi-automatic data processing tools. The resulting level of awareness and reflection is strongly correlated with both the quality and sophistication of the information obtained through the analysis of these traces. This usually involves identifying and calculating appropriate measures, called indicators, capable of reflecting the aspects of interest from the learners' behavior. Interaction indicators can be defined as follows:

Definition 3.3 (Interaction indicators)

Interaction indicators are "*variables that indicate [...] the mode, the process or the 'quality' of the considered 'cognitive system' activity, the features or the quality of the interaction product, the mode or the quality of the collaboration* (Dimitracopoulou et al., 2004).

Data indicators provide means of abstracting, synthesizing, inferring, and visualizing the information that they feature. When designed properly, these indicators can provide insightful knowledge for different purposes, dealing for instance with diagnosing learners problems (Gwizdka and Spence, 2007), learners' retention and learning outcomes (Edwards et al., 2017; Pardo et al., 2017), learners' motivation and engagement (Tempelaar et al., 2017; Nguyen et al., 2017; D'Mello et al., 2017; Carrillo et al., 2016), self-regulated learning (Kizilcec et al., 2017; Pardo et al., 2017), modeling learners' misconceptions (Liu et al., 2016) or learning behavior (Käser et al., 2016).

3.1.4.1 Classification of trace-based learning indicators

Dyckhoff et al. (2013) conducted an extensive literature review and identified approximately 200 popular indicators that were classified from two angles: the point of view a user might have on the same data (called *perspective*), and the *data source* that the indicators implement (student-generated data, context/local data, academic profile, evaluation, performance, or course meta-data).

A. Individual learning indicators

The most widely computed indicators are related to *individual learner's activity* on the learning platform. The activity consists in either using a resource (reading, listening, watching, etc.) or actively participating on the platform (contributing in the forums, editing wiki pages, doing exercises, etc.). The indicators calculated can be used for self-reflection and self-monitoring of learners. They can also be used by instructors to monitor the individual learning process of learners, for example for tutoring. Examples of the indicators include: *Number of content pages viewed per student* (Zorrilla and Álvarez, 2008), *Number of threads started per student* (May et al., 2011; Mazza and Dimitrova, 2007), *Number of messages read on forum per student* (May et al., 2011; Bratitsis and Dimitracopoulou, 2006; Mazza and Dimitrova, 2007), *Rate* *of messages read by a learner* (Brooks et al., 2006), *Content currently read* by one or more students (Brooks et al., 2006), *Relation between keywords and students* (Mochizuki et al., 2005), *Frequency a student used a keyword* (Mochizuki et al., 2005), *Student risk group/status* (Arnold, 2010).

B. Group learning indicators

The individual students indicators can be combined to self-reflect and analyze students *groups' behavior, learning, and academic success*. Examples include: *Number of participants per group* (Fritz, 2011; May et al., 2011), *Avg. number of posts per group* (Bratitsis and Dimitracopoulou, 2006), *Number of messages quoted per group* (May et al., 2011), *Number of files per group* (May et al., 2011), *Avg. thread depths/weight* (Bratitsis and Dimitracopoulou, 2006), *number of initiated threads per group* (Bratitsis and Dimitracopoulou, 2006), *Advice to groups concerning uncommunicative behavior* (Kosba et al., 2005). A few indicators are intended for teachers to allow them to reflect upon their teaching with a view to improving it. These indicators explicitly process teacher-generated data and correlate it with student-generated data. Examples of these indicators include *Sociogram of interaction between teacher and participant* (Bakharia and Dawson, 2011).

C. Content-related learning indicators

Other types of indicators aims to present data about the *course and its content*. Examples include: *Global accesses to the course* (Mazza and Dimitrova, 2007), *Number of distinct users* (Martín Fraile, 2007), *Avg. visit duration* (Martín Fraile, 2007), *Learning paths analysis* (Martín Fraile, 2007), *Resources that have not been accessed* (weekly, daily, hourly) (Zhang et al., 2007), *Learner isolation/students with limited connectivity* (Bakharia and Dawson, 2011). The indicators related to content allow to present the students' interactions with the content of a course. They explicitly take the perspective of a resource, lesson, quiz, etc. Examples include: *Number of unique users per resource* (weekly, daily, hourly) (Zhang et al., 2007), *Number of revisits per lesson/quiz* (Ali et al., 2012), *View counts per resource* (weekly, daily, hourly) (Schmitz et al., 2009; Zhang et al., 2007), *Resources frequently used together* (forum, mail, etc.) in each learning session (García-Saiz and Zorrilla, 2010), and *top pages/resources* (Martín Fraile, 2007).

3.1.4.2 Sources of the data used

An alternative classification of interaction indicators can be based on the data source. In general, this data can come from the activity and interaction of the learners on the platform, their academic profile and their performance evaluation.

A. Learners' activity and interaction

The data captured within learning environments can be related to different learners' behaviors and activities. This includes the *learners clickstreams* (Siemens, 2013; Wolff et al., 2013; Papamitsiou et al., 2014), *eyes movements* (Copeland et al., 2015), and *learners participation* in discussion forums (Xing et al., 2015; Agudo-Peregrina et al., 2014; Macfadyen and Dawson, 2010).

Some indicators can consist of just basic data from user traces, such as basic statistics (session information, number of visits, hits, duration, etc.). They can also contain complex types resulting from a calculation on several low-level data, for instance: Course access by a student per date (Mazza and Dimitrova, 2007), Overall time spent per student (weekly, daily, hourly) (García-Saiz and Zorrilla, 2010; Zhang et al., 2007; Zorrilla and Álvarez, 2008), Trends in students' activity (based on time spent) (Govaerts et al., 2012). Many indicators use the *context and local information* that surrounds the student, such as, local or mobile data, and influence the learning process. These indicators might consider the location of the learner, co-learners nearby, calendar information, email exchange, homework assignments, deadlines, or exam dates (Schmitz et al., 2009).

B. Academic profile

The student's *academic profile* is another source of data used. It may include demographic profile (gender, age, mother language, etc), and information about the field of study, previous knowledge, and grades from assignments (García-Saiz and Zorrilla, 2010; Zorrilla and Álvarez, 2008). High level indicators can be computed using this type of data; for instance, Arnold (2010) used it for computing an indicator related to groups of learners at risk of failure. *Evaluation data* is another source of information that can be tracked from learners' response to course questions, course evaluations, one-minute feedback, or questionnaires. Schmitz et al. (2009) used this type of data to define an indicator related to learners' level of comprehension.

C. Performance assessment

A set of indicators use performance-related data, like grades from assignments, quizzes, and exams, or attempts per quiz questions, mistakes made, etc (Fidalgo-Blanco et al., 2015; Snodgrass Rangel et al., 2015). Examples of indicators include quiz scores (Ali et al., 2012), Clusters of students who made a (specific) mistake (Scheuer and Zinn, 2007), Number of assignments submitted per student (May et al., 2011; Zorrilla and Álvarez, 2008), Advice to the teacher concerning excellent and weak students relative to the whole class (Kosba et al., 2005).

3.2 Analysis of learning traces

3.2.1 Knowledge discovery in digital data

Digital learning environments are able to record very detailed information regarding learners' behavior, resulting in a huge amount of data that is getting more and more voluminous. Their analysis and interpretation therefore require advanced data analysis techniques to be able to deliver the appropriate information.

The interdisciplinary field of *Knowledge discovery and data mining* focuses on designing suitable methodologies to extract useful knowledge from data. It leverages research in various fields, including statistics, databases, pattern recognition, machine learning and data visualization to provide advanced business intelligence and web discovery solutions. The term of *data mining* refers to the "step in the overall process of knowledge discovery that consists of pre-processing, data mining, and post-processing" (Witten et al., 2016). It is the process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data (Frawley et al., 1992; Fayyad et al., 1996). Rather than attempting to test prior hypotheses, it searches for new and generalizable relationships and findings from large amounts of data (Slater et al., 2017).

3.2.2 Educational data mining (EDM) and Learning analytics (LA)

The use of analytics in education is relatively new, compared to other science disciplines such as physics and biology. According to Baker and Inventado (2014), it has grown in recent years for four primary reasons: (1) a substantial increase in data quantity, (2) improved data formats, (3) advances in computing, and (4) increased the sophistication of tools available for analytics.

The application of knowledge discovery and analytics methods on learning traces is attracting increasing interest. Current trends are characterized by an increased technological use of features related to optimizing learning. All this enables the emergence of tools that rely on a data-based infrastructure to collect a wide variety of data without user intervention. As the combination of "big data" and computational progress emerges, efforts are focusing increasingly on improving the overall learning process, both within and outside the formal framework. The objective is to take advantage of the increasing use of online courses and of databases containing assessment results and behavioral records for the creation of large repositories of educational data. In order to harness this vast amount of data, the fields of *Learning Analytics* (LA) and *Educational Data Mining* (EDM) have emerged as a middle ground between learning sciences and data analysis. Their objective is to give education actors the appropriate means to improve understanding of teaching and learning and, more specifically, to adapt education more effectively to learners.

3.2.2.1 Educational data mining (EDM)

The application of knowledge discovery from data in education is mainly addressed within the field of *Educational Data Mining* (EDM). EDM bridges between two disciplines: education and computing sciences (in particular *Data Mining* and *Machine Learning*) (Bakhshinategh et al., 2017). Current research integrates the interdisciplinary research fields of *Statistics and Visualization*, *Psychological Education*, *Knowledge Discovery and Database*, *Machine Learning*, *Information Science*, and *Artificial Intelligent* to various educational data sets so as to resolve educational issues (Romero and Ventura, 2010). The field of EDM can be defined as follows:

Definition 3.4 (Educational data mining)

"*Educational data mining is the area of scientific inquiry centered around the development of methods for making discoveries within the unique kinds of data that come from educational settings, and using those methods to better understand students and the settings which they learn in*" (Baker et al., 2010).

The main reason for the rapid development of EDM research in recent years is due to the availability of huge amounts of educational data, mainly generated by online education systems, and the urgency of converting this data into useful information and knowledge.

	EDM	LA
Origins	educational software, student modeling and course outcomes prediction.	semantic web, intelligent curriculum, outcome prediction and systemic interventions.
Discovery	Focuses more on the automation of the discovery tasks.	More concerned with leveraging human judgment.
Reduction and holism	emphasis on reducing phenomena to components and analyzing individual components and their relationships.	emphasis on considering the full complexity of systems by understanding them as wholes.
Adaption and personalization	Models are often used for automated adaptation, without human intervention,	Models are often used to inform and empower instructors and students
Techniques and methods	include classification, clustering, bayesian modeling, relationship mining, discovery with models, and visualization	include social network analysis, sentiment analysis, influence analysis, discourse analysis, learner success prediction, concept analysis and sense-making models.

Table 3.1 Key distinctions between EDM and LA

3.2.2.2 Learning analytics (LA)

The purpose of trace data analytics is to "help us to evaluate past actions and to estimate the potential of future actions, so to make better decisions and adopt more effective strategies as organizations or individuals" (Cooper, 2012, p. 3). In the case of LA, this purpose is oriented towards education. Many definitions are associated with the learning analytics. One earlier definition discussed by the community suggested that "Learning analytics is the use of intelligent data, learner-produced data, and analysis models to discover information and social connections for predicting and advising people's learning". The most cited definition emerged from an open online course on learning and knowledge analytics and was adopted by the "Society for Learning Analytics Research" (SoLAR)[1] that defines this field as follows:

Definition 3.5 (Learning analytics)

Learning analytics is "*the measurement, collection, analysis, and reporting of data about learners and their contexts for purposes of understanding and optimizing learning and the environment in which it occurs* " (Siemens and Gasevic, 2012)

3.2.2.3 Educational Data Mining vs Learning Analytics

The EDM and LA communities are defined in relatively similar ways. They both reflect the use of data-intensive approaches in education. Their purpose is to provide opportunities for educational improvement by helping the community to better

[1] SoLAR (http://www.solaresearch.org) was created in summer of 2011 to develop and advance a research agenda in learning analytics, and to educate in the use of analytics in learning.

apprehend educational questions and make the appropriate adjustments. There is a significant overlap between the two research areas. Despite this, many differences are highlighted in the literature.

The emergence of learning analytics as a separate field means that there are now separate communities focused on the different challenges of analytical research (Ferguson, 2012). In this vein, Baker and Inventado (2014) consider the similarities and differences between the two communities to be mainly organic, representing the interests and values of researchers and therefore not reflecting a deeper philosophical separation. For Bienkowski et al. (2012), LA covers more disciplines: in addition to computer science, statistics, psychology, and the learning sciences, it deals with information science and sociology. Thus, even if the two domains share an important spectrum, their different origins and coverage make it possible to separate them. Siemens and Baker (2012) identified five key distinctions that reflect broad research trends of the two communities, summarized in Table 3.1.

3.2.3 Learning analytics lifecycle

In examining the methods of learning analytics, it is essential to conceptualize the process over which the flow of analytical information must be routed. For Campbell et al. (2007), data analytics in education can be seen as an engine that works in five steps: capture, report, predict, act, and refine. The decisions taken at the initial stages may profoundly affect the following stages. The definition of these steps has been adjusted for the context of the learning analytics by Pardo (2014) as follows:

1. *Capture* – this step is related to the selection of the data and appropriate measures, their level of granularity and how to retrieve and store this data.
2. *Report* – the data collected are intended to be processed so that they can be summarized or combined for reporting using appropriate tools. The report may range from simple descriptive statistics and visualizations to more complex dashboards that summarize or combine the data provided to stakeholders.
3. *Predict* – this stage is related to making predictions based on the captured data and the generated reports. The aim is to provide answers to previously formulated that initiated the data capture. Different prediction techniques can be used; their accuracy depends on the use of a reliable model.
4. *Act* – this stage can target any of the analytics stakeholders. It requires the use of prediction techniques from the previous step to generate actions (manually or automatically) that will modify a given aspect of the learning activity. The nature of the computed predictions influences the number and kind of the analytical interventions.
5. *Refine* – the objective of this stage is to make regular evaluations and adjustments to the overall process to improve the stability of the model. The refinements can target the quality of the captured data, the information included within the reports, the used prediction algorithms, and the actions needed to modify the learning experience (to make sure that they are applied to the right individuals, under the right conditions, and with maximal impact).

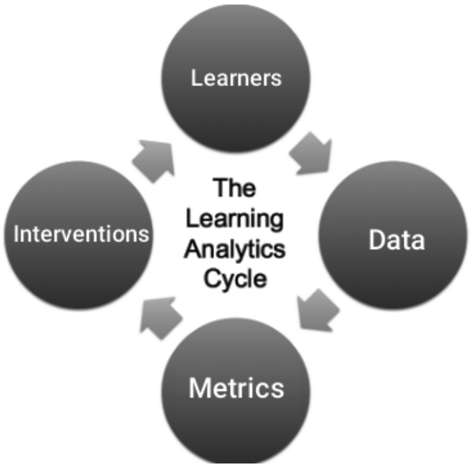


Fig. 3.2 The learning analytics cycle (Laurillard, 2002)

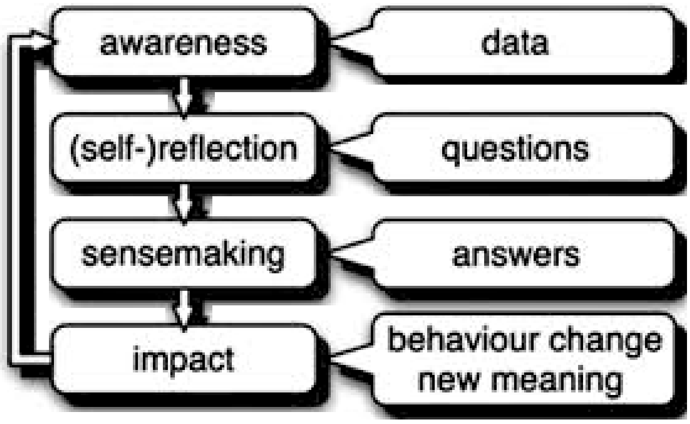


Fig. 3.3 Learning analytics process model (Verbert et al., 2013)

Based on Kolb's Experiential Learning Cycle (Kolb, 1984), Schön's work on reflective practice (Schön and DeSanctis, 1986) and Laurillard's conversational framework (Laurillard, 2002), Clow (2012) developed the *Learning Analytics Cycle* presented in Figure 3.2.

1. *Learners* – can be learners enrolled in formal or informal learning, participants at a research conference, or casual learners.
2. *Data* – consists in the generation and capture of data about or by the learners. This data can, for instance, be related to the learners' profiles or to their activity on the platform.
3. *Metrics* – are the heart of most learning analytics projects. Metrics give insight into the learning process in forms of visualizations, reports, dashboards, etc. While some metrics can be obtained automatically and directly, others may take more effort to generate.
4. *Interventions* – is the final stage of the cycle where the computed metrics are used for driving interventions that are supposed to have an effect on learners. This intervention can be for instance a dashboard, which shows the metrics directly to a learner, or to a tutor/instructor.

Quite similar to this cycle, Verbert et al. (2013) also elaborated another modeling of the learning analytics process with four stages (Figure 3.3):

1. *Awareness* – results from capturing the data and visualizing them as activity streams, tabular overviews, or other visualizations.
2. *Reflection* – shifts the focus from data to users' questions, their relevance, and their usefulness.
3. *Sensemaking* – focuses on users' answering the questions identified in the previous stage, and the creation of new insights.
4. *Impact* – aims to induce new meaning or change users' behaviors if necessary, depending on the answers and insights created in the sensemaking stage.

3.2.4 Methods, processes, and tools in EDM/LA

3.2.4.1 Collection of data

The first step in any analytics effort is to collect data from the educational environments. The learning systems provide different types of data, which involves different mining and processing methods. Various data sources can be used: students and instructors profiles, learning content and material, between students communication, and records of learning actions and usages (Romero et al., 2014).

When tracking learning activities, the granularity of the events to capture must be considered. Low-level traces are often used, such as keystrokes, mouse gestures, clicks, etc. Most learning environments store the learners' activity data in log files, structured into records. Each record corresponds to a timestamped event that reflects a user action. In Web-based learning, a logfile file contains requests made to the server in a chronological order. Following The *Common Log Format*[2], each line of the logfile contains the client's hostname or IP address, the timestamps (data and time) of the request, the operation type (e.g. GET, POST), the requested resource name (URL), a code indicating the status of the request and the size of the requested page (if the request is successful).

A second, higher level of granularity can also be considered in the analytics, generally that of activity (e.g., reading a resource, answering a question). Current initiatives aimed to develop standardized data formats for collating this kind of events in the Learning Analytics literature. This includes learning context ontologies (LOCO framework) (Jovanović et al., 2007), the *Contextualized Attention Metadata* (Schmitz et al., 2011), the *Caliper Analytics* developed by the *IMS Global Consortium*[3], SCORM[4] and xAPI[5] (See (Serrano-Laguna et al., 2017) for a review).

Since 2001, SCORM has been the widely used software specification for packaging learning content in a standard format. It is a product of *ADL Initiative*, a research group sponsored by the *United States Department of Defense*. It was first released

[2]https://www.w3.org/Daemon/User/Config/Logging.html#common-logfile-format (accessed on November 23th, 2018)

[3]https://www.imsglobal.org/activity/caliper (accessed on November 23th, 2018)

[4]https://scorm.com (accessed on November 23th, 2018)

[5]https://xapi.com/specification (accessed on November 23th, 2018)

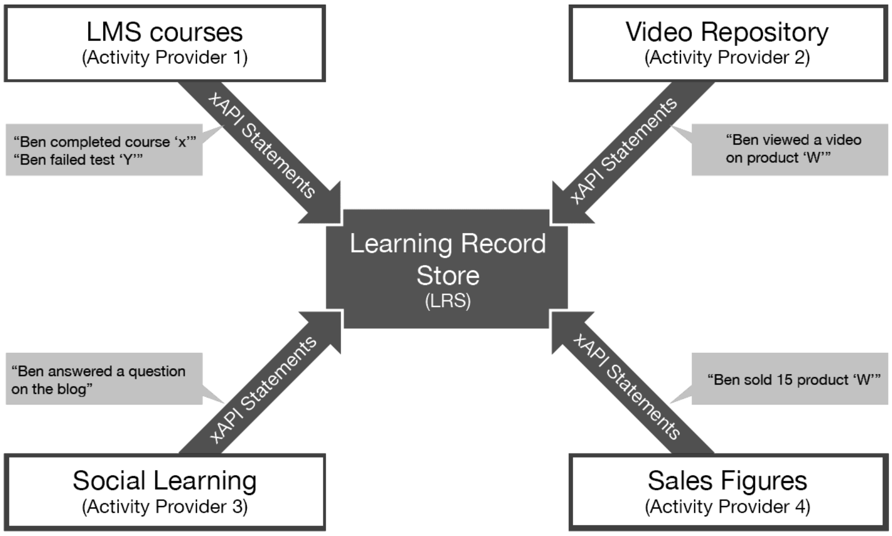


Fig. 3.4 Basic principles of xapi

in 2001, with a major revision in 2004. SCORM aims to standardize the indexing and sharing of educational content used in e-learning. It encompasses content management, runtime environment, communication with the LMS, as well as the navigation model. The tool is integrated into most LMSs and is used to monitor learners' progress and to upgrade e-learning modules.

However, since SCORM is closely linked to the LMS, it does not work outside the LMS and the browser. In addition, many groups of students use LMS only for mandatory tasks and not for all their learning activities. This made it clear to the ADL that SCORM needed to be updated. The US Government commissioned a study called *Project Tin Can* that resulted in the data transport and storage mechanism called *Experience API* (xAPI).

The Experience API (xAPI), created in 2013 by ADL, provides a platform-neutral formalism to collect events occurring in any learning experience. It is more flexible than its predecessors and enables the collection of all the data that a learner can produce. This standard integrates, recognizes, communicates and records information from mobile learning, simulations, virtual worlds, serious games, social learning, offline learning, collaborative learning, etc.

The fundamentals of xAPI are illustrated on Figure 3.4. Learning experiences can happen in many places. The tools used for recording these experiences (LMS, video repository, etc.) are called *activity providers*. The different activities related to the different learning experiences are saved into a *Learning Record Store* (LRS), which is often integrated into the LMS. A *statement* describes a learning activity using three fundamental elements: actors, verbs and objects, and a fourth optional element: context. Basically any activity provider can send xAPI statements, which are then collectively stored in an LRS.

3.2.4.2 Preprocessing

The data collected from the learning environments are often too large and/or involve many irrelevant attributes, which call for data preparation and preprocessing. Preprocessing is an important step in the analysis of this type of data and aims to produce quality data suitable for use by a particular algorithm or data mining framework. In education, this critical phase can take more than half of the total time spent on solving the data mining problem (Miksovsky et al., 2002). Several of the used preprocessing tasks are originated from the field of *Web Usage Mining* (WUM)[6]: data cleaning, data aggregation and integration, user and session identification, data transformation, data modeling, and path completion (Han et al., 2011; Liu, 2007; Romero et al., 2014).

A. Data Aggregation/Integration

Data collected from multiple sources and stored in different formats are consolidated in a unified format, usually within a single database(Lenzerini, 2002). While aggregation targets the same type of data, integration deals with data of different types. This allows, for example, to integrate learners' traces with their demographic information.

B. Data cleaning

Data cleaning (data cleansing, scrubbing) is the process of detecting and eliminating errors and possible inconsistencies in the data in order to improve its quality (Rahm and Do, 2000; Han et al., 2011). Its methods address various data quality issues such as noise, outliers, inconsistent data, duplicate data and missing values.

C. User identification

User identification is the association of each event with the corresponding user. This can be achieved in a number of ways, including the use of IP addresses, cookies and/or direct authentication (Romero et al., 2014). Users of learning platforms are often not anonymous as they provide user credentials (login and password), which facilitates immediate association of users with their actions.

D. Session identification

Session identification consists in cutting logs captured on the server side into delimited and sustained sessions closest to the actual sessions of activity of the users (Mobasher, 2007; Thomas, 2014). Two main classes of approaches for reconstructing user sessions exist: time-oriented and navigation-oriented. The first is based on the limitation of total session time or page-stay time. The navigation-oriented approach uses web topology to organize the logs into different sessions.

E. Feature Selection

The objective of feature selection and extraction is to choose a subset of relevant attributes of the data, eliminating those which are irrelevant or redundant or have little interest for the study objectives (Liu, 2007). It is an important stage within EDM where there exists, in general, a large number of attributes for learning schemes to handle in many practical situations, which may result in reducing the accuracy of a learning model due to over-fitting problems (Romero et al., 2014).

[6]*Web usage mining* refers to the automatic discovery and analysis of patterns in clickstream and associated data collected or generated from user interactions with Web resources. The goal is to capture, model, and analyze the behavioral patterns and profiles of users interacting with a Web site.

F. Data Filtering

Data filtering involves selecting a sample of representative data to convert large data into smaller and more manageable datasets (Han et al., 2011). In education, the techniques commonly used are the selection of subsets of data relevant to the intended purpose and the choice of the most practical grain size for the task at hand (Romero et al., 2014).

G. Data Transformation

With data transformation, new attributes can be derived from existing ones to facilitate the interpretation of information (Han et al., 2011). The main examples of data transformation algorithms in EDM include normalization, discretization, derivation, and format conversion.

3.2.4.3 Main methods and techniques

There are a wide variety of popular methods commonly used within EDM/LA. Many of these methods fall into general data mining categories like classification, clustering, association-rule mining and sequential mining. Baker et al. (2010) suggests five approaches/methods: prediction, clustering, relationship mining, distillation of data for human judgment, and discovery with models. These methods are found in both EDM and LA, the latter being more focused on human data interpretation and visualization, while the former is more interested in automated methods.

A. Prediction

The goal of prediction is to develop a model capable to infer a single aspect of the data (the predicted variable) from some combination of other aspects (predictor variables). Prediction models are prominent in both EDM and LA communities. In EDM, classification, regression, and density estimation are the most common types of methods. Research in LA focuses more on traditional classification and regression approaches than on latent knowledge estimation (Baker and Inventado, 2014).

B. Clustering

Clustering, and more broadly structure discovery, is very popular within LA/EDM. Clustering consists in splitting the full dataset into a set of groups called clusters. The grouping is performed in such a way that the objects of the same cluster are more similar (in one way or another) to each other than those of other clusters. Clustering is particularly useful when the common categories of the dataset are not known in advance. It can either start without prior assumption on the data clusters (such as the k-means algorithm with random restart), or it can start from a specific assumption (using, for example, the Expectation Maximization algorithm).

C. Relationship mining

Historically, various relationship mining methods have been the most important category in EDM research (subsequently more present in EDM than in LA) (Baker and Inventado, 2014). Their goal is to discover, in a dataset with a large number of variables, the relationships between them. For example, this may involve finding the variables that are most strongly associated with a single variable of particular interest or looking for possible relationships between two variables. Four types of methods exist: association rule mining, correlation mining, sequential pattern mining, and causal data mining.

D. Visualization

Visualization, or distillation of data for human judgment, corresponds to generating overview statistics and visualizations, where data is distilled to enable a human to quickly identify or classify its features. This may allow teachers and administrators, for example, to identify patterns of student learning, behavior or collaboration, and to label the data for use in developing a forecast model.

E. Discovery with models

Discovery with models is not common in data mining in general. These methods, however, are very popular in EDM and less common in LA (Baker and Inventado, 2014). Typically, a model of a phenomenon is developed via prediction, clustering, or in some cases knowledge engineering (by using human reasoning rather than automated methods). This model is then used as a component in a second analysis or model, for example in prediction or relationship mining.

3.2.4.4 EDM/LA application objectives

There are many applications that are of interest to the EDM/LA community. Different authors have reviewed the existing applications and proposed different categorizations (e.g., (Baker et al., 2010; Romero and Ventura, 2010; Hegazi and Abugroon, 2016)). On the basis of these different surveys, Bakhshinategh et al. (2017) introduced a more complete classification by distinguishing three main categories of applications (*Student modeling applications*, *Decision support systems*, and *Other applications*).

Student modeling is related to the representation of different cognitive aspects of learners' activities. This includes analyzing their performance and behavior, isolating underlying misconceptions, representing their plan and objectives, identifying prior and acquired knowledge, and describing personality characteristics. Chrysafiadi and Virvou (2013) distinguished five different characteristics that are generally involved when modeling students: (1) knowledge and skills, (2) errors and misconceptions, (3) learning styles and preferences, (4) affective and cognitive factors and (5) meta-cognitive factors. Student modeling can serve to predict students learning performance and to identify those with unusual or problematic behaviors, such as low motivation, and erroneous actions. It can also serve to profile and group students based on different variables and profiles information such as characteristics and knowledge.

Another important application of analytics is related to enhancing the process of teaching and learning by helping stakeholders, mainly instructors and teachers, making appropriate instructional decisions. Such systems are used to provide feedback, to generate reports and to alerts. They can also be used for planning and scheduling different actions related to teaching and learning.

Other applications include:

– Adaptive systems, which allows taking into consideration the difference between students' needs. They may consist in adapting the content of a course, the teaching pace, the content of tests, etc.

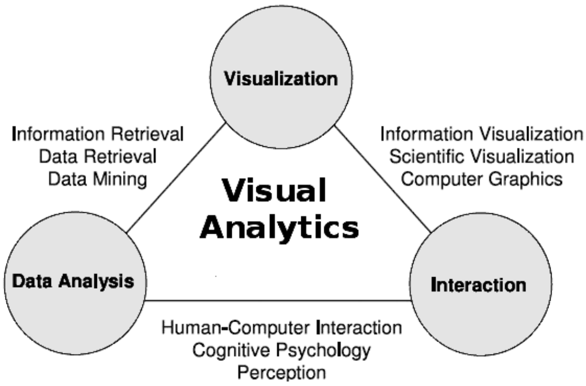


Fig. 3.5 Visual analytics and the related research areas

– Evaluation systems, which try to provide an evaluator to help the educators, either in exploratory learning environments and computer-based courses (Bakhshinategh et al., 2017).
– Scientific inquiry applications, which aim to test and even develop theories based on the knowledge that can be mined from education datasets. The targets here are mainly researchers.

3.3 Learning analytics dashboards

3.3.1 Information visualization and visual analytics

The amount of learners traces being logged can scale up quickly, creating an abundance of information that needs to be analyzed and reported (Charleer et al., 2014a). This overabundance of information induces a high cognitive load on the user. One approach to reducing this impact is to use visual representations of the data. With such approaches, non-visual data are associated with recognizable visual representations, either static or interactive (Kosara, 2007).

The research area of information visualization is intended to guide and assist users in exploring and understanding complex data, extracting information and, ultimately, acquiring knowledge and making sound decisions. This is achieved through progressive and iterative visual exploration that uses human capabilities to better process, understand, analyze and find relationships in the coded data, rather than examining the raw data (Slingsby et al., 2011). Information visualization of large data to support timely decisions is currently used in a variety of area (e.g., business success, clinical treatments, cyber and national security, and disaster management). The field of *visual analytics* is an evolution of the fields of *information visualization* but takes a more holistic approach (Figure 3.5). Cook and Thomas (2005) define visual analytics as the science of analytical reasoning facilitated by interactive visual interfaces. It results from the combination of automated analysis techniques and interactive visualizations for effective understanding, reasoning and decision-making based on very large and complex data sets (Keim et al., 2008). While information visualization is focused on visual encoding, visual analysis has a particular interest in linking interactive visual representations with underlying analytical processes (e.

g. statistical procedures, data mining techniques) so that complex and high-level activities can be performed effectively (e. g. making sense, reasoning, decision making). The methods and tools used synthesize information and extract knowledge from massive, dynamic and often conflicting data (Keim et al., 2008). They are found to be very convenient in areas of application where large amounts of information must be processed and analyzed (Brouns et al., 2015).

3.3.2 Educational dashboards

Information visualization techniques are leveraged in learning analytics research to bring the resulting findings into the hands of human experts(Charleer et al., 2017). As stated by Duval (2011), these techniques aim to connect visualizations not only to meaning or truth, but also to decision-making and action-taking. Educational dashboards are a widely recognized and relevant type of visual analytics in e-learning. Generally referred to as *Learning Analytics Dashboards* (LAD) (or *educational dashboards*, *dashboards for learning analytics*, *learning dashboards*), they consist in visual tools that are easy to understand, ensuring an intuitive and straightforward insight into the learning process (Khalil and Ebner, 2015).

3.3.2.1 Concept of dashboard

The dashboard metaphor has evolved with time. From the panel placed at the front of a horse-drawn car, it was later used to indicate a control panel in front of the driver in cars. Fostered by the exponential growth in data volume and applications, the business community has adopted the concept as a performance management system by displaying at a glance *key performance indicators* (KPIs) to help decision-making (Podgorelec and Kuhar, 2011). Influenced by information technology and digital devices, dashboards are being used extensively both in the business world and for personal use (Park and Jo, 2015). For Few (2013), a dashboard is a “visual display of the most important information needed to achieve one or more objectives that have been consolidated on a single computer screen so it can be monitored at a glance”. Ji et al. (2014) referred to dashboards as “a container of indicators”. Broadly speaking, a dashboard can be defined as follows:

Definition 3.6 (Dashboard)

“Dashboard is an easy to read, often single page, real-time user interface, showing a graphical presentation of the current status (snapshot) and historical trends of an organization's key performance indicators (KPIs) to enable instantaneous and informed decisions to be made at a glance. ” (Brouns et al., 2015)

3.3.2.2 Learning dashboards

Learning analytics dashboards are designed to use learners' traces to present the computed indicators and other visual elements in a clear and intuitive way (Brouns et al., 2015). They have emerged as applications for visualizing and interacting with data collected in a learning environment in various forms (Ramos-Soto et al., 2015). Steiner et al. (2014) referred to them as "visualizations of learning traces". For Yoo et al. (2015), a learning dashboard is "a display which visualizes the results of educational data mining in a useful way". Schwendimann et al. (2017) identified a lack of an agreed and shared definition and thus proposed the following:

Definition 3.7 (Learning analytics dashboard)

"A learning dashboard is a single display that aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations. " (Schwendimann et al., 2017)

Learning dashboards provide interactive, historical, customized and analytical displays that are based on the results of analyzing learning data (Park and Jo, 2015; Kim et al., 2015). By implementing visual and interactive analytics, they amplify human natural abilities to detect patterns, establish connections and make inferences. The produced visual outputs can significantly highlight aspects of interest from the mined and discovered knowledge (Duval, 2011).

Learning dashboards are suitable for online, face-to-face, and blended learning (Verbert et al., 2013). They can target different stakeholders: administrators, instructors, learners or all of them. Within a single display, indicators and visualizations about learners, learning processes and contexts are rendered using different shapes, from plain text to visual elements (e.g., tables, spreadsheet charts, scatterplot, 3D representations) to complex artifacts such as alerts and notifications that prompt interventions (Few, 2006; Podgorelec and Kuhar, 2011; Schwendimann et al., 2017). Currently, they are increasingly deployed as a meaningful component in learning analysis systems. For instance, they are currently used in studying progression through courses (Nicholson, 2012), learners level of attainment (Gutierrez-Santos et al., 2012), and learners' engagement from the cognitive and behavioral perspectives (Carrillo et al., 2017). Despite being fairly recent educational tools, the research found many benefits of using learning dashboards to improve learning performance (Arnold and Pistilli, 2012) and to increase learners' motivation (Verbert et al., 2013; Wise et al., 2016).

3.3.2.3 Design principles

Due to the recent emergence of learning analytics dashboards, there is still a scarcity of studies on their design principles (Echeverria et al., 2018). Yoo et al. (2015) argued that, since dashboards are an instrument of communication, effective design is tied to several theoretical foundations, such as human cognition and perception, situational awareness and visualization technologies. In other words, their conceptualization must be based on an understanding of how humans see and think.

Based on a number of theoretical principles in addition to his practical experience, Few (2013) outlined some good and bad examples of dashboard design. He claimed that the essential characteristics of a dashboard are: 1) to be visual displays; 2) to display the information needed to achieve specific objectives, 3) to fit on a single computer screen, and 4) to be used to monitor information at a glance. In terms of human perception, due to the limited working memory of humans, only three or four pieces of visual information can be stored at a time. Therefore, for more effective memory perception and retention, it is essential to incorporate graphic patterns such as graphs rather than individual numbers. In addition, there must be a proper and reasoned use of pre-attentive attributes such as colour, shape, spatial position and movement. From Few's principles, Yoo et al. (2015) drew three main implications:

1. the most important information should stand out from the rest in a dashboard, which usually has limited space to fit into a single screen;
2. the information in a dashboard should support one's situated awareness and help rapid perception using diverse visualization technologies; and
3. the information should be deployed in a way that makes sense, and elements of information should support viewers' immediate goal and end goal for decision making.

Situational awareness deals with disclosing the type of information that is important for a particular purpose or task (Endsley, 2016), and thus constitutes another design principle related to dashboards. Three levels can be distinguished:

1. perception of the elements in the environment;
2. comprehension of the current situation; and
3. projection of future status.

Situational awareness is commonly understood in terms of people being consistently aware of what is going on, in order to predict what will be happening as well as to prepare what must be done.

3.3.3 Types of dashboards

Verbert et al. (2014) classified the existing learning analytics dashboards, according to the purpose and context of their use, into three classes: 1) dashboards for traditional face-to-face lectures, 2) dashboards for face-to-face group work, and 3) dashboards for awareness, reflection, sense-making and behavior change.

3.3.3.1 Traditional face-to-face lectures dashboards

A number of dashboards are designed to help teachers in understanding students' learning experiences and adapting their teaching accordingly. For instance, Yu et al. (2012) designed a dashboard that alerts the teacher about the learner's agreement or disagreement during teaching. The tool tracks head shakes or shakes and voice with a built-in camera and microphone integrated to their computers. Other dashboards are used to engage students during lecture sessions. For instance, *Backstage* (Pohl et al., 2012) shows students' Twitter activity in a face-to-face course to allow them to compare themselves with their peers. For visualizing social collaboration, the dashboard *Classroom Salon* (Barr and Gunawardena, 2012) allows teachers to create, manage and analyze social networks called "Salons" where students can create, comment and edit documents collaboratively. Similarly, the framework Slice 2.0 (Fagen and Kamin, 2012) interconnects tablets of students with slides used by the teacher; a dashboard application allows the teacher to monitor students, to visualize their notes, and to interact with them for group discussion on a large display.

3.3.3.2 Face-to-face group work dashboards

This class of dashboards targets learning orchestration in terms of real-time classroom and workgroups management. For instance, in the context of monitoring collaboration on tabletops, *TinkerBoard* (Do-Lenh, 2012) is developed a dashboard that presents on a large display the activity of each group. *Collaid* (collaborative learning aid) (Martinez Maldonado et al., 2012) captures learner collaboration data on tabletops and presents the data to the teacher. Similarly, *Class-on* (Gutiérrez Rojas et al., 2011; Rojas and Garcia, 2012) visualizes learning activities on a tablet, in order to provide awareness for teachers. Data on students' progress and requests for help are presented to the teacher so that he or she can decide which group to help in a face-to-face session.

3.3.3.3 Awareness, reflection, sense-making and behavior change

Verbert et al. (2013) claimed that learning dashboard are mainly about *awareness* (through data visualization), *reflection* (concerned with users' asking questions and trying to understand how the data can be used), *sense-making* (questions and answers in reflection stage which leads the users to come up with new ideas), and the *impact* of the previous stages on users to change their attitude in learning. Many existing dashboards fall within this category. For instance, *Course Signals* (Arnold and Pistilli, 2012) is designed to predict students' learning outcomes based on data collected on their grades, time spent on learning tasks, and past performance. A similar dashboard is presented in (Dollár and Steif, 2012) which, in addition, includes data on self-evaluation activities. It gives an overview of the concepts that may require additional attention from the student and the way in which the student carries out the different activities of the course. *Student Activity Meter* (SAM) (Govaerts et al., 2012) is a highly configurable dashboard that targets both instructors and learners. It allows learners' progress in the course to be displayed and uses visualizations to show the time spent and resources used. Other dashboards within this category include *LOCO-Analyst* (Ali et al., 2012), *Moodle dashboard* (Podgorelec and Kuhar, 2011), and *GLASS* (Leony et al., 2012). They generally use the time spent and artifacts produced as visualizations to give the teacher an overview of student achievement.

Some learning dashboards include self-assessment results to give an indication of the learners' level of progress and understanding. For instance, *Student Inspector* (Scheuer and Zinn, 2007) uses data from the usage and self-assessment of the *ActiveMath* learning environment (test results, typical learner errors, and students' strong and weak subjects) to provide details on learner performance. The dashboard implemented within *CALMSystem* (Kerly et al., 2008) shows knowledge levels based on self-assessments results.

Some dashboards incorporate a learning schedule to support awareness. For instance, the tool presented in (Chen et al., 2008) enables learning status awareness (i.e., showing for the instructor the online availability of a learner), schedule awareness (i.e., presenting the scheduled assignments of instructors), and learning support awareness (i.e., sending notifications about assignments to learners).

Manual teachers' intervention is used in *Teacher Advisor* (TADV) (Kosba et al., 2005) to send automatically generated advice to learners. *StepUp!* (Santos et al., 2012) is another tool that aims to empower learners to let them reflect on their learning. *Learning Analytics Reflection & Awareness environment* (LARAe) (Charleer et al., 2014b) is a tool that aims to raise awareness about active individuals and groups and the content generated by them. It shows the history of students' social activities (e.g, blogs, tweets and comments) categorized by type and student groups.

3.3.4 Data used by learning dashboards

In general, learning dashboards use data resulting from the collection, the extraction and the processing of raw data stored within the learning system. Most existing dashboards use virtual sensors (software) that track learners' interactions within the learning environment. Physical sensors such as cameras or microphones to capture learners' actions are rarely used (Verbert et al., 2014). Systems like *Student Inspector*, *SAM*, and *GLASS* use data resulting from tracking learners' activity within different LMS (e.g., Moodle, WebCT, and Blackboard). Very few dashboards use their own tool (e.g., SNAPP (Bakharia and Dawson, 2011)) or rely on a third-play tracking system (e.g., StepUp! (Santos et al., 2012)) for the tracking purpose.

Some dashboards generate descriptive statistics on the data collected while others apply data mining methods like prediction on the raw data to compute more advanced usage metrics. In their study of learning analytics dashboards, (Verbert et al., 2014) identified some of the most relevant user actions used by the existing dashboards: the *artifacts produced by learners* (e.g. responses to questions, help requests, and annotations); *social interaction* (e.g. ratings, comments on blog and forum posts, and chat messages); *resource use* (e.g. reads of forum posts); *time spent* which can be used to identify potential students at risk; and *test and self-assessment results* to capture knowledge levels are used in blended or online-learning settings.

3.3.5 Evaluating learning dashboards

Learning analytics dashboards are in general evaluated using two types of evaluation: *formative* which aims at revising the quality of the studied tools (e.g., LOCO Analyst (Ali et al., 2012), SAM (Govaerts et al., 2012)), and *summative* which is conducted to determine the effectiveness of the dashboards (Park and Jo, 2015) (e.g., Students Inspector (Scheuer and Zinn, 2007), StepUp! (Santos et al., 2012; Verbert et al., 2013), Course Signal (Arnold and Pistilli, 2012), and Narcissus (Upton and Kay, 2009)).

Most previous studies used experimental models to verify the effects of the learning dashboards by examining dependent variables such as learning achievement (Chen et al., 2008), retention rate (Arnold and Pistilli, 2012), or usefulness of the dashboard (Dollár and Steif, 2012; Govaerts et al., 2012; Santos et al., 2012). (Kim et al., 2015). In general, the independent variable was the presentation of the dashboard to the subjects. Evaluation of the developed learning dashboards is conducted either with teachers or students, or both. These studies often involve asking teachers questions about finding at-risk learners or asking learners if they think they are doing well in a course.

A line of existing research focuses on usability and students' perceived usefulness (Govaerts et al., 2012). Some studies indicate a positive influence of learning analytics dashboards and visualizations on improving engagement (Nakahara et al., 2005), academic performance (Arnold and Pistilli, 2012), test results and assessments (Brusilovsky et al., 2011; Kerly et al., 2008), and retention rates (Arnold and Pistilli, 2012) of the overall population of students. A large number of studies that focus on assessing learning impact have been carried out in limited experimental settings (Brusilovsky et al., 2011; Kerly et al., 2008). There are also few studies that have been investigated in course settings at a large-scale, such as (Arnold and Pistilli, 2012). Some studies evaluated the impact of learning dashboards in terms of engagement (Nakahara et al., 2005), progress (Brusilovsky et al., 2011), academic achievement (Arnold and Pistilli, 2012) and retention rates (Arnold and Pistilli, 2012). Out of these few, most are small-scale studies that rely on controlled experiments in lab settings isolated from an actual learning context (Brusilovsky et al., 2011; Kerly et al., 2008; Nakahara et al., 2005).

The effectiveness of learning dashboards has been measured in terms of *better engagement*, *higher grades* or *post-test results*, *lower retention rates*, and *improved self-assessment*. In most cases, it is evaluated in controlled settings that consist in single session with an experimental group using the dashboard and a control group without such support. Questionnaires are often used to gain an indication of perceived usefulness for improving learning and teaching. *Course Signals* (Arnold and Pistilli, 2012) is among the few dashboards that have been evaluated in a large-scale study over three academic years. The efficiency of dashboards was measured in an evaluation experiment of *Class-on* (Rojas and Garcia, 2012) and assessed whether the use of a dashboard during classroom sessions helps to distribute time for a teacher in a fairer way. Although still preliminary, some trends in the data are shown that indicate improved efficiency during face-to-face group work. In general, most evaluation studies focused on the presentation of functions and usability of the interface and aimed at highlighting potential impact on learning, neglecting to prove the effects of the dashboards as a pedagogical remediation tool (Verbert et al., 2013).

3.3.6 Limitation of the existing dashboards

3.3.6.1 Lack of theoretically informed design

One obstacle to the adoption of dashboards is the often existing gap between visual analyses and the objectives of the study (Roberts et al., 2017). Sometimes, to represent the analyzed data from different angles, designers use complex representations and visualizations that are rather difficult for end users to interpret, especially "at a glance" (Duval, 2011). According to the survey reported in (Reimers and Neovesky, 2015), the existing dashboards generally have poor interface design and lack of usability testing. The selection of data to be visualized is generally not what the stakeholders in the analysis want or really need because they have not regularly been involved in the design process (Holstein et al., 2017). Bodily and Verbert (2017) also noted the absence of design choice justifications in the conception of several learning dashboards.

A primary concern of dashboard designers must be the identification of what type of visual representations to implement, and what kind of interaction to offer. Gašević et al. (2015) argue that, without careful considerations, the design of dashboards can result in the implementation of fragile and undesirable instructional practices by promoting ineffective feedback types and methods. In order to encourage adoption of learning dashboards, the design needs to be further informed by theories related to learning sciences and educational psychology. Holstein et al. (2017) argued that the success of the dashboards depends on the degree to which its stakeholders have been involved in co-designing them.

3.3.6.2 Selection of the input data and the computed indicators

A rich variety of measured data and indicators are used and computed in existing dashboards. Dashboard solutions are heavily based on trace analysis, and little attention has been paid to use other data sources such as direct feedback or the quality of the produced artifacts. Moreover, as noted by Schwendimann et al. (2017), there is little work on comparing which indicators and which visualizations are most suitable for the different user data literacy levels. In most cases, the chosen visualizations are rather similar to those in other areas of dashboard applications (e.g., web analytics), which highlights the lack of specific visualizations and visual metaphors that address the activities of learning and teaching (another potential area for future research) (Schwendimann et al., 2017).

3.3.6.3 Evaluation of the actual impact on learning

The majority of the existing dashboards proposed are exploratory or not deployed in a real learning context. Consequently, they are either unevaluated or have not been subject for detailed evaluation (Charleer et al., 2014b; Leony et al., 2012; Schwendimann et al., 2017). The experimental approach for evaluating dashboards answer the qualitative question "Are dashboards effective on the dependent measures?". However, much is not yet known about the quantitative question of "How much effective?". The relative scarcity of long-term evaluations of this kind of tools is noteworthy, especially for users considering their adoption in everyday practice.

A good proportion of the evaluated prototypes use data gathered from authentic educational situations (e.g., past or present courses) in order to build analyses and visualizations. The dashboards evaluated are based on assessing the tool's acceptance, usefulness and ease of use as perceived by learners (Jivet et al., 2018) using feedback questionnaires and interviews, or through controlled lab studies. The impact of these tools in terms of student learning gains or learning-related constructs remains so far very little studied and evaluated (Arnold and Pistilli, 2012; Brusilovsky et al., 2011; Kerly et al., 2008; Nakahara et al., 2005; Schwendimann et al., 2017). As stated by Kim et al. (2015), to investigate the effects of dashboards on teaching and learning, it is necessary to analyze actual behavior patterns of the teachers and students. More generally, according to Park and Jo (2015), there is so far a lack of data on the impact of these dashboards on users' behaviors. Indeed, it is essential to investigate in order to better understand the possible relationship between the visualizations of information and analysis results and the quantity and quality of users' reactions.

3.4 Summary

This chapter introduced the areas of learning analysis and educational data mining. These new areas of research are made very active by the popularization of the use of learning tools with logging capabilities, the availability of ever-increasing amounts of data resulting from learner monitoring, and the sophistication of analysis and calculation methods. Different concepts, methods and tools related to educational process monitoring and analyzing were examined. As the outcomes of the analytics process often require to be reported visually in the most intuitive and meaningful way, the use of analytical learning dashboards for these purposes was finally discussed. The review of existing tools highlighted several weaknesses in their conception, design and evaluation, which prevent them from being fully exploited not only for analysis and reporting, but also as decision-making tools.

4

Summary and discussion of the related research

The purpose of this chapter is to review the related research presented in the first part of the thesis. We first discuss the importance of providing quality courses to support learners' reading and comprehension (§4.1). Because of this importance, it is necessary for authors to maintain their courses through continuous and sustained revisions. However, several challenges remain for the authors with regard to the revision process (§4.2), which calls for approaches to assist them. Learners' feedback can be a valuable source for the author to evolve the content of his course. Rather than using a direct interaction approach with learners, monitoring their activity can be effective in detecting their needs. This requires the definition of appropriate behavioral indicators, computed and analyzed using an analytical approach to learning (§4.3). We thus conclude this chapter by discussing the potential of learning dashboards as a means of reporting the results of the analysis to authors, who can use them to trigger appropriate revisions to their courses (§4.4).

4.1 Importance of course quality for comprehension

Technological advancement induced an important shift in the educational landscape, and in learners' reading practices. Besides the multiple positive implications for learners, this also brought them new challenges such as managing cognitive overload and disorientation induced by digital reading, with a direct impact on their level of understanding. Although researchers have been examining paper reading for decades, they paid much less attention to learners' digital reading experience, even though this mode is becoming more common and a widely used strategy for learning in today education (Kong et al., 2018).

The main purpose and strongest measure of reading performance is probably comprehension (Al Madi and Khan, 2016) which level reflects the quality of the mental representation constructed by the learner while reading. Among the factors that shape this level and thus impact the success of learning, besides learners' differences (e.g. skills, attitudes, goals, background, reading strategies), "course quality" and the ease of processing afforded by its content (e.g. layout, plan, linguistic properties, etc.) play a decisive role (McNamara and Magliano, 2009; Dascalu et al., 2014). Notwithstanding that many institutions offer digital courses to learners, there is less effort and expense devoted to developing effective e-learning content (Ma et al., 2003). Yet it is axiomatic that providing accessible and up-to-date content - which best matches learners' capacities - maximizes learners' understanding and more broadly learning outcomes (Crossley et al., 2017).

Course quality has a direct and significant impact on the learners' level of understanding. Detecting comprehension barriers within a course can highlight parts and aspects of the course that need to be revised to meet learners' needs. Consequently, authors need to continuously monitor learners' reading and comprehension and enhance their contents by performing timely enhancements and updates.

4.2 Course revision

The revision process is a cognitively and procedurally demanding part of writing (Flower et al., 1986). It requires the author not only to reflect upon his document to identify existing barriers to understanding, but also to diagnose and solve these problems. (Witte, 2013). Prior research showed that not only lower-ability authors revise their content infrequently and superficially, but also that they do very little revision unless they receive assistance and feedback (Patchan and Schunn, 2015). Authors can have difficulties within the revision process related to a limited understanding of the revision as a process, a difficulty in assessing one's own work and diagnosing any problems, a lack of appropriate strategies for making revisions and a lack of understanding of the public and its needs (Philippakos, 2017).

1. *Problem detection.* Difficulties are related to the author's inability to detect problems during writing as errors are often automatically corrected in their minds.
2. *Problem diagnosis.* Difficulties are related to the correct diagnosis of the problem detected, especially when the problem is poorly defined or when the appropriate revision strategy is not obvious.
3. *Strategy selection.* Difficulties are related to the choice of a resolution strategy once the problem is detected and the diagnosis is made.

In order to initiate revision actions, the author must be able to detect those parts and aspects of the content that challenge learners' understanding. For this purpose, one approach is to use a readability assessment by applying appropriate formulas. Designed to reflect the complexity conveyed by a document, these measures, however, were found to perform poorly in predicting the readers' judgments of text comprehension (Crossley et al., 2017). An alternative and more reliable approach to assess course quality would be to collect feedback from learners about their reading problems and comprehension barriers. Yet, apart from some attempts to use learners' explicit feedback (e.g. (Pattanasri et al., 2012)), little attention has been devoted to assess what learners actually understand, and very few efforts consider comprehension from readers' point of view (Dascalu et al., 2014). This is in part due to the difficulty to monitor comprehension, which requires sensitive observation skills and an active learning environment.

Many researchers argue that feedback is an effective way to identify problems or even provide advice on possible solutions. Learners' feedbacks allow authors to improve documents from the readers' perspective, which is known to be a successful strategy to guarantee a better level of understanding (Cho and MacArthur, 2011). Schriver (1992) claimed that authors may profit more from confrontations with responses of genuine readers because it helps them to build mental models of comprehension processes and readers' needs. For Haar (2006, p. 14), revision means movement: "turning from self to reader; drafting both up and down, out and in; heeding interior and exterior voices". They can be seen as input from the readers to the author, which often gives rise to further revisions. Direct and/or indirect readers' feedback may contribute to both authoring and revising. However, getting feedback is very difficult for authors, since usually a considerable distance in time and/or space keeps them separated from their readers (Couzijn and Rijlaarsdam, 2005).

4.3 Monitoring digital reading in e-learning

With the popularization of learning platforms with logging capabilities, automated methods for capturing and analyzing learners' behavior emerged. These methods are not based on direct interaction with learners and are shown to be unobtrusive, more objective and more reliable than collecting direct feedback (Cocea and Weibelzahl, 2011). The traces left by the learners can be used to identify the aspects and parts that are difficult for them, and thus deduce the necessary course improvement actions. Authors will thus have a reliable knowledge base from which to make informed and motivated decisions on how to improve the quality of their contents over time.

The analysis of learners' behavior when consuming educational contents makes it possible to better follow and frame their learning progress and effectiveness. Their activities on the educational platform are diverse; they are composed of different actions. Automatically tracking and scrutinizing these actions provide a framework for modeling their behavior and detecting their preferences and needs. The use of mining and analytics methods on learners' traces may unveil aspects and parts of courses content that may hinder proper comprehension, and generate appropriate remediation interventions. Building assistive tools that disclose learners' comprehension needs and that generate appropriate revision would empower course authors with more awareness and would motivate them to revise their courses more frequently. Learners' log analysis and data visualization are a process abundantly described within the *Educational Data Mining* and *Learning Analytics* fields.

Trace data captures the actual user behavior and not recalled behaviors or subjective impressions of interactions (Dumais et al., 2014). Using appropriate methods and tools, the traces can become potential containers of knowledge that could be formalized, shared and reused (Cordier et al., 2013). From the captured traces, patterns of reading usages can be assessed and used to identify needs and/or preferences of each individual reader or group of readers, and subsequently, to customize and evolve the content and/or structure of the documents.

One of the challenges of learning analytics is the definition of meaningful indicators for the description of the learning process. These indicators are usually the result of the transformation and processing of raw data. This is often studied on both the *course-level* (e.g. percent of readings, mean visit time, and percent of the course having been read) and *part-level* (e.g. part popularity in terms of visits, revisits, readers). Solely relying on request-based information to study reading has a major drawback: requesting a page is not necessarily equivalent to reading everything that it presents (Hauger et al., 2011). However, a session-based perspective (i.e. *session-level*) may provide more insightfulness in learners' understanding. Indeed, sessions indicators encode the navigation behavior of users over time (Mobasher, 2007), a valuable aspect that advocates their use to analyze reading efficiently beyond the course and page levels perspectives, through appropriate indicators.

4.4 Towards assistive dashboards

By mining learners' traces tracked from their actions on learning platform(s), formerly unreachable knowledge can be discovered and visually represented, through dashboards. Learning dashboards are developed to make informed decisions (Verbert et al., 2013) and can be used not only to provide overviews of the data but also to suggest and even undertake specific actions upon analysis (Gutierrez-Santos et al., 2012; Van Leeuwen et al., 2014). The application of learning analytics methods on reading data is convenient for assessing comprehension and discovering related issues. Building dashboards that disclose this knowledge would empower course authors with more awareness and would motivate them to revise their courses more frequently. Nevertheless, the effectiveness of these dashboards often depends on the extent to which stakeholders have been involved in their co-design (Holstein et al., 2017). This co-design is linked to the selection of the indicators used, the features deployed and to the conception of the user interfaces. Moreover, to be effective, this design must also be informed by theories related to learning sciences and educational psychology.

Despite the great potential that learning analytics and dashboards can provide, many studies showed that instructors and course authors often lack technical skills and adequate support and training to use the analytics facilities (Peerani, 2013). The proper design of learning dashboards requires the integration of features for triggering stakeholders' reactions and assisting them through the realization of these reactions. Providing authors with appropriate dashboards that assist them throughout the revision process would motivate them to regularly evolve their courses. The main requirements of these tools include analyzing learners' understanding, detecting their reading issues from their direct or indirect feedback, and generating appropriate solution suggestions for these detected issues.

4.5 Summary

The analysis of reading traces makes it possible to study the reading behavior of learners, and to evaluate their level of comprehension (Huang and Liang, 2015). The application of learning analytics methods on reading data seems convenient for assessing comprehension and discovering related issues. Building dashboards that disclose this knowledge would empower course authors with more awareness and would motivate them to revise their courses more frequently. As instructors and course authors often lack technical skills and adequate support and training to use the analytics facilities, it is important not only to present to authors revision needs but also to suggest them possible remediation actions to detected problems. Such analysis and visualization tools would enable authors to tune the learning context settings by "reengineering" the delivered contents based on usage data, an approach that remains unaddressable by the e-learning community (Brooks et al., 2014).

In the next part of this thesis, we will build on the state of the art already discussed and contribute to addressing some of the problems that remain in this area, related to using learning analysis methods on the traces of reading to support learners' understanding. . The objective is provide methods and design tools that can assist authors of online courses in revising these courses to meet learners' needs.

Part II

Contributions

5

Usage-based document reengineering for sustaining reading and comprehension

Research Questions and Objectives of the Chapter

(RQ1) *"What is the general conceptual framework for supporting authors to improve their courses and solve learners' understanding issues?"*

RO1.1– To define a methodology for analyzing reading usages in order to identify understanding problems and support authors in solving those problems.

(RQ2) *"What are those understanding issues ?"*

RO2.1– Identify the most important document properties that contribute to the level of ease of understanding afforded by these documents.

RO2.2– To identify the reading issues that may arise from these properties.

(RQ3) *"According to those understanding issues, what remediation can be proposed to authors?"*

RO3.1– To design appropriate suggestions for solving these understanding issues.

Building on the work discussed in the first part of this thesis, we present in this second part our proposals aimed at contributing to our research goal: "*To investigate the use of reading analysis on learners' traces in order to identify their comprehension issues and to assist authors in improving their contents accordingly.*". We start this chapter by introducing the concept of document reengineering and by elaborating a general framework for the process of updating documents based on readers' usage (§5.1). Subsequently, we conceptualize the reengineering activity and build a taxonomy of the associated actions (§5.2). We then identify the different factors related to the structures of the document that impact the level of ease for comprehension afforded by the document (§5.3). Finally, we associate appropriate reengineering actions to the different issues that can be originated from these factors, in order to sustain document reading and comprehension.

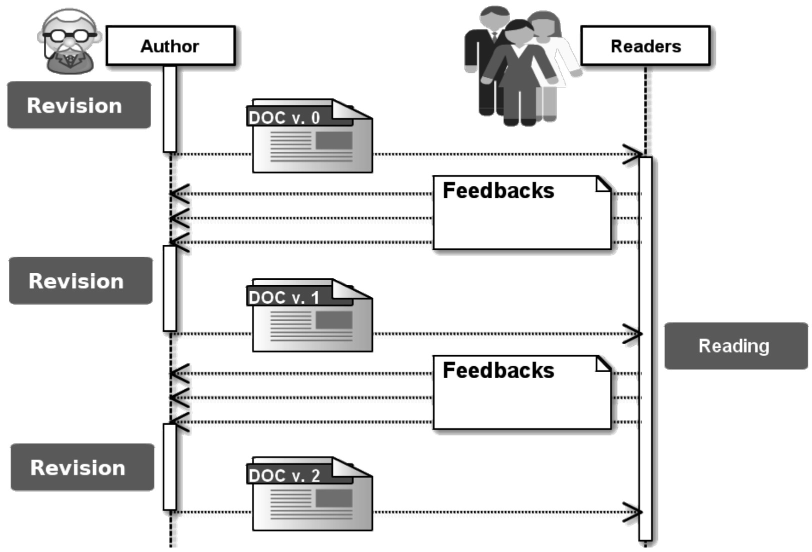


Fig. 5.1 Document reengineering based on readers' feedback

5.1 Educational document reengineering

5.1.1 Document reengineering

According to (Balinsky and Simske, 2011), "digital documents are no longer single-version with static content, they are "*live*": multimedia, multi-user, dynamic and thus multi-version". Consequently, they are never in a final state of absolute stability: *reengineering* can be applied to them.

Document engineering is related to principles, tools and processes that improve our ability to create, manage, and maintain documents in any form and in all media. According to (Chikofsky et al., 1990), "*reengineering, also known as both renovation and reclamation, is the examination and alteration of a subject system to reconstitute it in a new form and the subsequent implementation of the new form*".

In the digital publishing and reading context and from our point of view, the main goal of what we call "document reengineering" is to revise the structure and the content of the document in order to facilitate its appropriation by readers. As illustrated on Figure 5.1, we define *usage-based document reengineering* as follows

Definition 5.1 (Usage-based document reengineering)

Usage-based document reengineering is the examination and alteration of document content and structures to reconstitute it in a new form, in response to readers' explicit feedback (i.e. comments), or implicit ones (i.e. reading traces).

5.1.2 A conceptual framework for usage-based document reengineering

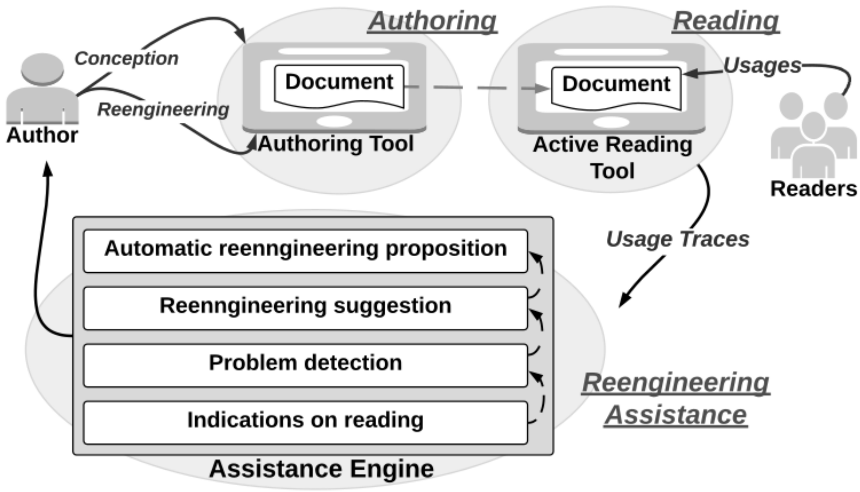


Fig. 5.2 Overview of the usage-based reengineering framework

We propose the usage-based document reengineering framework presented on Figure 5.2. Instrumenting an active reading tool, data about usages (reading traces and annotations) are collected and then analyzed to assess possible and appropriate document reengineering actions. This framework is based on three components:

Authoring tool The authoring tool allows the author to design a new document, defining its structure and including content. It also provides the possibility to update documents that have already been produced and delivered at any time. Once a new document is conceived or modified by an author, it is released into the reading environment.

Active reading tool The document reading tool provides an appropriate rendering interface for presenting documents and implements a set of features that enable and promote active reading. The user's actions constitute what we call *usage traces*, and are collected by a *Source Collector* that is installed on the reading tool. Considering usages and feedback for reengineering purposes requires that the reading tool has the ability to first monitor readers, to intercept and eventually to interpret their interactions. The relevance of this data to the reengineering of documents depends greatly on readers' involvement in the reading process.

Assistance engine The collected data is then sent into the *Assistance engine* to be processed and analyzed. Various *reading indicators* can be computed to characterize readers' interaction against a specific monitored feature (e.g.: unread sections, visited/unvisited links, interaction level, spent time on specific parts). The results can be used by authors for reengineering their documents.

Levels of assistance

We identify four main levels of author assistance, each level exploiting data from the previous one.

Level 0: Indications on reading. The assistance engine can compute and present the author with indications of how the document has been read. *Example*: giving the author the percentage of readers that have followed a given link may help him understand the relevance of that link.

Level 1: Problem detection. Based on the previous level, the assistance engine may detect problems in the reading process without giving any suggestion on how to fix them. *Example*: if a video element has never been watched further than its first seconds, the engine reports it to the author as an unexpected behavior.

Level 2: Reengineering suggestion. At this level, not only the system detects problems but in addition, it may supply suggestions. However, the system is unable by itself to carry out the suggested modifications. *Example*: if many readers of a document usually go back to a previous chapter, the engine may suggest to include a recall of the main concepts already seen in a previous lesson unit.

Level 3: Automatic reengineering proposition. At this level, the engine may detect problems and resolve them automatically. Consequently, a reengineering proposal can be presented to the author for review and validation. *Example*: if many zooms are performed on a textual part of the document, the system can automatically readjust and increase its size or fonts.

The author can be assisted during the reengineering tasks along the four levels. He can choose to consider an arbitrary set of feedback originated from a single reader, a given group of readers or the entire readership. The end result is a new version of the document which can, in turn, be subject to further improvements.

Practical use requirements

The reengineering framework is conceptual and allows to describe a methodology for assisting authors in evolving their documents based on readers' usages. It can be adapted for different contexts, with no particular constraints on the document and trace structures. During this chapter and the next one, we will elaborate on an instantiation of the approach that will target educational context. For this purpose, we firstly need to identify:

1. the different aspects of a document that affect the readers' degree of understanding;
2. the kinds of reading issues that readers may face as a result of the design of a document;
3. the set of actions that can be carried out by the author for evolving his document; and
4. suggestions that would allow a document to be revised so as to solve the reading problems that result from its design.

5.1.3 Document model

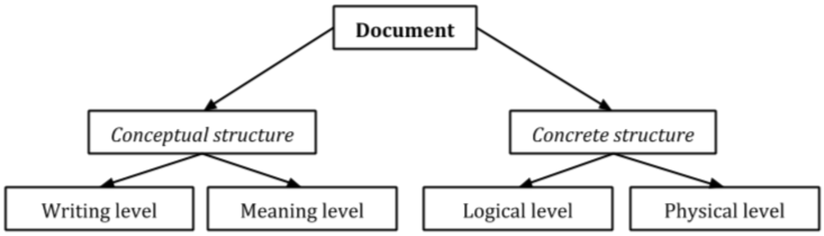


Fig. 5.3 Document structures

A digital document can be seen as the result of translating knowledge into a medium. Therefore, it includes a concrete structure, which is rendered (sequence of 2D images of paragraphs, etc.), and a conceptual structure which is related to knowledge, message and meaning (Figure 5.3). The ease of understanding of the document therefore depends on the conjunction of these two structures.

Document creation corresponds to the author's encoding of the conceptual structure into a concrete structure. Reading allows the reader to do the reverse, i.e. decode the concrete structure to reconstruct the conceptual one. The deviation between the decoded conceptual structure and the encoded one reflects the reader's level of understanding. The purpose of comprehension support is therefore to reduce this gap as much as possible. In our framework, this support can be done upstream, by reviewing the elements that caused the decoding deviation.

5.1.3.1 Concrete (surface) structure

The surface or concrete structure describes the organization of the document and the relations between the individual units it is composed of. The concrete structure is built on two complementary levels: the physical level and the logical level.

- The *logical level* defines the atomic compositional units as well as the nesting schemes of these units to construct a document.
- The *physical level* describes the organization in space and time of the logical units on the rendering interface, as well as the navigation features.

We represent a document as the nesting of blocks of content referred to as *document element* (e.g. sub-chapters, chapters) into others document elements that correspond to different levels of granularity (i.e. sub-chapters into chapters, chapters into course). Formally, we can express the organization of a document as follows:

```
document = <doc_element+>
doc_element = <doc_element+>
```

An element can have any granularity, from the basic atomic unit to that of a document, thanks to the nesting mechanism. The levels of granularity available depend on the instantiation of the model. These elements are logically arranged to define the document structure (corresponding to the document outline or plan) with possible navigation links between them and to outer resources. The document is rendered within a given layout that determines its appearance, following the generic multimedia document models (cf. §2.2.2.3).

5.1.3.2 Conceptual structure

The conceptual structure reflects what is expressed by the author and how it is expressed, in terms of data, information and/or knowledge, as well as their materialization, as reported in the document. By conceptual structure, we thus mean the abstract structure that

– depicts the various parts of the global data/information/knowledge that are spread over multiple places within the same document;

– describes the translation of each part of the data/information/knowledge on the support; and

– defines a meaningful organization of these parts in a sequence that follows a coherent narrative.

In other terms, it refers to the signified of the concrete (sometimes physical) document, and thus corresponds to the "textbase" level of the common comprehension models (e.g., (Kintsch and Van Dijk, 1978)). This structure has a local level related to expressing the ideas, the writing (the *microstructure* in comprehension models) as well as a global level that represents the desired semantic (*the macrostructure* in comprehension models):

– The *writing level* is related to all the structures that are processed, or described, at the local or short-range level (graphics, words, phrases, clauses, sentences, and connections between sentences). It represents the directly "expressed" structure of the document.

– The *semantic* (or *meaning*) *level* is a higher and more abstract level that organizes the writing, interaction, and cognitive processing of the different elements. It is related to the overall meaning, the intention of the author and the way he conveys his and translates his message.

5.2 Taxonomy of document reengineering actions

5.2.1 Modeling reengineering

Document reengineering involves applying a set of actions to one or several elements composing a document, with the intention of producing an amended version. To model a *reengineering action*, we use the following symbolic formalism:

```
reengineering = <action+>
action = <primitive, target, dimension>
dimension =<(style | structure | content | link)+>
```

A *target* is the element on which a reengineering action operates. The possible targets depend on the units that compose the document model. Most of the existing edition taxonomies target at sentence or paragraph levels. In our model, this level corresponds to that of *document element* that we have introduced in 5.1.3).

A reengineering action can be decomposed into a set of elementary actions that we call edition *primitives*. A primitive impact a specific dimension of its target: the *style*, the *structure*, the *content*, or the *links* of the document element. Each primitive has an effect on the target, which can be either *addition*, *modification* or *suppression*.

5.2.2 Types of reengineering primitives

The specialization of the reengineering effects according to the different dimensions allows to define four classes of primitives, inspired from the most common edition actions in digital content production: *restyling*, *restructuring*, *rewriting* and *linking* (Table 5.1). Formally, a primitive can be expressed using the following symbolic formalism:

```
primitive = <type , effect >
type = <restyling | restructuring | rewriting | linking>
effect = <addition | modification | deletion>
```

	Addition	*Modification*	*Deletion*
Style	*Add style*	*Alter style*	*Delete style*
Structure	*Add element*	*Retitle – Move* *Merge – Split*	*Delete element*
Content	*Insert* *Explain* *Illustrate* *Remind*	*Organize – Summarize* *Extend – Deepen* *Reformulate – Simplify* *Correct – Update* *Translate*	*Delete content*
Links	*Add ref./link*	*Modify ref./link*	*Delete ref./link*

Table 5.1 Taxonomy of reengineering primitives

5.2.2.1 Restyling primitives

This class impacts the presentation of the target element on the user interface, for instance for personalization and accessibility purposes. It mainly expresses the *surface* changes in the Feigley model (Faigley and Witte, 1981). Since our research is more focused on content than on presentation, we do not elaborate on this class.

5.2.2.2 Restructuring primitives

These primitives are mainly targeted at the *logical structure* of the document, with possible repercussions on the content and the other concrete and conceptual structures.

Addition The addition primitive defines a new level on the document outline by supplying it a new element with a title and a content.

Modification The modification consists in either changing a specific entry point by moving and placing the element somewhere else, merging the element with another one, splitting the element into many others or just retitling it.

Deletion The deletion primitive allows removing an element along with its content, its sub-elements and its entry point from the document.

5.2.2.3 Rewriting primitives

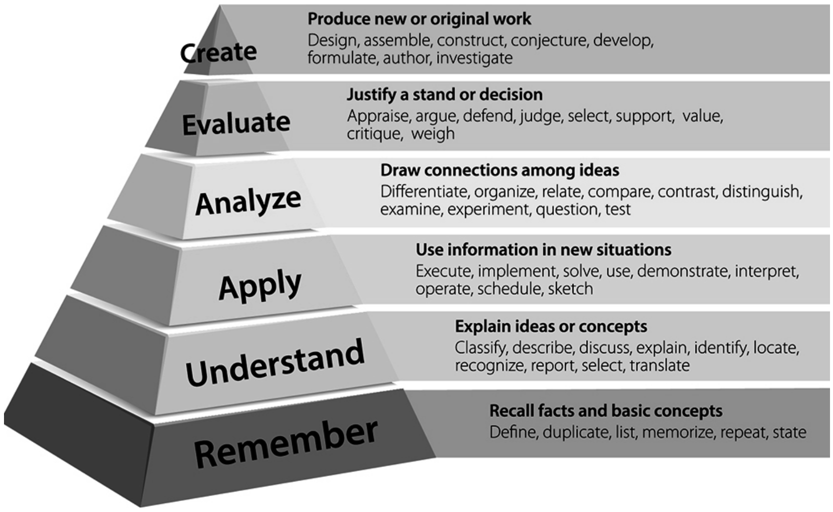


Fig. 5.4 Bloom's taxonomy and the associated action verbs (Anderson et al., 2001)

To identify the most relevant primitives that can be performed to enhance comprehension, we were inspired by the action verbs introduced by the *Bloom Taxonomy* (Bloom et al., 1956; Anderson et al., 2001). This taxonomy represents a framework for classifying educational goals and objectives into a hierarchical structure that represents different forms and levels of learning (Figure 5.4). For each level, Bloom identified a list of suitable action verbs for describing that level in written objectives. A level of interest for us within this taxonomy is the *Comprehension* level. This level requires being aware of the literal meaning of the message contained in the communication, and involves demonstrating understanding of facts and ideas by organizing, comparing, translating, interpreting, giving descriptions, and stating the main ideas. We selected and grouped relevant actions verbs for our context from this level and classified them into actions aimed to *add*, *modify* and *remove* a content.

Addition Content addition can have two purposes: inserting original content or updating an existing content. In the second case, the actions can be depicted on either explaining the target content, illustrating (exemplifying) it or adding reminders.

Modification The modification of an element content can consist in organizing, summarizing, extending, deepening, reformulating, simplifying, correcting, updating or translating it.

Deletion Suppression consists in deleting the element content or a part of the content.

5.2.2.4 Linking primitives

An element can contain two types of links: (1) a *reference* which is an internal link to the document and (2) a *link* which is an external link to an external resource. The linking primitives can change the navigational structure of the document by adding, modifying or deleting a link or a reference.

5.3 Reading issues and reengineering actions related to document structures

As discussed in the first part of this thesis, the understanding of a document depends both on the intellectual faculties of the reader and on the intrinsic properties of the document. In the following, we examine the aspects related to the document, its design and the contained information. We assume that any problem encountered by readers and arising from the construction of a document can be broken down into one or more sub-problems, each of which impacts one of the document's structures. Therefore, we will investigate these structures individually to identify the types of issues that can be raised by each characteristic of a given structure (We associate a `code` to each of these issues in order to be able to refer to them in other parts of this manuscript). Subsequently, this will allow us to consider reengineering actions for the different types of problems we have identified.

5.3.1 Comprehension at the surface structure

At the surface level, comprehension depends on two sets factors related to:

- the manner in which the various elements of the document have been designed and organized (*logical level*)
- the manner in which the elements are placed on the rendering surface, synchronized when they are timed, and linked to each other and possibly to external resources (*spatial level*).

5.3.1.1 Reading issues on the logical level, and associated reengineering actions

The logical structure is reflected in the organization and outline of the document. As a result, it has a direct impact on the readers' level of understanding. The factors influencing this level are related either to the definition of the elements or to the order in which they are associated. Table 5.2 lists the significant issues that these factors can produce and enumerates lists of reengineering primitives that might resolve them.

Issue		*Reengineering action*	
Code	*title*	*Type*	*Primitives*
Selection of elements			
*LL*1	Unnecessary/bulky element	Restructuring	REMOVE
*LL*2	Non suitable title		RETITLE
*LL*3	Element to decompose		SPLIT
*LL*4	Element to combine with others		COMBINE (with)
Document outline and elements sequence			
*LL*5	Element not in its best position	Restructuring	MOVE (to)
*LL*6	Late position of the element		MOVE (backward)
*LL*7	Early position of the element		MOVE (forward)

Table 5.2 Issues and reengineering primitives associated to the logical level

A. Selection of elements

A thoughtful and judicious definition and choice of the elements that make up a document would increase the probability of a high level of comprehension by readers. Failure to do so can result in several problems, in particular:

UNNECESSARY/BULKY ELEMENT (*LL*1) – corresponds to the definition of an element that is not necessary or should not be included. Possible reengineering actions include:

- *(Restructuring)*: REMOVE the element

NON SUITABLE TITLE (*LL*2) – denotes a title that is inappropriate or not soundly chosen. The possible reengineering actions include:

- *(Restructuring)*: RETITLE the element

ELEMENT TO DECOMPOSE (*LL*3) – indicates that the element needs to be broken down into several other elements. Possible reengineering actions include:

- *(Restructuring)*: SPLIT the element. This results in new elements that must be built from the original and correctly inserted into the document (the original one is then DELETED).

ELEMENT TO COMBINE WITH OTHERS (*LL*4) – indicates that the element must be merged with one or several other elements. A possible reengineering action is:

- *(Restructuring)*: COMBINE the element with the appropriate element or set of elements (to be identified if not specified).

B. Document outline and elements sequencing

The logical organization of a document determines its outline and the sequencing of all its elements within it. At this level, among the problems that may arise we can mention:

ELEMENT NOT IN ITS BEST POSITION (*LL*5) – indicates that the position of the element within the document outline is not appropriate. The associated reengineering action is:

- *(Restructuring)*: MOVE the element to a more appropriate position (to be identified if not specified) within the document structure.

Late position of the element (*LL*6) – indicates that element needs to be introduced earlier then its current position within the document outline. Possible reengineering actions include:

- *(Restructuring)*: `Move` the element backward to a specific position in the document structure.

Early position of the element (*LL*7) – indicates that element needs to be introduced later then its current position within the document outline. Possible reengineering actions include:

- *(Restructuring)*: `Move` the element forward to a specific position in the document structure.

5.3.1.2 Reading issues on the physical level, and associated reengineering actions

The physical structure defines the rendering of the document. Any imbalance in the definition of the spatial dimension (in terms of elements dimensions and locations) and/or the temporal dimension (in terms of timing and synchronization) can have a negative impact on the reading experience, and thus on the comprehension. Moreover, since digital reading often implies the use of the document links, the proper definition of the navigational dimension is important for reading and comprehension.

From a physical level point of view, the factors that can influence the level of understanding are related either to the location of the elements, the synchronization of the latter, or the definition of navigation links between them. Table 5.3 lists the significant issues that these factors can produce and enumerates lists of reengineering primitives that might resolve them.

Issue		*Reengineering action*	
Code	*title*	*Type*	*Primitives*
Placement on the layout			
PL1	Bad location	Restyling	`Modify` (location)
PL2	Inadequate size		`Modify` (size)
Timing and synchronization			
PL3	Inadequate temporal information	Restyling	`Modify` (timing)
PL4	Bad synchronization		`Modify` (synchronization)
Linking and navigation			
PL5	Inappropriate/useless link	Linking	`Delete` (link)
PL6	Needed link missing		`Add`(link)
PL7	Broken link		`Modify` or `Delete` (link)

Table 5.3 Issues and reengineering primitives associated to the physical level

A. *Placement of the elements on the layout*

Bad location on the document layout (*PL*1) – indicates incorrect or not optimal placement of the element. Possible reengineering actions include:

- *(Restyling)*: `Modify` the rules that control the spatial properties of the element so as to adjust its placement.

Inadequate size (*PL*2) – of the element or of some content of the element reflects the needs to resize the element or part of the element. Possible reengineering actions include:

– *(Restyling)*: `Modify` the rules that control the spatial properties of the element so as to adjust the size or length of its content.

B. Timing and synchronization of the elements

Inadequate temporal information (*PL*3) – of some timed content of the element (begin, end, duration). Possible reengineering actions include:

– *(Restyling)*: `Modify` the rules that control the temporal properties of the element so as to adjust its its begin/end timecodes and/or its duration.

Bad synchronization (*PL*4) – between some timed content of the element , or with other elements. Possible reengineering actions include:

– *(Restyling)*: `Modify` the rules that control the temporal properties of the element so as to adjust the synchronization information.

C. Linking and navigation between elements

Inappropriate/useless link (*PL*5) – indicates that a given link to or from the element is inappropriate or unnecessary because it does not provide the intended information. Possible reengineering actions include:

– *(Navigation)*: `Delete` the link from/to the element.

Needed link missing (*PL*6) – indicates that it is important to define an inner ou outer navigational link from or to the element or a part of it. Possible reengineering actions include:

– *(Navigation)*: `Add` a link to/from the element

Broken link (*PL*7) – indicates that a target of a link defined within the element is no longer available. Possible reengineering actions include:

– *(Navigation)*: either `Modify` the link or `Delete` it.

5.3.2 Comprehension at the conceptual structure

At the conceptual level, comprehension involves the extraction of semantic information, by transforming words to meaning, in order to derive a locally and globally well-structured cognitive representation of the text. The effectiveness of this process is thus a factor of the properties of both the writing (microstructure) and the meaning (macrostructure) levels.

5.3.2.1 Reading issues on the writing level, and associated reengineering actions

According to Hall-Mills (2009, p. 3), microstructure analysis generally examines a writer's conveyance of meaning at that level and typically includes measures of *productivity* (e.g., number of words, or ideas), grammatical *complexity* (e.g., mean length of the textual units, clause density), and lexical *diversity* (e.g., number of different words). The level of understanding afforded at this level reflects the readability of the content. Justice et al. (2006) found two main factors that characterize this level: *productivity* mainly related to the syntax and *complexity* related to the sophistication of writing. We used these findings to determine the list of significant problems that can occur at this level (Table 5.4) and to assign them reengineering primitives that might solve them.

Issue		*Reengineering action*	
Code	*title*	*Type*	*Primitives*
Productivity and readability			
WL1	Language and lexical weakness	Rewriting	Reformulate and Correct
WL2	Bad syntactic construction		Reformulate and Correct
Complexity			
WL3	Many new complex information	Rewriting	Reformulate, Summarize and Clarify
		Restructuring	Split
WL4	Complex construction	Rewriting	Reformulate and Correct
WL5	Recall problems	Rewriting	Add (reminders)
		Linking	Add (links)

Table 5.4 Issues and reengineering primitives associated to the writing level

A. Productivity and readability

Productivity factor primarily comprised measures of word class usage, syntactical construction, lexical diversity, or production of paraphasias. Accordingly, among the issues related to these measures, we define the following:

Language and lexical weakness (*WL*1) – indicates a poor readability due to the low quality of writing (lack of lexical diversity, language, etc.) and/or the use of low quality of richmedia content. Possible reengineering actions include:

– *(Rewriting)*: Reformulate and Correct the content of the element.

Bad syntactic construction (*WL*2) – indicates a poor readability caused by grammatical complexity of sentences, and possible syntactic error. Possible reengineering actions include:

– *(Rewriting)*: Reformulate and Correct the content of the element.

B. Complexity

Complexity factors comprise measures of syntactic organization related to the complexity and the degree of sophistication of the sentences and clauses within the content. Accordingly, among the issues related to these measures, we define the following:

Many new and complex information (*WL*3) – reflects the presence of a lot of complex statements and information within the content of the element. Possible reengineering actions include:

– *(Rewriting)*: Reformulate, Summarize and Clarify the content of the element and/or
– *(Restructuring)*: Split the element.

Complex construction ($WL4$) – reflect a complex construction of the sentences, which reduces the element readability. Possible reengineering actions include:

- *(Rewriting)*: `Reformulate` and `Correct` the content of the element.

Recall problems ($WL5$) – reflects that the information conveyed within the element depend on other information already studied in other elements but which is hard to recall. Possible reengineering actions include:

- *(Rewriting)*: `Add` reminders of the needed information to the element.
- *(Restructuring)*: `Add` links from the element *ELT* to elements that contain the relevant information.

5.3.2.2 Reading issues on the semantic (meaning) level, and associated reengineering actions

The semantic level is related to meaning and thus corresponds to the "macrostructure". This level of analysis examines how the author conveys meaning throughout his discourse (Hall-Mills, 2009, p. 7). The measures of quality at this level correspond to some rules of textuality (Armstrong, 2000). According to De Beaugrande and Dressler (1981), there are the following seven conditions for a comprehensible text: `cohesion`, `coherence`, `intentionality`, `acceptability`, `informativity`, `situationality`, and `intertextuality`. We adopted the definition of these factors for the context of this research, which allowed us to introduce the possible issues and associated reengineering action for each of these factors. Table 5.5 lists the significant issues that these factors can produce and enumerates lists of reengineering primitives that might resolve them.

Issue		Reengineering action	
	title	Type	Primitives
Consistency			
ML1	Lack or loss of thematic unit	Rewriting	UPDATE, CORRECT
		Restructuring	MOVE or DELETE
ML2	Contradictions	Rewriting	UPDATE and CORRECT
ML3	Unclear semantic relationship	Rewriting	REFORMULATE and CORRECT
		Restructuring	DELETE
Cohesion			
ML4	Unclear connection between ideas	Rewriting	REFORMULATE, ORGANIZE , EXPLAIN and EXTEND
ML5	Incoherent ideas	Rewriting	REFORMULATE, CORRECT, EXPLAIN and CLARIFY
		Restructuring	MOVE or DELETE
Intentionality and acceptability			
ML6	Misunderstanding	Rewriting	REFORMULATE, EXPLAIN, CORRECT, CLARIFY, ILLUSTRATE and DEEPEN
Informativity			
ML7	Marginal or uninformative	Rewriting	DEEPEN, ADD
		Restructuring	MERGE or DELETE
ML8	Overwhelming	Restructuring	SPLIT
		Rewriting	CLARIFY, EXPLAIN, SIMPLIFY and SUMMARIZE
Situationality			
ML9	Inadequacy	Restructuring	MOVE or DELETE
Intertextuality			
ML10	Prerequisites needed	Rewriting	ADD
		Restructuring	MOVE the element or ADD links

Table 5.5 Issues and reengineering primitives associated to the meaning level

A. Consistency

Consistency (coherence) is what makes a text semantically meaningful. It expresses the logical consistency of the statements in terms of content and how the different components of an element (words, proposals, sentences, paragraphs) are linked and used for effective communication. It is thus the connection of different information to create larger, more global structures of meaning. The issues relating to coherence include:

LACK OR LOSS OF THEMATIC UNIT (*ML*1) – reflects the fact that the line of the subject that is developed at a given level (document, chapter, element) is not maintained by the content of the element. Possible reengineering actions include:

- *(Rewriting)*: UPDATE and CORRECT the content of the element , Or
- *(Restructuring)*: Either MOVE the element to a more appropriate position, Or DELETE it.

CONTRADICTIONS (*ML*2) – indicate that the element conveys contradictions or conflicts with other proposals (within the element or with other elements) taken for correct. Possible reengineering actions include:

– *(Rewriting)*: UPDATE and CORRECT the content of the element.

UNCLEAR SEMANTIC RELATIONSHIP (*ML*3) – indicates that the reasoning used within the element has no explicit or implicit relationship between the ideas conveyed (in terms of cause, condition, consequence, addition, opposition, etc.). Possible reengineering actions include:

– *(Rewriting)*: REFORMULATE and CORRECT the content of the element , Or
– *(Restructuring)*: DELETE the element.

B. Cohesion

Cohesion relates to how the significant elements are linked in a sequence through semantic and grammatical relationships. It is intended to attach, syntactically and lexically, the text together to create a single textual unity. The issues relating to cohesion include:

UNCLEAR CONNECTION BETWEEN IDEAS (*ML*4) – indicates a lack of logical or rhetorical relation used within the ideas expressed within the element. Possible reengineering actions include:

– *(Rewriting)*: REFORMULATE the element, ORGANIZE its ideas, EXPLAIN and EXTEND its parts if needed.

INCOHERENT IDEAS (*ML*5) – indicate a lack of cohesion with the related elements. Possible reengineering actions include:

– *(Rewriting)*: REFORMULATE the element, CORRECT any error, EXPLAIN and CLARIFY the ideas, OR
– *(Restructuring)*: Either MOVE the element to a more appropriate position, Or DELETE it.

C. Intentionality and acceptability

Intentionality is related to the author's attitude that the content of an element should be cohesive and coherent, while acceptability is related to the reader's attitude. These factors inform whether or not a given element is worthy of acceptance as being coherent, cohesive and useful. we defined the issue "misunderstanding" as an issue related to these factors:

MISUNDERSTANDING (*ML*6) indicates that the knowledge inferred does not correspond to the one carried by the content. Possible reengineering actions include:

– *(Rewriting)*: Rewrite the content of the element to avoid misunderstanding, REFORMULATE and EXPLAIN it, CORRECT any possible error, and CLARIFY, ILLUSTRATE and DEEPEN the discussion of the presented ideas.

D. Informativity

Informativity is a function of its substantive knowledge content and concerns the extent to which the content of an element is already known or expected as compared to unknown or unexpected. This factor can be the origin of the following issues:

MARGINAL OR UNINFORMATIVE (*ML*7) indicates that the element does not provide interesting knowledge, and thus is perceived as disturbing and boring, or even rejected. Possible reengineering actions include:

- *(Rewriting)*: If the element is worth presented as an element on its own, `ADD` new content on it and `DEEPEN` the presented ideas.
- *(Restructuring)*: `MERGE` the element with appropriate elements, OR simply `DELETE` it.

OVERWHELMING (*ML*8) indicates that the content is overwhelming and complicated because of too much information. Possible reengineering actions include:

- *(Restructuring)*: `SPLIT` the element `and/or`
- *(Rewriting)*: `CLARIFY` and `EXPLAIN` the ideas carried by element *E* (or the resulted elements), `SUMMARIZE` the complicated or long parts, and `Simplify` the writing.

E. Situationality

Situationality focuses on the role that represents the context in any form of communication. It thus concerns the factors that make a content relevant to a given situation, and to the relationship between a certain element and other elements which share characteristics with it. This factor can explain the following issues:

INADEQUACY (*ML*9) indicates that the conveyed information is not suitable or interesting to the current context. Possible reengineering actions include:

- *(Restructuring)*: If the element is worth presented, `MOVE` it to a more suitable position; elsewhere `DELETE` it.

F. Intertextuality

Intertextuality relates to the factors which make the utilization of the content of an element dependent upon knowledge of one or more previously encountered elements. If the reader does not have prior knowledge of a relevant element, communication may break down because the understanding of the current element is obscured. Among the issues related to intertextuality:

PREREQUISITES NEEDED (*ML*10) indicates that there is a lack of prerequisites or further information for correct or better understanding. Possible reengineering actions include:

- *(Rewriting)*: `ADD` needed prerequisite content and reminders if possible; and/or
- *(Restructuring)*: `MOVE` the element to a more suitable position and/or `ADD` links to relevant content

5.4 Summary

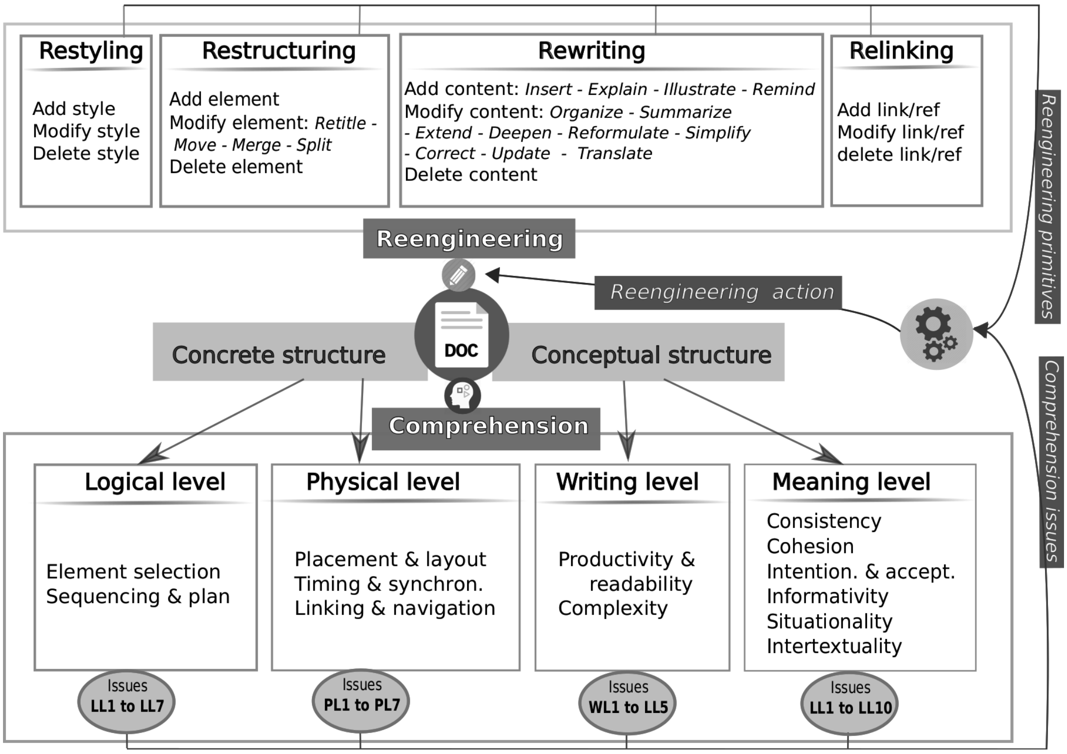


Fig. 5.5 Summary of document reengineering based on comprehension issues related to document structures

In this chapter, we have introduced a process for generating reengineering actions based on the detection of readers' needs. Figure 5.5 summarizes our approach and presents a schematic representation of the different components of this process. We first defined the structures of a document, then listed the factors related to these structures that have an impact on the level of understanding. This allowed us to identify the range of comprehension issues that readers may encounter in relation to the document structures. We also investigated the editing actions that an author can initiate on his document, and deduced from them the possible reengineering actions that an author can perform in order to modify the structure or the content of a document. This has allowed us to link and associate for each comprehension problem, a set of possible reengineering actions for the author to undertake to improve the quality of the document and thus its understanding. The process we have presented in this chapter provides us with a theoretical basis for the next chapter to propose a course revision methodology aimed at using the learners' reading traces of online courses to revise these courses in the perspective of supporting their understanding and thus enhancing the learning outcomes.

6
Usage-based Course Reading Analytics

Research Questions and Objectives of the Chapter

(RQ4) How is it possible to detect those issues and associate suitable remediation actions?

RO4.1– To elaborate a reading analytics approach for reengineering courses based on learners' usages.

RO4.2– To conceive a reading activity model allowing the analysis of learners' traces.

RO4.3– To build an informed synthesis of reading activities using indicators.

RO4.4– To build a strategy based on these indicators to detect the reading issues and to suggest remediation actions.

Digital educational documents have various interactive forms and are at the heart of a variety of distance learning activities, many of which are based on reading. This makes the quality of course materials crucial for the success of learning. In order for learners to better understand the pedagogical contents, we propose to use their reading traces as a means of identifying their needs and discovering other opportunities for improving the offered courses. In this chapter, we apply our general usage-based reengineering framework (cf. §5.1.2) to online course revision. We advocate the use of "reading analytics" to provide online course authors with innovative tools that help them maintain the quality of their courses while addressing the needs of learners. Accordingly, we first describe a conceptual approach to the analysis of online course reading (§6.1). In order to provide meaningful representations that model the reading activity from a behavioral perspective, we introduce the concept of "reading sessions" (§6.2). Based on this modeling, we elaborate a set of indicators to characterize learners consumption of the course (§6.3). Finally, the chapter describes and discusses the use of indicators to detect reading issues and to generate revision suggestions that can be the basis for authors to improve the quality of their courses (§6.4)

6.1 Reading analytics approach for course revision

6.1.1 Reading analytics

In the context of e-learning, we define a reading trace (or log) as *the temporal sequence of reading actions recorded from interactions between a learner and a course document, through a reading tool afforded by the learning environment*. We refer to tracking and analyzing learners' reading behavior as "reading analytics", which we define as follow:

Definition 6.1 (Reading analytics)

As a subfield of learning analytics, reading analytics refer to the tracking, collection, analysis, and reporting of data about learners' reading usages of the learning contents as well as the context in which the reading activity occurs.

The aim of what we call reading analytics is thus to understand and optimize the outcomes of reading-based learning. We propose to instantiate our usage-based document reengineering framework to course reading analytics. The results of the analytics are used to provide authors different levels of assistance of enhancing the quality of their courses.

6.1.2 Course reengineering approach based on reading analytics

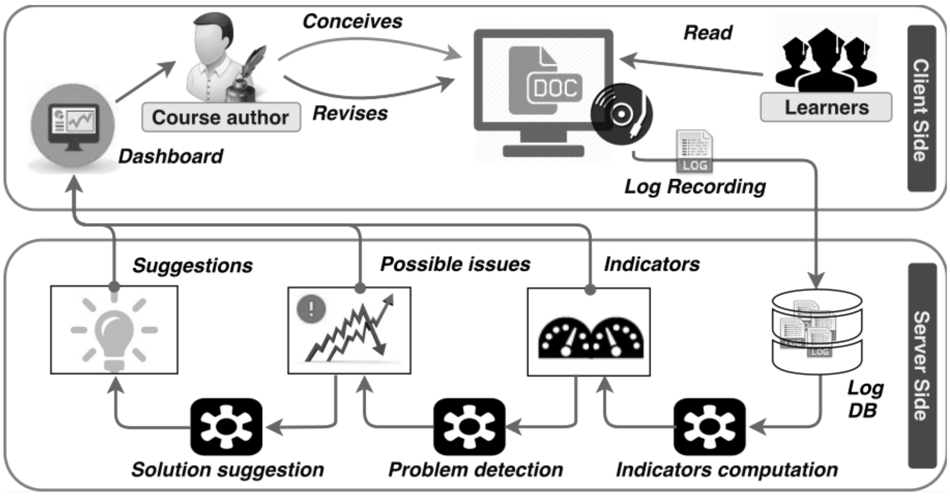


Fig. 6.1 Author assistance approach

Following our usage-based reengineering framework (§5.1.2), we elaborated a reading analytics approach that is intended to demonstrate how course authors can be assisted in the evolution of their courses to meet the needs of learners (Figure 6.1) The approach is meant for analyzing the reading of online courses without targeting a specific learning environment. In this approach and in the subsequent parts of this thesis, the terms *revision* and *reengineering* refer to the same phenomena. In conformance with the conceptualization of a digital document that we presented in the previous chapter (§5.1.3), we model a course as a digital document composed of several *course elements* at different levels of granularity. These elements are arranged by the author according to the course outline, with the option of defining navigation links between the different elements (and to external resources).

The revision approach deals with the first three levels of assistance for document reengineering: computing *reading indicators*; detecting *reading issues*; and providing *revision suggestions*. Given the complexity and sensitivity of the educational context, we do not deal with the fourth level of assistance, related to *automatic generation* of revised courses.

The approach is based solely on the learners' traces captured on the server side of the learning platform. We do not consider the tracing of learners on the client side, nor do we collect direct feedback from learners. To take these types of data into account, it is necessary to design more specific tools with appropriate functionalities. To instantiate the approach, the first step is to develop a suitable data model for describing the reader traces. This would make it possible to elicit a set of indicators permitting to provide course authors with the different levels of assistance necessary for the revision of their courses.

6.2 Modeling learners' reading activity

6.2.1 Rationale

The tracking and analysis of online learners' behavior can be conducted at different levels of interaction (site level, page level, action level, etc.). The most elementary level of data abstraction from the user's point of view is that of a page. However, from the behavioral perspective, the most basic level of abstraction is that of a session (Mobasher, 2007). User sessions encode the navigational behavior of users over time and thus provide information not available using only page view perspective.

6.2.2 Reading sessions

In general, users' actions are recorded as traces (or logs, footprints) within the application server. A trace contains different data on the recorded actions, including user identification, the resource requested and the date and time of access. A user may have thousands of such records. Instead of conducting an analysis of learner behavior by examining the low level of granularity implied by this vast amount of data, it is more effective to group users' actions into activity sessions and so focus the analysis on the different patterns induced by this higher level representation.

A session represents the actions taken by a user over a period of time or with respect to the completion of a given task. In the context of e-learning, we use the concept of "*reading session*" to denote the active period during which a reading activity takes place. It refers to a set of consecutive actions from a learner that can be considered continuous (apart from small interruptions, e.g. for reading email). This means that a learner who actually spends one-hour time on a course will carry out a one-hour reading session. Similarly, this concept has been used in former studies to characterize reading, for instance on Wikipedia (Lehmann et al., 2014).

6.2.3 Constructing learners' sessions of reading

Accurate identification of users' actual periods of activity is essential to any analytical approach regarding users behavior. Since most e-learning platforms are web-based, the partitioning of learners' activities into active user periods leads to session identification, which consists of splitting logs captured on the server side into delimited and sustained sessions.

Different methods for segmenting the trace users into individual sessions are available. They can be grouped into two classes: (a) proactive methods that enforce correct mappings during the activities of each visitor and (b) reactive methods that perform the mappings a posteriori using the recorded traces (Berendt et al., 2002).

6.2.3.1 Proactive methods

In proactive session identification methods retrieve directly from the Web the information needed to determine the pageviews related to the particular session. This information can be retrieved by a using cookie enabled on the client/browser of the user, or using a user authentication mechanism. The task of maintaining user based state information in a logical connection between the server and the user device is known as *web-session* (or simply session). Web session management allows the web server to exchange state information to recognize and track every user connection and uses session identifiers (*session IDs*) to identify each session. Data about the session is often stored at the client-side using cookies. A cookie is a piece of code associated with a Website, installed on the user's host to identify the user's browser. Whenever the user requests a page from the Web server, the cookie identifier is attached to the request and returned to the server.

A session can be terminated by the user when he selects to logout of the system. However, a server can never be sure that a user will always logout of the system after finishing the use of the application. For this reason, the server needs to remove the sessions that have not been used for a period of time. This type of session termination, also known as relative timeout, can be accomplished by defining a limit for the duration of an inactive period. Any session that has not been active over a reasonable time is removed from the session storage.

A. Limits of the proactive methods

Proactive session identification strategies have many drawbacks, mainly related to security issues and restrictions on changes to the internal structure of websites (Bayir et al., 2012). Indeed, users can disable logging mechanisms for privacy reasons, or delete cookies to disable tracking by a website (or even by multiple websites).

The web-sessions that result from the proactive methods may differ from the learners' actual reading session, as illustrated on Figure 6.2. The time of a web-session does not always correspond to the time of reading activity: "gaps" appear within the web-session (corresponding to "breaks" or "idle time" periods). Therefore, a web-session can contain actions that belong to different reading sessions. On another hand, the learner can also take a very short break or just close and reopen his browser, without necessarily stopping his reading-session (while his web-session will probably differ): Actions from the same reading session of a learner can therefore be distributed over several web sessions. In short, real reading sessions can be composed of actions that belong to different web sessions; and actions from the same web sessions can belong to different reading sessions. Therefore, there is evidence that the use of a proactive delimitation method is not precise enough to reflect the learner's actual reading sessions.

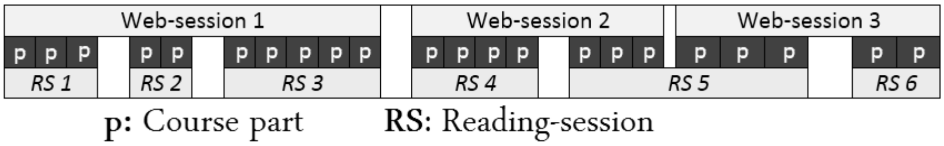


Fig. 6.2 Reading-sessions definition
e: Course element; *RS*: Reading session

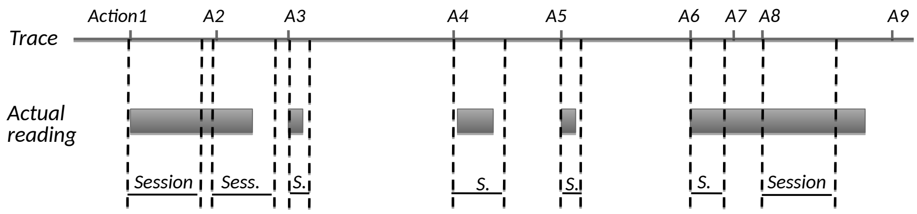
6.2.3.2 Reactive methods

When there is no information to retrieve directly the sessions of the user, reactive sessionzatin methods must be applied. These methods reconstruct the user sessions using the information recorded in the web server log. Methods originated from the field of Web usage mining are often used for session identification within this category. Research in this field has defined two main classes of approaches for reconstructing user sessions: time-oriented and navigation-oriented methods.

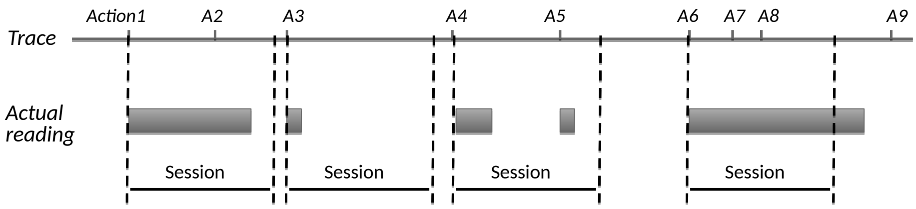
A. Time oriented heuristics

These heuristics define use an upper bound (*threshold*) on the total session time or page-stay time (Marquardt et al., 2004; Spiliopoulou et al., 2003). In the first case, the threshold is defined for the total duration of the session: a given action can be appended to the current session only if the time difference with the last action of the session does not exceed that threshold; otherwise, a new session is assumed to start with that page request (Bayir et al., 2012). Formally, given t_0 the timestamp of the first action for a session S, then an action with timestamp t will be assigned to session S, if only it is performed by the same user and if $t - t_0 \leqq \theta$ (Liu, 2007). A threshold of $\theta = 30$ *minutes* is generally used to split the action logs. This value resulted from the work of Catledge and Pitkow (1999) who measured the average Web user spends that much time in a given website. They found a value of 9.3 minutes. By adding 1.5 standard deviations, they derived a 25.5 minute as the maximum time for the duration of a visit. This has been rounded to 30 minutes and is currently used as default value in many Web servers for maximal session length. Nevertheless, the universality of this 30-minute inactivity threshold is debated extensively by many authors (Mehrzadi and Feitelson, 2012; Jones and Klinkner, 2008; Halfaker et al., 2015). Other thresholds values were proposed: 60 min (based on the distribution of action durations) (Wise et al., 2013) or even 7 hours (Perera et al., 2009).

In the second class of time-oriented methods, the time threshold is related to the maximum time spent on any page. formally, given $t_i, i \geqq 0$ an action timestamp assigned to session S, a record with timestamp $t_j, j > i$ is assigned to S if $t_j - t_i \leqq \vartheta$. In this case, a threshold estimate of $vartheta = 10$ *minutes* is often used as a conservative value, which would give the user enough time to load a web page and then examine all its content. If a long time elapses between two accesses of the user, it is likely that the latter request is the first of a new session (Bayir et al., 2012). However, there is no agreement on a threshold for page-stay time, due to the fact that this time is affected by the types of content delivered on the page and to the time needed to establish communication line (Spiliopoulou et al., 2003).



(a) 10 min-page threshold



(b) 30 min-session threshold

Fig. 6.3 Constructing sessions using time-based heuristics

B. Navigation oriented heuristics

The navigation heuristics exploit behavioral habits associated with Web navigation (Spiliopoulou et al., 2003). This approach, pioneered by Cooley et al. (1999) and extended by Nadjarbashi-Noghani and Ghorbani (2004), uses web topology and considers webpage connectivity, without requiring the existence of hyperlinks between two consecutive page. If a web page is not connected with the previously visited page in a session, then it is considered as a different session. Berendt et al. (2002) demonstrated however that this method shows poor performance on sites with framesets due to implicit assumptions about web architecture. Halfaker et al. (2015) concluded that the sheer complexity of this strategy and its developmental focus on a task over session make it unsuitable as a replacement for time-oriented heuristics in practice for session reconstruction.

C. Limits of the reactive methods

In the context of online courses, the navigation-based methods for identifying sessions is not suitable since navigational links may exist between all pages that constitute a course. The time-based approaches are thus more appropriate. Many authors (e.g., (Marquardt et al., 2004)) recommend the use of a time threshold for the educational context. Yet, the transposition of e-learning characteristics into the Web usage mining application is not a trivial task (Zaïane and Luo, 2001).

A unique fixed value of threshold would give imprecise results and not reflect the actual usages neither differentiate elements based on their content. Some elements may be read faster while others may need more than the fixed value time for reading. As illustrated with one of the courses (the `TCP` course) that we analyzed as part of our evaluation studies (cf. §8.1.3):

– Using a unique threshold for page stay (such as 10 minutes) results in sessions that can be different from the actual ones (Figure 6.3a).

– Using a unique threshold for total session duration (of 30 minutes) would cut many continuous long sessions and merge other short ones (Figure 6.3b)

For our context, we have identified three major drawbacks for using a single threshold value, whether for the page-stay or for the total session duration:

1. *E-learning activities are diverse*: in e-learning, a variety of activities can be orchestrated (such as reading, research, posting a message, conducting evaluations, etc.). Depending on the underlying difficulty, some activities are easier to perform and hence take much less time than others. The existing solutions however do not make distinction of the different learning tasks.
2. *Activity context may change*: a context is related to the learning activity (e.g. time needed to make an assessment depends on the questions difficulties, navigating within a learning portal may be more time demanding than a news one). Hence, each website (course) being unique should have its own time thresholds (Munk and Drlík, 2011).
3. *Elements (pages) of the same online course are different*: as educational learning platforms may contain courses with complex structures and contents, different difficulty levels can be associated to its different elements (introductory parts may be easier to read and understand than more complex ones). As a matter of fact, each element (containing for instance one chapter or one part) of the same course is different (with regard with its inner-complexity) and thus requires a dedicated reading time.

6.2.4 A dynamic and local session identification method

6.2.4.1 Rationale and overview

When using the time-based approach for session identification, incorrectly specifying the timeout delimiter can result in one of two types of error: the marking of a session as having ended when in fact it has not (*session addition error*) or considering a session as continuing when it has ended (*session subtraction error*). To overcome these issues, we propose an approach where reading sessions are delimited more efficiently. The core principles underlying this approach are as follows:

– *The method is specific to reading activity*. The monitored activity being *reading*, the computed thresholds must correspond to theoretical values that represent the time needed for reading the amount of content contained within the pages.
– *The stay-time thresholds is computed for each element*. Each course element (page of the course) has its own content which may differ from others in terms of size and in presented concepts complexity. Since we suppose that each element is presented in a single page, we associate an individual threshold value to the element (the result is a threshold per course element).
– *The threshold computation is based on the actual time the learners spent reading each element*. The computed thresholds originate from data to reflect the actual reading time for reading. Using actual learner data makes it possible to develop a dynamic process that periodically estimates the threshold values of different

pages, allowing for the splitting of the logs into sessions that are getting more precise over time.

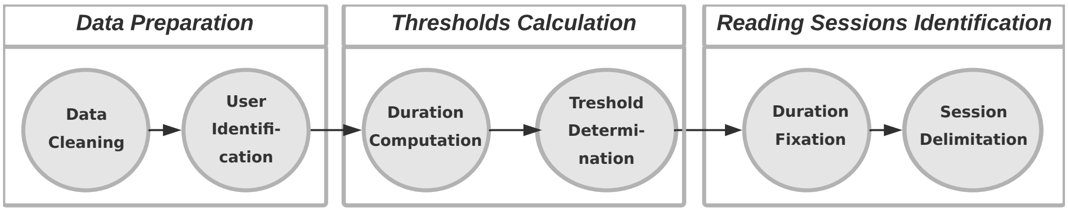


Fig. 6.4 Steps for computing reading sessions from learners' log data

The approach consists of six consecutive steps (grouped into three analytical phases), the first two of which are necessary preprocessing of the logged trace data. These phases are represented in Figure 6.4 and the corresponding synthetic algorithm is provided in Listing 6.1.

Listing 6.1: Synthetic algorithm for reading session computation

```
// 1.  Computing end timecodes and durations
foreach User in Data do
    foreach (Action,NextAction) of User do
        Action.End = NextAction.Begin
        Action.Duration = Action.End − Action.Begin
// 2.  Computing elements thresholds
foreach Element in Data do
    ElementData = List < Actions from Data observed on Element>
    ElementDurations = Array <action.duration, for each (action in ElementData &&
      action.Duration ≠ unknown)>
    Element.Threshold = Max(Peirce(ElementDurations))
// 3.  Dealing with unknown durations
foreach Action in Data with Action.Duration = unknown do
    Element = Action.Element
    Element.duration = Element.Threshold
// 4.  Computing reading sessions per learner
foreach User in Data do
    FirstAction = getFirstActionOf(User)
    FisrtAction.RS = 1
    foreach (Action,NextAction) of User do
        if Action.duration ≤ Element.Threshold then NextAction.RS = Action.RS;
        else NextAction.RS = Action.RS + 1;
```

6.2.4.2 Data preparation

A. Data cleaning

Data preparation refers to the set of preprocessing tasks that are performed on the traces to transform them into a suitable format for an easy and effective analysis. These tasks include common cleaning, detection and removal of possible errors and inconsistencies to improve the data quality.

B. User identification

In the context of e-learning, unlike other web-based domains, user identification is often not an issue because in most cases, learners must connect using their unique identifier. In our approach, we use this data as a means to identify unique learners. If the user identification is available, we reconstruct a set of requests for each learner. If we lack this information or if we suppose that the identification is not required, we assume that each web session is connected to a dedicated anonymous learner, each anonymous user being different from the others.

6.2.4.3 Thresholds computation

A. Actions duration estimation

Reading traces refer to the ordered set of timestamped requests representing learner interactions with the system. Because the explicit end time of learners' actions (an action being between two consecutive requests of the same learner) is not captured by server-based logging systems, actions duration is not directly available. Therefore, we use the time order in requests to compute actions end times and durations. For every two consecutive actions of the same learner, the start time of the second action is assumed to correspond to the end time of the first action.

B. Element-threshold values computation

Server-based monitoring can result in the recording of very long events, up to several days for elements that can be read in few minutes. This is because a learner may access a course element then change his activity momentously, for a long time or definitively. Moreover, some events may be very short and hence not correspond to actual reading actions. To minimize the impact of these actions on the threshold calculation, we solely use "normal actions", excluding duration-excessive and duration-insignificant actions. We apply *Peirce's criterion*, a method that eliminates the presence of several suspicious data values (outliers) (Ross, 2003). The maximum value of the subset of the data obtained after removing the outliers is hence taken as the element reading *threshold*. This threshold is used delimiting reading sessions.

6.2.4.4 Reading session identification

A. Fixing unknown durations

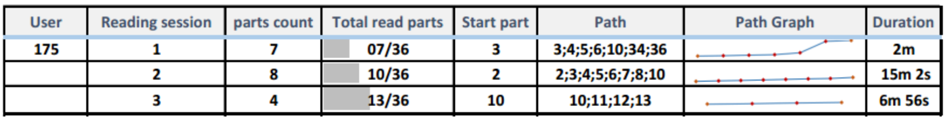
As already explained, we compute the duration of each course element as the time interval between the begin time of that action and the begin time of the action that follows. Unknown durations occur for the last action since no other request can be used to define its end time. In order to not affect the data corpus, and rather than skipping these actions, we assign them with the threshold values of the elements that have been visited with these actions.

B. Delimiting reading session

We use the reading thresholds of the course elements to split the logs of each learner into sessions. A reading session is assumed finished when the time spent for reading an element is greater than the time threshold of that element. The element that follows that last element is therefore assumed to belong to a different session.

Illustration example

The evaluation of the capabilities of the session identification algorithm will be introduced and discussed later in this dissertation (§8.2), using a set of courses and actual learner data. Figure 6.5 illustrates the first three reading sessions of a randomly chosen learner for one of the studied courses (about the TCP protocol). Chapters are numbered sequentially according to their position on the course outline. The figure shows for each reading session, the number of elements read, the ordered reading path along with the corresponding graph, the duration of this reading session. For this particular learner, the reading is mainly sequential with some jump, especially in the first reading-session where, for instance, the learner goes from element 10 to element 34. Some of the elements not read in the first reading-session have been read in the next ones (e.g., elements 2, 7, 8, etc.).



User	Reading session	parts count	Total read parts	Start part	Path	Path Graph	Duration
175	1	7	07/36	3	3;4;5;6;10;34;36		2m
	2	8	10/36	2	2;3;4;5;6;7;8;10		15m 2s
	3	4	13/36	10	10;11;12;13		6m 56s

Fig. 6.5 Reading sessions data of a learner on a course

6.3 Reading session-based indicators

For an analytical project to develop a meaningful behavioral model from activity traces, the rigorous definition of indicators and their calculation methods is of paramount importance. Modeling learner activity through reading sessions provides an ideal representation for behavioral analysis. We use this representation to build a set of indicators, derived from metrics widely used in navigation analysis. Their primary goals are to best reflect the reading behavior of learners and to uncover the comprehension problems they encounter.

These indicators make use of a subset or the whole of the reading sessions. The complete set is organized into four classes intended to describe reading from different viewpoints.

1. the *Stickiness* class reflects the ability of each course element to attract and hold learners interest;
2. the *Rereading* class describes how the learners revisit the course elements;
3. the *Navigation* class describes the order of visits to the course elements; and
4. the *Stops and resumes* class describes how learners stop the reading activity and how they resume reading the course.

6.3.1 Stickiness and interest

In the context of web analytics, a website's "stickiness" (or retention level) reflects its ability to attract and retain users by fostering their level of engagement. It represents thus a reflection of the popularity and usefulness of the website (Burton and Walther, 2001) and an indirect measure of the effectiveness, usability and organization of the site (Nemzow, 1999). While no standard formula exists for assessing stickiness, different metrics are often used to estimate it: the *bounce rate* (the percentage of visitors who come to the website but do not engage and leave the website after a few seconds or only visit a single page), the number of pages visited in one website session, the average session length (number of pages visited within a session), and the total amount of time spent at the site.

We evaluate the stickiness of a course element using indicators related to *element readings*, *number of unique learners*, *reading speed* and *number of reading session* indicators. Typically, the larger the number of learners and the longer the duration of their visit, the more sticky the course element is. Listing 6.2 provides the pseudocode algorithm for computing these indicators.

Listing 6.2: Synthetic algorithm for computing stickiness indicators

```
// Course data
Visits_Course = total count of the visits observed on the course
Readers_Course = total count of the unique readers of the course
RS_Course = total count of the unique reading sessions of the readers
foreach element in Course do
    // Element data
    Visits_element = total count of the visits observed on course elements of a given
      granularity
    Readers_element = total count of the unique readers of the element
    RS_element = total count of the unique reading sessions that contain the element
    Size = size of the element in words
    Time = average reading time of the element
    // Computing indicators
    VisitsRatio = Visits_element / Visits_Course
    ReadersRatio = Readers_element / Readers_Course
    RSRatio = RS_element / RS_Course
    Speed = Size_element / Time_element
```

Visits. A visit results from accessing a course element and reading its content for a given period of time. The number of these visits reflects the degree of popularity of the element. However, a simple counting of visits is a superficial measure that does not allow for accurate diagnosis (Bhat et al., 2002). Consequently, we define the indicator `Visits` as the *the percent of visits observed on the course element among all the course element (of the same granularity) visits*. A relative form, expressed in terms of frequency, makes it possible to compare the value of this indicator on a given element with its values on the other elements.

Readers. A reader is a learner that has at least one session on the course element. The number of individual learners who have visited and read a course element can be used to reflect the attractiveness of that element. As for visits, we use a relative form for this indicator. Consequently, we define this indicator as *the percent of unique learners who read the course element among all the readers of the course*.

Reading sessions. The number of reading sessions that contain a course element gives an indication about the stickiness of this element. It provides information on how often the course element is being read, which cannot be captured using other indicators. Using the relative form, we define the `Reading session` indicator as *the percent of reading sessions containing the element among all the reading sessions of the learners, constructed on the course*.

Reading speed. In Web usage mining, it is assumed that the more time users spend on a web page, the more important that page is. For online courses in particular, however, the time spent depends on the size and level of complexity of the content read. Speed relates to both the reading time and the element size, and allows by definition to use a relative form. Thus, we have opted to consider the reading speed instead of time, which we define as the *average reading speed of the studied element, expressed in words per minute*.

Interest. We define the indicator `Interest` as a global measure of stickiness. Its value is computed as the mean of the different values of this class indicators.

6.3.2 Rereading

In order to compensate for any deficiencies in the initial processing of the course, learners can reread parts of this course a number of times. Rereading corresponds to revisitation, which is a very common navigation strategy and one of the most prevalent study methods that learners report using on a sustained basis (Karpicke et al., 2009). It is a strategy used spontaneously by struggling readers (Akçapınar et al., 2010; Wise et al., 2012) and thus it can predict potential user disorientation Akçapınar et al. (2010); Gwizdka and Spence (2007).

We differentiate rereads that occur on the same reading session (*Within-session rereads*) from those that are performed on different reading sessions (*Between-session rereads*). We therefore define three distinct rereading indicators whose pseudocode calculation algorithm is illustrated on Listing 6.3.

Listing 6.3: Synthetic algorithm for computing rereading indicators

`// Utility functions`

$RevisitsCount(p, session = all)$: *counts the number of visits to the element p that are revisits from the same readers.*

- *session = all: count all revisits*
- *session = within: count only revisits within the same reading sessions*
- *session = between: count only revisits that occur in different reading sessions*

$Visits(p)$ = total count of the visits observed on the element p

`// Computing the indicators for each course element`

`foreach` *element* in *Course* `do`

  $RereadsRatio$ = $RevisitsCount(element, session = all)$ / $Visits(element)$

  $WSRereadsRatio$ = $RevisitsCount(element, session = within)$ / $RevisitsCount(element, session = all)$

  $BSRereadsRatio$ = $RevisitsCount(element, session = between)$ / $RevisitsCount(element, session = all)$

Rereads. This indicator provides the rate of reading actions that correspond to rereading (the element being already read by the same learner at least once

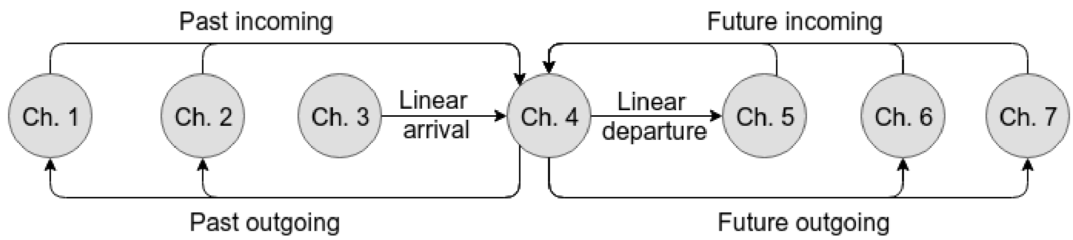


Fig. 6.6 Transitions to and from a chapter of a course
The course is composed of 10 chapters, numbered according to their position in the course outline. The transitions are illustrated for Chapter 4

before). It is defined as *the percent of returning visits (from the same learners) to the course element*.

Within-session rereads. Among a course element rereads, some may have occurred during the same reading sessions. Such a rereading corresponds to successive or very close readings of the same content by the same learner. It can suggest that the learner is struggling with that content. This indicator provides the *percent of rereads that occurred within the same reading session*.

Between-session rereads. Among a course element rereads, some may have taken place in separate reading sessions. This may indicate that the readers need a reminder of the earlier read content (e.g., to understand new concepts presented later or to replace himself within the course context). This indicator provides the *percent of rereads that occurred across different reading sessions*.

6.3.3 Navigation

In spite of the hypertextual construction of a course, its elements are usually organized in linear logics to represent the semantic organization of ideas within the course structure. Learner's navigation corresponds to his reading path within the course and results from the transitions (arrivals and departures) he made between the visited elements. This order, tightly related to comprehension (Hahnel et al., 2016), characterizes the deviation of the reading paths from the author's expected one. A navigation is said linear when it corresponds to a reading that strictly follows the course plan.

We can distinguish six types of transitions that we illustrate on Figure 6.6 (this example refers to a course composed of ten chapters numbered according to their position in the course plan; the transitions are represented for the fourth chapter):

- arrival from the preceding chapter (*linear arrival*),
- arrival from a chapter situated far ahead (*past incoming*),
- arrival from a chapter situated after (*future incoming*); and
- departure to the following chapter (*linear outgoing*),
- departure to a chapter situated before (*past outgoing*),
- departure to a chapter situated after far ahead (*future outgoing*).

We study the navigation behavior using a set of indicators whose pseudocode calculation algorithm is given on Listing 6.4.

Listing 6.4: Synthetic algorithm for computing navigation indicators

// Utility functions

Transitions$(from = p, to = q)$: *counts the number of transitions from the element p to the element q.*

- $p = *$: *any element of the course*
- $p = past$: *any element situated before the other element within the function, according to the course plan*
- $p = future$: *any element situated after the other element within the function, according to the course plan*

Precedent(p): *the element that precedes p within the course plan*
Following(p): *the element that follows p within the course plan*
Past(p): *any element situated before p within the course plan*
Future(p): *any element situated after p within the course plan*

// Computing the indicators for each course element
foreach *element* in *Course* do

$NavigationLinearity = (Transitions(from = Precedent(element), to = element) + Transitions(from = element, to = Following(element))) / (Transitions(from = *, to = element) + Transitions(from = element, to = *))$

// Arrival indicators

$ArrivalLinearity = Transitions(from = Precedent(element), to = element) / Transitions(from = *, to = element)$

$PastArrival = Transitions(from = Past(element), to = element) / Transitions(from = *, to = element)$

$FutureArrival = Transitions(from = Future(element), to = element) / Transitions(from = *, to = element)$

// Departure indicators

$DepartureLinearity = Transitions(from = element, to = Following(element)) / Transitions(from = element, to = *)$

$PastDeparture = Transitions(from = element, to = Past(element)) / Transitions(from = element, to = *)$

$FutureDeparture = Transitions(from = element, to = Future(element)) / Transitions(from = element, to = *)$

NAVIGATION LINEARITY. The navigation linearity indicates whether the order of reading corresponds to the same order defined by the course plan. This indicator *provide the percent of navigation to the element situated just after or from the element situated just before, within the course plan*.

ARRIVAL LINEARITY. The *arrival linearity* characterizes the elements being read just before the given element. This indicator is defined as the *percent of arrivals from the element situated just before within the course plan*.

DEPARTURE LINEARITY. The *departure linearity* is concerned with the elements being read just after the given element. This indicator is defined as the *percent of departures to the element that directly follow within the course plan*.

FUTURE ARRIVALS. This indicator is intended to characterize jumps to the current element (for reading or rereading) from elements that are supposed to be read after the current one. It is defined as the *percent of arrivals that come from elements situated after the element in the course plan*.

Past Arrivals. This indicator is intended to characterize jumps to the current element from elements that are further back, located even before the previous one. It is defined as the *percent of arrivals that come from element situated before the element that precedes current in the course plan*.

Future Departures. This indicator is intended to characterize the jumps from the current element to very distant elements, ahead of the element which follows. It is defined as the *percent of departures that go to course elements situated after the next element in the course plan*.

Past Departures. This indicator is intended to characterize the jumps from the current element to elements that are supposed to be already read, wards very distant elements, ahead of the element which follows. It is defined as the *percent of departures that go to course elements situated far before the given element, apart from the next element*.

6.3.4 Reading stop & resume

A reading interruption indicates the end of a reading session. The analysis of these interruptions helps to explain how and why learners interrupt reading, and how they resume it when they do so. According to DeStefano and LeFevre (2007), reading interruptions are correlated to a decrease in readers' comprehension. Some interruptions are final (reading *final stops*), meaning that the learner no longer returns to complete the reading of the course. No final stops (*reading halts*) are followed by resumes on generally either the same element or on the following one (*linear resume*).

We study this aspect of reading using a set of indicators whose calculation algorithm is provided in Listing 6.5.

Listing 6.5: Synthetic algorithm for computing stop & resume indicators

```
// Utility functions
```

ReadingSessionStops$(at = p, resume = NULL)$: *counts the number of reading sessions ended on the element p.*

- $at = p$: *count the reading stops that occurred on the element p*
- $at = *$: *count all the reading stops that occurred on the course*
- $resume = NULL$: *count all the reading stops, regardless resuming*
- $resume = *$: *count only the reading stops with resumes*
- $resume = -$: *count only the reading final stops (with no resume)*
- $resume = q$: *count only the reading stops with resumes on the element q*

Precedent(p): *the element that precedes p within the course plan*
Following(p): *the element that follows p within the course plan*
Past(p): *any element situated before p within the course plan*
Future(p): *any element situated after p within the course plan*

```
// Computing the indicators for each course element
foreach element in Course do
```

$FinalReadingStops$ = $ReadingSessionStops(at = element, resume = -)$ / $ReadingSessionStops(at = any, resume = -)$
$ReadingHalts$ = $ReadingSessionStops(at = element, resume = *)$ / $ReadingSessionStops(at = any, resume = *)$
$ResumeLinearity$ = $(ReadingSessionStops(at = element, resume = element)$ $+ReadingSessionStops(at = element, resume = Following(element)))$ / $ReadingSessionStops(at = element, resume = *)$
$ResumeToPast$ = $ReadingSessionStops(at = element, resume = Past(element))$ / $ReadingSessionStops(at = element, resume = *)$
$ResumeToFuture$ = $(ReadingSessionStops(at = element, resume = Future(element))$ - $ReadingSessionStops(at = element, resume = Following(element)))$ / $ReadingSessionStops(at = element, resume = *)$

Reading Halt. A halt occurs when a learner breaks his reading and thus terminates the corresponding session, with or without resume. This indicator is defined as the *percent of reading sessions terminated on the element*.

Reading Stop. This indicator shows where readers tend to stop reading the course. If some interruptions are trivial (for instance, the last chapters of the course), other cases may indicate that learners have lost their motivation and interest in the course. To do this, a stop rate is calculated for each element by providing the *percent of the reading stops which are final and have occurred on the element*.

Resume Linearity. A reading resume is normally performed either on the same element on which reading halted or on the element that follows on the course plan; such resumes are said to be *linear*. This indicator is defined as the *percent of resumes that occur on the same element on which the reading has stopped, or on the following element in the course plan*.

Future Resume. This indicator serves to study one case of abnormal (non-linear) resume: when it occurs on elements situated after of the next element. It is thus defined as the *percent of reading resumes that occur on elements far ahead from the current element and its direct following one in the course plan*.

Past Resume. This indicator serves to study another case of non-linear resumes, which is when they occur on the element that was supposed to be already read. It is defined as the *percent of reading resumes that occur on previous elements*.

6.4 Indicator-based reading issue detection and revision suggestion

6.4.1 Rationale

Behavioral indicators that are defined and measured using learner monitoring data are intended to characterize the course elements, by dissipating and mitigating as much as possible the learners' intrinsic differences. This would ensure that the information provided by the indicators can be related to the properties of the course element and not to the learners. The level of confidence that can be accorded to the knowledge provided by these indicators strongly depends on the size of the population being monitored. The level of confidence that can be accorded to the knowledge provided by these indicators strongly depends on the size of the population being monitored. Indeed, for an indication on a behavioral pattern to be taken as real, it is essential for it to have been observed in a significant rate of a fairly large population.

These indicators are analyzed to identify elements of the course that could have caused issues for learners. For this purpose, it is important to first have the general model of these indicators, on all the elements of the course. Subsequently, elements whose indicator values differ significantly from the common values of the other course elements are perceived as posing difficulties in relation to the aspects studied with these indicators. Depending on the nature of the indicator, the content and context of the element that potentially causes reading problems for learners, revision actions can be generated. To do this, it is first necessary to understand what the problems are and what properties of an element can be the source of these phenomena. This makes it possible to associate appropriate actions that can target the element and possibly its context.

6.4.2 Issue detection method

The indicators we defined are univariate numeric variables. An indicator can have distinct values on the different elements of the course. Given that we have adopted a relative representation for these values, it is possible to compare them. Therefore, we consider values that are outside the overall indicator model as outliers, and that they can indicative of reading issues observed on the course elements in question. In the end, the problem detection task can be modeled as the search for extreme values among all the values of each indicator.

Technically, in order to detect outliers from the indicator values, we use the median absolute deviation (*MAD*) method. Contrary to common methods based on the standard deviations from the mean, MAD is a robust method insensitive to the presence of outliers (Leys et al., 2013). By applying this method on the values of a given indicator, a set of outliers can be detected. Being the extreme observations, the outliers detected may include the sample maximum, the sample minimum, or both. Depending on the indicator under study, an outlier does not necessarily correspond to a problem (e.g., a very high value of interest).

Listing 6.6: Synthetic algorithm for issue detection

```
// Course data
CourseIndicators = course indicator types;
CourseIssues = [];
// Condition for marking outliers as issues
IssueCondition_min = ['VisitsRatio','ReadersRatio','RSRatio','Speed','...'];
IssueCondition_max = ['Speed','...'];
foreach indicator in CourseIndicators do
    // Get the different values of the indicators
    Values_indicator = [];
    foreach element in Course do
        Indicator_element = selectIndicator(type = indicator, from=element);
        Values_indicator = merge(Values_indicator,Indicator_element);
    // Apply MAD to find the extreme values
    Outliers = MAD(Values_indicator)
    Outliers_min = select(from = Outliers, condition = "<"& median(Values_indicator));
    Outliers_max = select(from = Outliers, condition = ">"& median(Values_indicator));
    if indicator in IssueCondition_min then
        CourseIssues = merge(CourseIssues, Outliers_min);
    if indicator in IssueCondition_max then
        CourseIssues = merge(CourseIssues, Outliers_max);
```

6.4.3 Issues and revision suggestions related to stickiness

The stickiness indicators describe the element's ability to attract learners' attention. Consequently, the issues related to this class describes mainly low attractiveness of the element. Stickiness being very subjective, the related issues are difficult to interpret. Without wider investigation, only broad revision actions can be suggested. These appeal to the author opinion to review the element and to decide whether it is more judicious to keep it unchanged, retitle it to attract more readers, move it to a more appropriate place, merge it with another element or merely delete it.

A. Very little interest

The lack of attractiveness of an element can be reflected by the low number of visits to the element, the low number of unique learners who engage in reading the element, and the low number of sessions that include that element. Features related to the construction of a given element having an impact on reading interest include:

Indicator	Computation for each course element p	Outliers
	Stickiness indicators	
Visits	$Count(Visits_p)/Count(Visits_{course})$	Min values
Readers	$Count(UniqueReaders_p)/Count(UniqueReaders_{course})$	
Reading Session	$Count(ReadingSession_p)Count(ReadingSession_{course})$	
Reading Speed	$Size_p/Average(ReadingTime_p)$	Min/Max values
Interest	$Mean(Visits, Readers, Read.Session, Read.Speed)$	Min values
	Rereading indicators	
Reread	$Count(Revisits_p)/Count(Visits_p)$	Max values
Within Session Reread	$Count(Revists_{p,type=WS})/Count(Revisits_p)$	
Between Session Reread	$Count(Revists_{p,type=BS})/Count(Revisits_p)$	
	Navigation indicators	
Navigation Linearity	$(Count(Arrivals_{from=p-1,to=p})+$ $Count(Departures_{from=p,to=p+1}))/$ $Count(Transitions_p)$	Min values
Arrival Linearity	$Count(Arrivals_{from=p-1,to=p})/$ $Count(Arrivals_{from='any',to=p})$	
Departure Linearity	$Count(Departures_{from=p,to=p+1})/$ $Count(Departures_{from=p,to='any'})$	
Future Arrivals	$Count(Arrivals_{from='future',to=p})/$ $Count(Arrivals_{from='any',to=p})$	Max values
Past Arrivals	$Count(Arrivals_{from='past',to=p})/$ $Count(Arrivals_{from='any',to=p})$	
Future Departures	$Count(Departures_{from=p,to='future'})/$ $Count(Departures_{from=p,to='any'})$	
Past Departures	$Count(Departures_{from=p,to='future'})/$ $Count(Departures_{from=p,to='past'})$	
	Stop & Resume indicators	
Reading Stop	$Count(ReadingSessionEnd_{at=p,resume='no'})/$ $Count(ReadingSessionEnd_{at='any',resume='no'})$	Max values
Reading Halt	$Count(ReadingSessionEnd_{at=p,resume='any'})/$ $Count(ReadingSessionEnd_{at='any',resume='an'})$	
Resume Linearity	$(Count(ReadingSessionEnd_{at=p,resume='p'})+$ $Count(ReadingSessionEnd_{at=p,resume='p+1'}))/$ $Count(ReadingSessionEnd_{at='any',resume='no'})$	
Future Resume	$Count(ReadingSessionEnd_{at=p,resume='futur'})/$ $Count(ReadingSessionEnd_{at='p',resume='any'})$	
Past Resume	$Count(ReadingSessionEnd_{at=p,resume='past'})/$ $Count(ReadingSessionEnd_{at='p',resume='any'})$	

p: the studied element; p-1 and p+1: the element that resp. precedes and follows p in the course outline. 'ws': within-session; 'bs': between-session. 'any': any course element; 'past' and 'future': elements located resp. before and after the element in the course outline.

Table 6.1 Reading indicators computation and issue detection

– On the *logical level*: the title of the element may not interest the learners, or perhaps even when they visit it, they end up being not interested in the content (*Issue LL*2).
– On the *meaning level*: Learners may find that the element is uninformative or even boring, which may explain their lack of interest (*Issue ML*7). The subject developed by the element may also differ from the overall topic of the course (*Issue ML*1), or the information provided is not appropriate or does not correspond to the expected objectives of the course (*Issue ML*9).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *" If the element is worth presenting on its own: 1) Move it to a more suitable position; 2) and give it a more meaningful and attractive title; and 3) Enrich the element with new content, use graphics and richmedia when possible, and update, correct and deepen the existing content. Otherwise, merge it with an appropriate element or simply delete it"*

B. Fast reading speed

A very fast reading speed can also indicate that readers find little interest in reading the element. Features related to the construction of a given element promoting fast reading speed include:

– On the *logical level*: the learners seem to find the element not interesting (*Issue LL*1).
– On the *meaning level*: learners seem to have not been able to follow the reasoning developed by the element (*Issue ML*3), or that the information conveyed is either not suitable or not interesting with regard to the course goals (*Issue ML*9). They also may find the element not informative and boring, which results in a lack of interest and rejection (*Issue ML*7).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *" If the element is worth presenting on its own: 1) Move it to a more suitable position; 2) and give it a more meaningful and attractive title; and 3) Enrich the element with new content, and update, correct and deepen the existing content. Otherwise, merge it with an appropriate element or simply delete it. "*

C. Slow reading speed

An unintentional slow reading of an element can often indicate difficulties in understanding and interpreting the presented content. When the reading speed of a course element is usually very slow compared to the reading speed of the other course elements, this may indicate that its content is rather complex and difficult to understand. Features related to the construction of a given element resulting in slow reading speed include:

– On the *logical level*: the element needs to be split into several other elements to facilitate the reading (*Issue LL*3).
– On the *readability level*: The element content has probably low readability caused by the grammatical complexity of sentences, and possible syntactic error (*Issue WL*2). It has a complex construction (*Issue WL*4) with many new and complicated information (*Issue WL*3).
– On the *meaning level*: Learners probably lack needed prerequisites to understand the element (*Issue ML*10), which is found to be overwhelming and complicated because of too much information (*Issue ML*8).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *"In order to reduce the complexity of the element and the information it contains, perform a thorough rewrite of the content. Reformulate, synthesize and clarify the complicated or long parts, and simplify the writing. It would also be useful to divide the element into several elements to allow a progressive reading of the given information, or to move the element to a position that would facilitate its reading and understanding".*

6.4.4 Issues and revision suggestions related to rereading

Amount of rereading can be used to indicate for each course element aspects related to learners' disorientation and intellectual processing difficulties.

A. Lot of rereading

In general, revisiting previously seen content reflects intellectual processing difficulties (Hyönä et al., 2003). According to Smith (1996), a higher amount of revisitation is an indicator of lostness, which should be viewed in terms of degradation of user performance. Herder (2003) also has found evidence that combined metrics on revisitation and median view times can be indicators of user disorientation. It is a strategy commonly used by struggling readers and often requires from the author to better clarify the discourse to make it more accessible. Features related to the construction of a given element having an impact on rereading include:

– On the *physical level*: there may exist too many links to the element (*Issue PL*5).
– On the *readability level*: The element has a complex construction (*Issue WL*4) and its information is hard to recall (*Issue WL*5).
– On the *meaning level*: overwhelming and complicated element (*Issue ML*8).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *"In order to minimize rereading of the element, facilitate its memorability: reformulate its content, synthesize and clarify the complicated or long parts,* *and simplify the writing. Some rereads may be due to the existence of many references to this element: delete some of these links or replace them with short reminders.".*

B. Lot of within-session rereading

Reading the same content many times may be a potential indicator that readers are struggling with it. This case requires as already mentioned reworking the content in order to make it more accessible to readers. Features related to the construction of a given element promoting rereading within sessions include:

– On the *readability level*: The element is probably hard to read because of lack of readability due to the low quality of writing (lack of lexical diversity, language, etc.) (*Issue WL*1), and grammatical complexity of sentences with possible syntactic error (*Issue WL*2). Moreover, of a lot of complex statements and information within the content of the element are probably used (*Issue WL*3), constructed in a very complex manner (*Issue WL*4).

– On the *meaning level*: the element may be overwhelming and complicated because of the presence of too much information (*Issue ML*8) and the lack of logical or rhetorical relation between the expressed ideas(*Issue ML*4).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *"In order to minimize this kind of rereading, enhance its readability and facilitate its understanding: reformulate, synthesize and clarify the complicated or long parts, and simplify the writing. "*

C. Lot of between-session rereading

The rereads situated in different sessions can be seen as the expression of readers needing reminders of the earlier visited elements (e.g. to understand new concepts presented later). This can be lowered by using reminders of the read content but also by simplifying it to be easily memorized. Features related to the construction of a given element promoting rereading between sessions include:

– On the *logical level*: The element is probably not in its best position within the course (*Issue LL*5).

– On the *physical level*: many inappropriate or useless links may exist from/to the element (*Issue PL*5).

– On the *readability level*: the information the element conveys or conveyed by the related elements is hard to recall (*Issue WL*5).

– On the *meaning level*: the lack of logical or rhetorical relation between the expressed ideas(*Issue ML*4), and the lack of needed prerequisites (*Issue ML*10). It is also possible that the element conveys contradictions or conflicts with other proposals (*Issue ML*2).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

> **Synthetic suggestion:** *"To minimize this kind of rereading, try to move the element to a more appropriate position that would enhance its memorability, or to split it between different positions. Do a thorough rewrite by reformulating, synthesizing and clarifying the complicated or long parts, and simplify the writing. Some rereads may be due to the existence of many references to this element: delete some of these links or replace them with short reminders".*

6.4.5 Issues and revision suggestions related to navigation

Navigation properties are important indicators of the success of the learning task (McEneaney, 2001). They can, therefore, be used to indicate the cases of comprehension problems that learners experience during the course reading. For instance, an important deviation often indicates possible readers' disorientation and cognitive overload (Gwizdka and Spence, 2007). When two non-adjacent elements are often visited in sequence, this may suggest a possible issue in either the content of the element or in its position within the structure of the course. For instance, an element for which readers arrive from future distant elements may suggest that it was not fully understood and the learners often go back to it as it may be a requirement for future ones. In such cases, the course author can reduce the structural disorientation possibly caused by the document structure to guide at best learners, in constructing an effective reading path and a coherent mental model for it (Amadieu et al., 2009).

A. Lot of non-linear navigation, arrivals and/or departures

The navigation linearity indicates whether the order of reading corresponds to the same order defined by the course plan. This order, tightly related to comprehension (Hahnel et al., 2016), characterizes the deviation of the reading paths from the author's expected one. An important deviation often indicates possible readers' disorientation and cognitive overload. In such cases, the course author can reduce the structural disorientation possibly caused by the document structure to guide at best learners, in constructing an effective reading path and a coherent mental model for it (Amadieu et al., 2009).

Features related to the construction of a given element impacting the linearity of navigation include:

- On the *logical level*: The element is probably not in its best position within the course (*Issue LL*5).
- On the *physical level*: many inappropriate or useless links may exist from/to the element (*Issue PL*5).
- On the *readability level*: the information the element conveys or conveyed by the related elements is hard to recall (*Issue WL*5).
- On the *meaning level*: Learners may have perceived lack of cohesion within the element and with the related ones (*Issue ML*5), and failed to find logical or rhetoric link within and between them (*Issue ML*4) or to identify the relationship between the ideas conveyed (in terms of cause, condition, consequence, addition, opposition, etc.) (*Issue ML*3).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *"To advocate a linear reading of the element, move it to a more appropriate position. Facilitate its memorability: reformulate its content, synthesize and clarify the complicated or long parts, and simplify the writing. Also, think to delete some links to/from distant elements from/to this element and replace them with quick reminders of the relevant content where and when needed."*

B. Lot of future incoming

Features related to the construction of a given element promoting this type of behavior include:

– On the *logical level*: The element is probably not in its best position within the course (*Issue LL*5). It probably needs to be introduced later (*Issue LL*7).

– On the *physical level*: many inappropriate or useless links may exist from/to the element (*Issue PL*5).

– On the *readability level*: the information the element conveys or conveyed by the related elements is hard to recall (*Issue WL*5).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *"Consider moving forward the element to a more appropriate place. Alternatively, delete links from future elements and replace them when needed using reminders of the relevant content. Importantly, facilitate its memorability: reformulate its content, synthesize and clarify the complicated or long parts, and simplify the writing."*

C. Lot of past incoming

Features related to the construction of a given element promoting this type of behavior include:

– On the *logical level*: The element is probably not in its best position within the course (*Issue LL*5). It probably needs to be introduced earlier (*Issue LL*6).

– On the *physical level*: many inappropriate or useless links may exist from/to the element (*Issue PL*5).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *"Consider moving backwards the element to a more appropriate place or deleting links to it from elements situated before it."*

D. *Lot of future departure*

Features related to the construction of a given element promoting this type of behavior include:

- On the *logical level*: The learners probably judge the element that follows to be uninteresting for the course (*Issue LL*1), or that it is not in its best position within the course (*Issue LL*5) and that it needs to be introduced later (*Issue LL*7). They are probably not attracted by the title, and hence avoiding visiting the element, or may visit the element to find it not interesting (*Issue LL*2).
- On the *meaning level*: For learners, the information conveyed by the element that follows is either not suitable or not interesting with regard to the course goals (*Issue ML*9).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

> **Synthetic suggestion:** *" If the element that follows is worth being presented, give it a more meaningful and attractive title, and enrich it with new content, use graphics and richmedia when possible, and update, correct and deepen the existing content. Alternatively, move it to a more appropriate position, or simply delete it."*

E. *Lot of past departure*

Features related to the construction of a given element promoting this type of behavior include:

- On the *logical level*: The element is probably not in its best position within the course (*Issue LL*5). It probably needs to be introduced earlier (*Issue LL*6).
- On the *readability level*: the information the element conveys or conveyed by the related elements is hard to recall (*Issue WL*5).
- On the *meaning level*: Learners may have perceived lack of cohesion within the element and with the related ones (*Issue ML*5). They probably failed to find logical or rhetoric link between the information expressed by the element with that of the related ones (*Issue ML*4) or to identify the relationship between the ideas conveyed (in terms of cause, condition, consequence, addition, opposition, etc.) (*Issue ML*3).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

> **Synthetic suggestion:** *"Review this element and the related past ones to simplify their understanding, facilitate their memorability and help learners make a meaningful link between the expressed ideas: reformulate, update and correct the content of these elements, synthesize and clarify the complicated or long parts, and simplify the writing. Also, consider either moving this element back to a more appropriate place or adding reminders of the presented content. "*

6.4.6 Issues and revision suggestions related to stops & resumes

Indicators related to this class provide information about where and how learners interrupt the course momentarily or definitively. The analysis of these indicators allows identifying different issues to which we associate a set of revision actions.

A. Many stops

Reading interruptions are correlated to a decrease in readers' comprehension. While some reading stops are trivial (e.g. last chapters of the course), other cases can indicate that learners lost motivation and interest on the course. The author may need to rewrite the elements that cause reading to stop, by providing more elaborated explanations. Features of the element construction promoting this type of behavior include:

- On the *readability level*: The element is probably hard to read because of lack of readability due to the low quality of writing (lack of lexical diversity, language, etc.) (*Issue WL*1), and grammatical complexity of sentences with possible syntactic error (*Issue WL*2). Moreover, of a lot of complex statements and information within the content of the element are probably used (*Issue WL*3), constructed in a very complex manner (*Issue WL*4).
- On the *meaning level*: The learners halts or stops reading at this element probably because they find the element to develop on a subject that does not follow the line of the global subject of the course (*Issue ML*1), lacking cohesion with other elements (*Issue ML*5). They probably failed to find logical or rhetoric link between the information expressed by the element with that of the related elements (*Issue ML*4) or to identify the relationship between the ideas conveyed (in terms of cause, condition, consequence, addition, opposition, etc.) (*Issue ML*3). Maybe also they lack the needed prerequisites for reading the element or the course successfully (*Issue ML*10).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *"If the element is worth being presented, move it to a more suitable position. Otherwise, merge it with an appropriate element or simply delete it. Also, rewrite the content to enhance its understanding by reformulating and simplifying it, further explaining it and illustrating the ideas. Verify, correct any possible error and update the outdated content. "*

B. Non-linear resume

Many abnormal resumes indicate that learners need to navigate elsewhere to understand the presented information. Thus, the author may need to enhance the writing and provide further explanations. Features related to the construction of a given element promoting this type of behavior include:

- On the *logical level*: The element is probably not in its best position within the course (*Issue LL*5).

– On the *physical level*: many inappropriate or useless links may exist from/to the element (*Issue PL*5).

– On the *readability level*: the information the element conveys or conveyed by the related elements is hard to recall (*Issue WL*5).

– On the *meaning level*: Learners may have perceived lack of cohesion within the element and with the related ones (*Issue ML*5). They probably failed to find logical or rhetoric link between the information expressed by the element with that of the related elements (*Issue ML*4) or to identify the relationship between the ideas expressed by the content (*Issue ML*3).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *"To advocate a linear resume after a halt on the element, move it to a more appropriate position. Facilitate its memorability: reformulate its content, synthesize and clarify the complicated or long parts, and simplify the writing. Also, think to delete some links to/from distant elements from/to this element and replace them with quick reminders where and when needed "*

C. Future resume

A *resume on future* consists in resuming reading by jumping to an element situated far after the one on which the reading stop occurs. Probably the learners judge the current and the following elements not really relevant or interesting. Hence, the author needs to review the skipped elements and possibly, either merge them with other elements or remove them. Features related to the construction of a given element promoting this type of behavior include:

– On the *logical level*: The learners probably judge the element that follows to be uninteresting for the course (*Issue LL*1), or that it is not in its best position within the course (*Issue LL*5) and that it needs to be introduced later (*Issue LL*7). They are probably not attracted by the title, and hence avoiding visiting the element, or may visit the element to find it not interesting (*Issue LL*2).

– On the *meaning level*: For learners, the information conveyed by the element that follows is either not suitable or not interesting with regard to the course goals (*Issue ML*9), or that it lacks cohesion within the element and with the related ones (*Issue ML*5).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *" If the element that follows is worth being presented, give it a more meaningful and attractive title, and enrich it with new content, use graphics and richmedia when possible, and update, correct and deepen the existing content. Alternatively, move it to a more appropriate position, or simply delete it."*

D. Past resume

A *resume to past* can indicate that learners need to recall content that has already been seen. The author is thus suggested to either review this knowledge in order to facilitate its memorization or to add reminders. Hence, the author needs to review this content in order to facilitate its memorization or to add reminders where needed. Features related to the construction of a given element promoting this type of behavior include:

– On the *logical level*: The element is probably not in its best position within the course (*Issue LL*5). It probably needs to be introduced earlier (*Issue LL*6).

– On the *readability level*: the information the element conveys or conveyed by the related elements is hard to recall (*Issue WL*5).

– On the *meaning level*: Learners may have perceived lack of cohesion within the element and with the related ones (*Issue ML*5). They probably failed to find logical or rhetoric link between the information expressed by the element with that of the related elements (*Issue ML*4) or to identify the relationship between the ideas conveyed (in terms of cause, condition, consequence, addition, opposition, etc.) (*Issue ML*3).

By combining the revision actions that we identified for these factors, we formulate the associated revision suggestion as follows:

Synthetic suggestion: *"Review this element and the related past ones to simplify their understanding, facilitate their memorability and help learners make a meaningful link between the expressed ideas: reformulate, update and correct their contents, synthesize and clarify the complicated or long parts, and simplify the writing. Consider also moving this element back to a more appropriate place or adding reminders of the presented concepts. "*

6.5 Summary

This chapter described a reading analytics method to detect content enhancements opportunities, based on the analysis of learners' traces of reading. We introduced the concept of "reading session" as a means to model document reading, to denote the actual activity periods of learners. These sessions are computed using an algorithm grounded on data that represent learners' interactions with document parts, and that takes into account each part characteristics. We proposed a new method for delimiting learners' reading sessions by computing page per page thresholds.

Modeling the reading activity using sessions allows computing indicators that describe the underlying process from behavioral perspectives. We, therefore, proposed a set of interaction indicators originated from widely used metrics in navigation analysis that we have specialized using the reading session concept. Their aim was to better represent and explain how learners consume and assimilate the content offered on the learning platform.

7
CoReaDa: The COurse READing DAshboard

Research Questions and Objectives of the Chapter

(RQ5) What kind of systems and tools can effectively support authors for course improvement?

RO5.1– To identify functional and design requirements for implementing assistive systems that present the information timely and appropriately.

RO5.2– To implement these requirements through a functional prototype for course reading analysis, comprehension issues detection and remediation actions taking.

Providing course authors with assistance in using analytics facilities would encourage them to revise their courses more frequently and soundly. Therefore, we developed *CoReaDa* – the Course Reading Dashboard [1], an analytics and visualization tool that targets authors of online courses, based on our different proposals. In this chapter, we first describe the rationale, the conception methodology, and the main design and functional features of the tool (§7.1.1). After describing the architecture of the system and the technology used for the implementation (§7.2), we present the two main components of the tool: the server-side analytics engine (§7.3) and the client-side course assistance interface (§7.4).

7.1 Rational and design methodology

7.1.1 Conception methodology

Information visualization techniques implemented in learning dashboards are an intuitive and powerful way to represent data regardless of its structural complexity or quantity. However, as discussed in §4.4, the proper design of learning dashboards requires to involve the analytics stakeholders and to integrate features for triggering their reactions and supporting them. This has led us to adopting a user-centered design approach through a co-design strategy. We have involved online course authors and three HCI (Human-Computer Interaction) researchers, through focus

[1] http://bit.ly/coreada

groups, in order to identify the principal functionalities and the design requirements for developing the tool, and to test and validate the intermediate prototypes.

7.1.2 Functional features

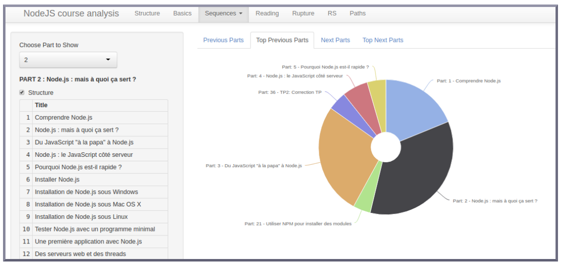
The active participation of end-users has allowed us to better understand their requirements and needs. Several functionalities and options were discussed, some of which were implemented and supplied with the tool. The majority of the features correspond to the numerous proposals that were formulated in this thesis. This includes the provision of the different levels of assistance: in addition to presenting reading issues and revision suggestions, as well as the different indicators and other statistics related to the course reading. This allows the author to perform a lower level analysis in addition to the one provided by the tool.

Due to the number of the proposed indicators, the amount of data provided can be overwhelming. In order to reduce the author's possible cognitive overload, the list of indicators is sorted according to the importance of the available information and the severity of the problems detected. The classification by severity level is based on the distance between the average values of the indicators and the values reported as indicative of reading problems (outlier values).

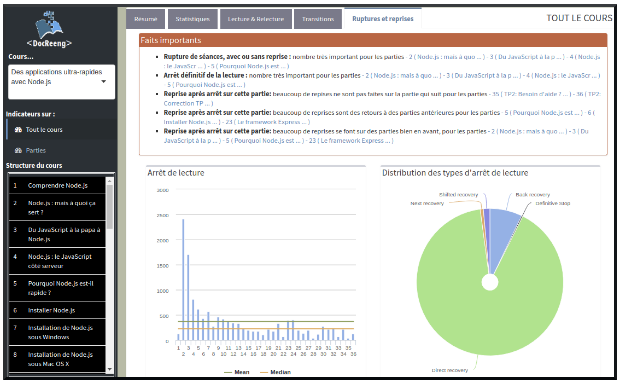
The proposed suggestions can be used by the author to plan revision tasks. Thus, the tool integrates a *task manager* where authors can plan and manage revision actions. A task can be derived from a suggestion provided by the tool, or be entirely initiated by the author.

7.1.3 Design methodology

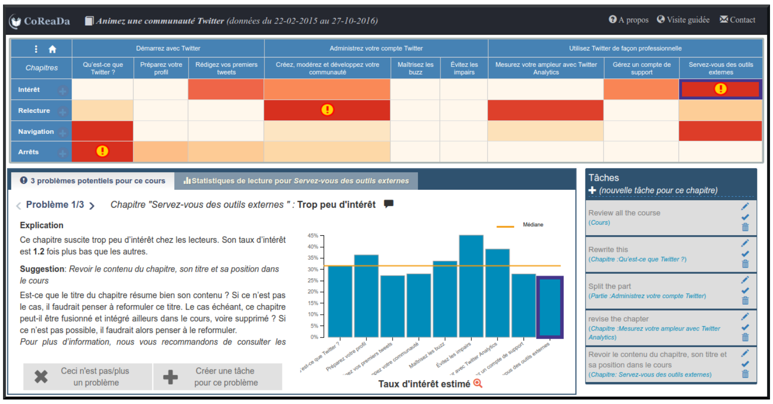
Through the co-design process, the design of the tool has been discussed repeatedly with course authors, through multiple iterations, driven and refined with the HCI researchers. This led to multiple early and intermediate versions of the prototype, as illustrated on Figure 7.1. Before reaching the current version, we prepared and discussed several low-fidelity sketches to solidify and visualize a few key design ideas that came up during the research and the focus-group sessions.



(a) The earliest prototype



(b) A low-fidelity prototype



(c) Current prototype

Fig. 7.1 The different prototypes of the dashboard

We have designed CoReaDa by conforming as closely as possible to the requirements identified in the field of visual analysis and dashboards (e.g. (Few, 2006; Ganapati, 2011)):

– The dashboard presents a one-page interface, simple in its design, presenting only the relevant information provided in a sparse way.

– The one-page interface aims to avoid fragmenting information between different screens or pages, preventing users from losing the connection between the elements being studied.

– Appropriate visualizations are used, avoiding the purely decorative components.

– Graphical representations are used to represent complex data in a condensed way to give visual trends or comparisons.

– The graphical components are combined with textual ones to provide self-contained explanations and details (Ganapati, 2011).

According to Dürsteler (2002), the main problem of information visualization is the insufficient space, which restricts the user in showing detail and context contemporaneously, is called "presentation problem". Finding an effective and efficient spatial representation of the information is difficult and can be considered as the most important tasks in information visualization. The design of CoReaDa follows the mantra formulated by Shneiderman (1996): "*Overview first, Filter and zoom, Details on demand*". This mantra was recently adjusted by Keim et al. (2006) to bring its focus toward Visual Analytics: "*Analyze first, Show the Important, Zoom, filter and analyze further, Details on demand*". We thus combined three approaches: *Overview+Detail*, *Focus+Context* and *Contextual Cues* design approaches:

– An *overview+detail* interface design is characterized by the simultaneous display of both an overview and detailed view of an information space, each in a distinct presentation space (Cockburn et al., 2009).

– The *Focus+context* system allows the user to show detailed information linked with the context, by also having the possibility to focus on other information by interacting with the system. *Focus+Context* seamlessly integrates detail and context information in the same view (Leung and Apperley, 1994).

– *Contextual Cues* techniques augment the detail view with glyphs meant to help locate parts of interest that are outside the view area (Burigat and Chittaro, 2013). This can be obtained by displaying abstract shapes like arrows and arcs as visual references to the off-screen context.

With the *overview+detail* perspective, CoReaDa offers the author the same interface with multiple views that differ in the number of details provided. The first view is an overview of the data empowered with options to get more detailed views. With a *focus+context* design approach, the selected detail is put into its context by surrounding it with the related information. Many contextual cues are integrated to the user interface to help the authors in understanding, using and acting upon the information displayed.

7.2 System architecture and technological choices

7.2.1 Architecture overview

CoReaDa is designed using a three-tier architecture in which presentation, application processing, and management are logically separated processes. It thus consists of three important layers: data, logic, and presentation. A popular paradigm for the implementation of this model is the *MVC* (Model-View-Controller) architectural pattern. In MVC, the logic, data, and visualization are separated into three types of objects, each handling its own tasks (Figure 7.2):

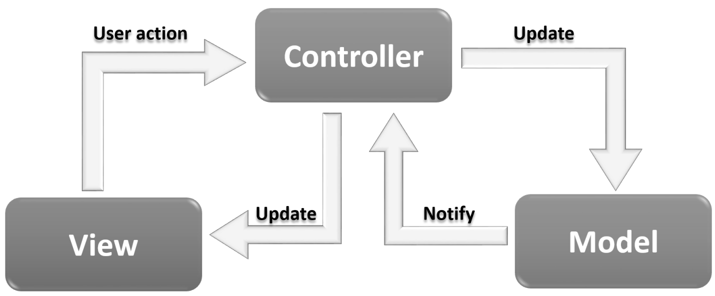


Fig. 7.2 Common MVC architecture communication

– The *View* handles the visual part, focusing on the user interactions.
– The *Controller* responds to system and user events, commanding the Model and View to change appropriately.
– The *Model* handles data manipulation, responding to requests for information or changing its state according to the Controller's instructions.

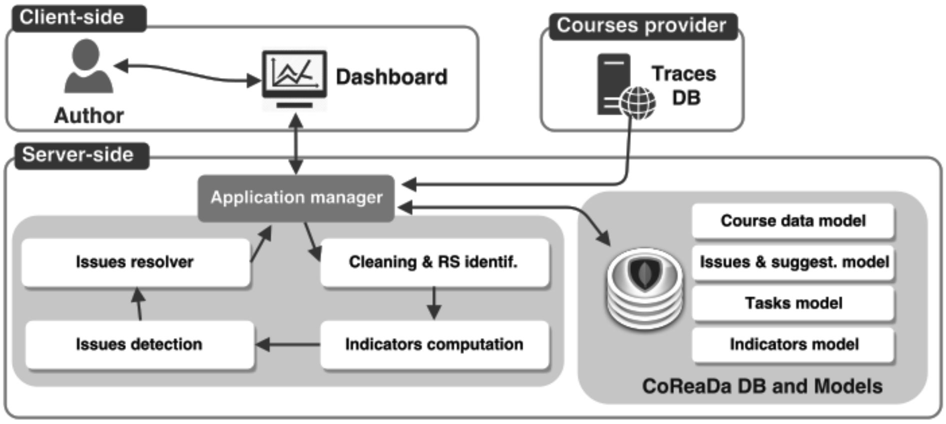


Fig. 7.3 Architecture of CoReaDa

Figure 7.3 represents the architecture of CoReaDa. The application structure consists of a database, a server logics, a client logics, and a client UI. The client-side code is responsible for coordinating the interaction with the author, while the server-side code implements the analytics and the business logics and determines the control flow of the application. The persistent data for the application is stored in a backend datastore and is accessed and modified by the server-side code based on the author interactions.

7.2.2 The development stack

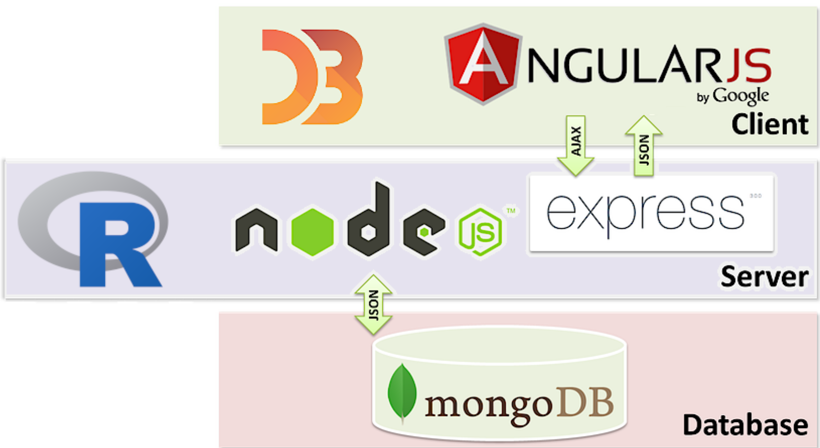


Fig. 7.4 Overview of the used technological stack

It is very challenging to create a complete software product using a single technology, without having to combine several tools and programming languages. For client-server applications, there are usually different technologies that cover each of the two layers. This motivated the introduction of development approaches called *full stack development* with the aim to cover both layers through a coherent set of technologies[2]. Two different types of technologies were used for implementing CoReaDa, illustrated in Figure 7.4 (Appendix A provides some technical details about these technologies):

- Modern Web-based framework for data presentation and user interaction.
- Statistical computing tools for data analytics and processing tasks (preprocessing, sessions delimitation, indicator computation, and issue detection).

We implemented CoReaDa using the *MEAN* stack which is gaining popularity thanks to a combination of very efficient open source technologies: *MongoDB*, *Express.js*, *AngularJS* and *Node.js*. *Node.js* supports an effective connection for server execution and *Express.js* provides assistance with website design. Increased efficiency for data storage is ensured thanks to the flexibility of *MongoDB*. On the client side, *AngularJS* serves an ideal way to enhance cooperative functions and Ajax-driven rich components. The exchange between client and server is made simple since *JavaScript* is fully supported both in the browser and on the server as well. One of the greatest advantages of this combination is the possibility to use *JavaScript* to write all the code for both the client and server sides and to use *JSON* to transfer the data. It thus improves productivity by reducing the required development effort, while ensuring effective, efficient and large-scale implementation.

The data analytics functions are written in *R language*[3], a free platform-independent open-source analysis environment. It is a popular open source software for statistical computing, considered by many statisticians as the de-facto standard for data analysis. The software is well established and the huge R community provides a wealth of contributed packages in a variety of fields.

In order to the Web application to communicate with R, we used *Rserve*[4], a R library that supports the communication between R and other languages (including C/C++, Java, PHP, Python, Ruby, and Node.js). It is an abstract network interface of R allows other programs to use facilities of R from various languages without the need to initialize R or link against R library. To connect CoReaDa server to Rserve, we use the RIO (R Input Output) package[5]. This package provides support of different types of data, plain text, and encrypted authentication.

7.3 CoReaDa Analytics (server-side)

7.3.1 Application manager

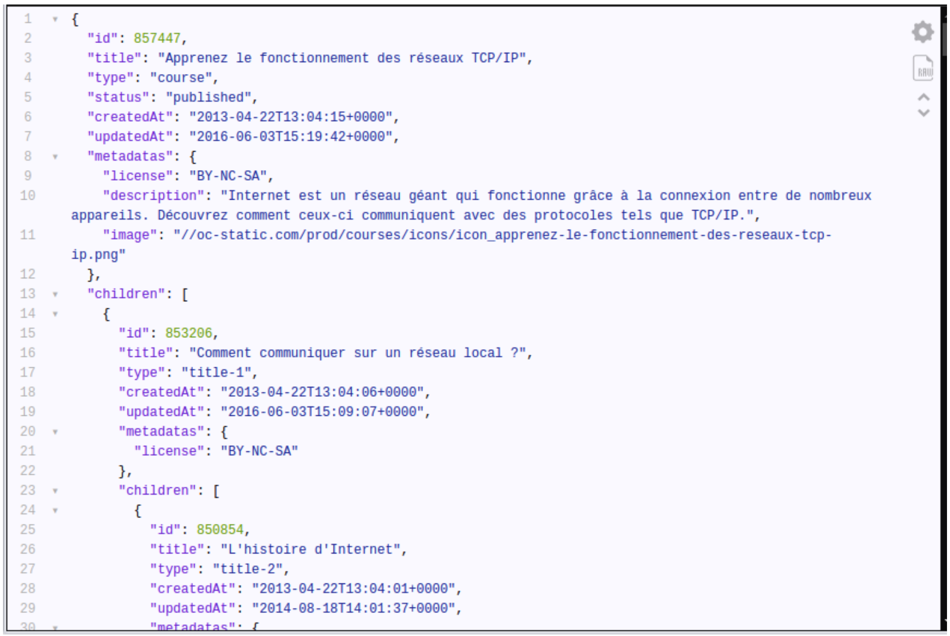
On the server side, the application manager pools learners' logs from the course provider. Integration with the learning platform requires a connection to its log database using the needed credentials. Once connected and trace logs pooled and anonymized, the application manager populates its own databases. The structure of courses within the platform needs to provide, as a JSON file, the following data:

[2]For instance, the *LAMP* stack combines *Linux*, *Apache*, *MySQL*, and *PHP*.
[3]https://www.r-project.org (accessed on November 23th, 2018)
[4]https://cran.r-project.org/web/packages/Rserve/index.html (accessed on November 23th, 2018)
[5]https://cran.r-project.org/web/packages/rio/index.html (accessed on November 23th, 2018)

`<id, type, status, createdAt, updatedAt, metadata*, children*>`

- *id* is a unique identifier of the course element;
- *type* identifies the type of the element, according to its level in the structure. Its value can be either *course*, *level-1* (course part), *level-2* (chapter) or *level-3* (subchapter).
- *status* indicates whether the element is still in draft mode, published or removed.
- *createdAt* and *updatedAt* provide creation and update timestamps.
- *metadata* contains different information concerning the element (e.g. a description, the running license of the element content, an illustrative image).
- *children* allows the nesting of elements to define a hierarchical organization that translate the course plan.

Figure 7.5 presents an excerpt of a json document that provides the structure of a course from the platform provider used in the evaluation studies (cf. §8.1).



```
{
  "id": 857447,
  "title": "Apprenez le fonctionnement des réseaux TCP/IP",
  "type": "course",
  "status": "published",
  "createdAt": "2013-04-22T13:04:15+0000",
  "updatedAt": "2016-06-03T15:19:42+0000",
  "metadatas": {
    "license": "BY-NC-SA",
    "description": "Internet est un réseau géant qui fonctionne grâce à la connexion entre de nombreux appareils. Découvrez comment ceux-ci communiquent avec des protocoles tels que TCP/IP.",
    "image": "//oc-static.com/prod/courses/icons/icon_apprenez-le-fonctionnement-des-reseaux-tcp-ip.png"
  },
  "children": [
    {
      "id": 853206,
      "title": "Comment communiquer sur un réseau local ?",
      "type": "title-1",
      "createdAt": "2013-04-22T13:04:06+0000",
      "updatedAt": "2016-06-03T15:09:07+0000",
      "metadatas": {
        "license": "BY-NC-SA"
      },
      "children": [
        {
          "id": 850854,
          "title": "L'histoire d'Internet",
          "type": "title-2",
          "createdAt": "2013-04-22T13:04:01+0000",
          "updatedAt": "2014-08-18T14:01:37+0000",
          "metadatas": {
```


Fig. 7.5 An excerpt of a *json* file providing the structure of a course

A log of a learner is the set of his activity events recorded on the server side of the e-learning platform during an observation period. A record within the data corpus has the following structure:

`<id, user_id, course_id, part_id, session_id, date>`

Each record contains information related to the identification of the action (*id*), the time of observation (*date*) , the identification of the web session (*session_id*), the identification of the learner (*user_id*, `null` if anonymous), the identification of the accessed course (*course_id*), and the identification of the course element (*part_id*). Figure 7.6 presents an excerpt of a document that provides the logs observed on a course.

	A	B	C	D	E	F
1	**id**	**user_id**	**course_id**	**part_id**	**session_id**	**date**
2	95	d9686458af021829d11a8104fe2b0b12	857447	850854	hd1rdhkjnlc7i39p80cdr59p67	2014-10-31 17:28:29
3	970	3fa0493d9ebcfaa3046ef425c87f7198	857447	850854	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 11:14:16
4	1131	3fa0493d9ebcfaa3046ef425c87f7198	857447	850854	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 11:47:23
5	1259	3fa0493d9ebcfaa3046ef425c87f7198	857447	850854	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 12:05:47
6	9415	3fa0493d9ebcfaa3046ef425c87f7198	857447	851033	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 11:47:32
7	20270	1580aa4853d58c559d30f90b8608f3b1	857447	851376	9449tskldh1j2h6vhi19qrbph0	2014-10-31 23:59:18
8	30842	3fa0493d9ebcfaa3046ef425c87f7198	857447	852634	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 12:11:34
9	38215	3fa0493d9ebcfaa3046ef425c87f7198	857447	853038	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 12:05:52
10	40525	3fa0493d9ebcfaa3046ef425c87f7198	857447	853038	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 12:16:16
11	43303	3fa0493d9ebcfaa3046ef425c87f7198	857447	853205	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 11:47:38

Fig. 7.6 An excerpt of a *csv* file describing the logged actions on a course

7.3.2 Analytics engine

The analytics engine is designed as an external pluggable application that can provide its full functionality in a full service oriented manner through standardized interfaces. It comprises a dedicated database instance and a set of RESTful web services to interact with the application controller. The engine implements a set of processing procedures that make it possible to perform the following functions:

1. *Data preparation*: The logs are cleaned and preprocessed in order to prepare the data. Detection and removal of abnormal and non-consistent data are performed. This includes the elimination of duplicate observations and irrelevant data like entries to .jpg, .css, .png files. The data with missing mandatory fields (e.g. identification of a course, date, etc) are also eliminated.

2. *Reading sessions identification*: The cleaned data is sorted by user identification and access date. A segmentation of user activity records is done from each identified user into reading sessions, each representing a complete reading path of the course. The reading sessions of each user are then computed.

3. *Indicators computation*: The different indicators are computed for the course elements using the prepared data that contain the learners' reading sessions.

4. *Issues resolution*: The function of the issues resolver module is to provide remediation suggestions for the detected issues. It behaves as an inference engine that applies logical rules to the knowledge base to deduce the appropriate reengineering actions based on the types of the reading problems that were provided on input. Knowledge bases consist of the encoding of suggestions for the reading issues based on some *production rules* (Davis et al., 1977). These rules are expressions of the form:

   ```
   if <issue> then <suggestion>
   ```

   When an issue is detected, an appropriate revision suggestion is formulated and sent back to the author. The engine hence uses a forward-chaining, a top-down method which takes issues when introduced and attempts to draw revision actions (from satisfied conditions in rules) which lead to suggestions being proposed.

7.3.3 Data models

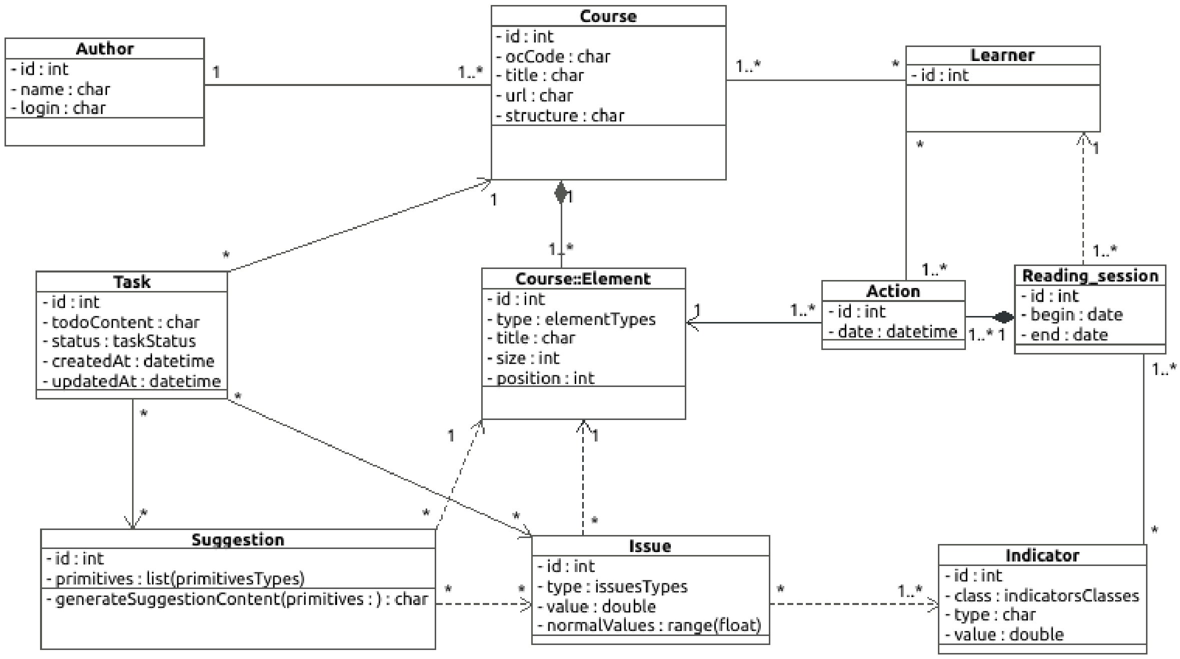


Fig. 7.7 Overview of the class diagram

The data used by the application is stored within the application database which defines a set of data models, derived from the general class diagram of Figure 7.7.

A. Author and learner models

The author model contains personal and login information of the author, while the learner model has only an identification field since all the trace data are anonymized.

B. Course model

The course model (Table 7.1) contains the information that allows describing a course for which data has been harvested from the course provider (including the title, its link and its identifier on the course provider website, its structure), as well as the identification of the author.

Attribute	Description
`id`	Unique identifier of the course within the system
`ocCode`	The identifier of the course within the course provider platform
`title`	Title of the course
`author`	Author of the course
`url`	The web url of the course on the course provider website

Table 7.1 Course model

C. Element model

The element model (Table 7.2) provides the information that allows characterizing a course element: the type of the element (part, chapter, or subchapter), its title, its content size (in words and figures), and its position within the course outline

Attribute	*Description*
`id`	Unique identifier of the element within the system
`courseId`	Identification of the course
`title`	Title of the course element
`type`	Type of the element (part, chapter, or subchapter)
`size`	Size of the element (in words and figures)
`position`	Position of the element in the course outline

Table 7.2 Course element model

D. Reading session model

The reading session model (Table 7.3) presents the structure used to store the sessions computed from the data. It includes attributes to identify the course and the learner, as well as the start and end dates of the session.

Attribute	Description
`id`	Unique identifier of the reading session within CoReaDa
`userId`	Identifier of the learner
`courseId`	Identifier of the course
`begin`	Start time of the session, corresponding to the datetime of the first reading event of the session
`end`	End time of the session, corresponding to the datetime of the last reading event of the session plus its computed duration

Table 7.3 Reading Session model

E. Action model

The action model (Table 7.4) presents the structure used to store the processed and expanded form of the trace data of the user on the learning platform. Each action is described by the identifiers of the element having on which the action was performed, the date and time of occurrence of the action, and the identification of the reading session to which it belongs.

Attribute	Description
`id`	Unique identifier of the reading event within the system
`elementId`	Identifier of the course element on which the action was performed
`date`	A DateTime containing the value of reading event date and time
`rsId`	Identifier of the reading session to which belongs the action

Table 7.4 Action model

F. Indicator model

The indicator model (Table 7.5) contains the structure of the computed indicators. An indicator is described by its class (among the other classes we have defined) and type, by course element to which it relates, and by its calculated value on the associated element.

Attribute	Description
`id`	Unique identifier of the indicator
`class`	Class and type of the indicator
`type`	Type of the indicator
`elementId`	Identifier of the course element
`value`	The computed value of the indicator on the course element identified by *elementId*

Table 7.5 Indicator model

G. Issue model

The Issue model (Table 7.6) describes the structure of an issue computed using a specific indicator. An issue is identified in particular by the type and identifier of the indicator to which it is associated, by a value indicating the degree of severity of the issue relative to the range of values considered acceptable.

Attribute	Description
`id`	Unique identifier of the issue
`indicatorId`	Identifier of the corresponding indicator
`type`	Type of issue
`value`	The computed value of the issue as reported by the indicator identified by *indicatorId*
`normalValues`	The range of normal values of the indicator identified by *indicatorId*

Table 7.6 Issue model

H. Suggestion model

The suggestion model (Table 7.7) contains the structure of the generated revision suggestions. A suggestion is described by the identifier of the associated issue, the set of revision primitives used, and the function that that allows to generate a revision suggestion using the set of primitives and the context associated to the issue.

Attribute	Description
`id`	Unique identifier of the suggestion
`issueId`	Identifier of the issue to which corresponds the suggestion
`actionPrimitives`	The set of action verbs used for generating the suggestion
`generateSuggestionContent()`	A function to generate a suggestion using the primitives

Table 7.7 Suggestion model

I. Task model

The task model (Table 7.8) gives the general structure of a revision task. A task is assigned to a course and possibly has the objective of solving an issue indicated by its identifier. A task therefore has a content and a status (to be done, done, deleted). It also has a creation and last modification date associated with it.

Attribute	Description
`id`	Unique identifier of the task
`courseId`	Identifier of the course
`associatedIssueId`	Identifier of the issue to which corresponds the task
`todoContent`	The content of the task
`status`	Status of the task
`createdAt`	A DateTime containing the value of the creation date of the task
`updatedAt`	A DateTime containing the value of the modification date of the task status and/or content

Table 7.8 Task model

7.4 CoReaDa User Interface (front-end)

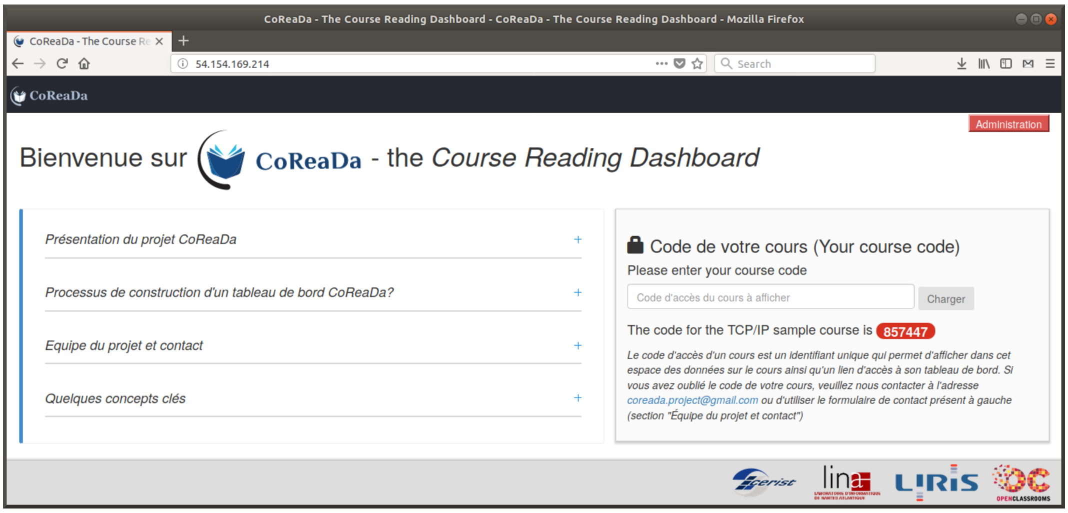


Fig. 7.8 The Welcome screen of CoReaDa

We have designed the dashboard interface as a single-page application that does not require updating with each server request. Figure 7.8 presents the home page of the application (the *Welcome screen*).

The dashboard communicates directly with the application manager, which constantly checks for the presence of newly recorded data to discretely update the interface. The left side of the interface presents the project, define the related concepts, explains the analysis process, and provides instructions for using the tool. The right part of the interface allows an author to connect to his instance by entering a secret code associated with his course. At the top of the interface, an administration button is displayed for management purposes (cf. §7.4.3).

7.4.1 Course analysis layout

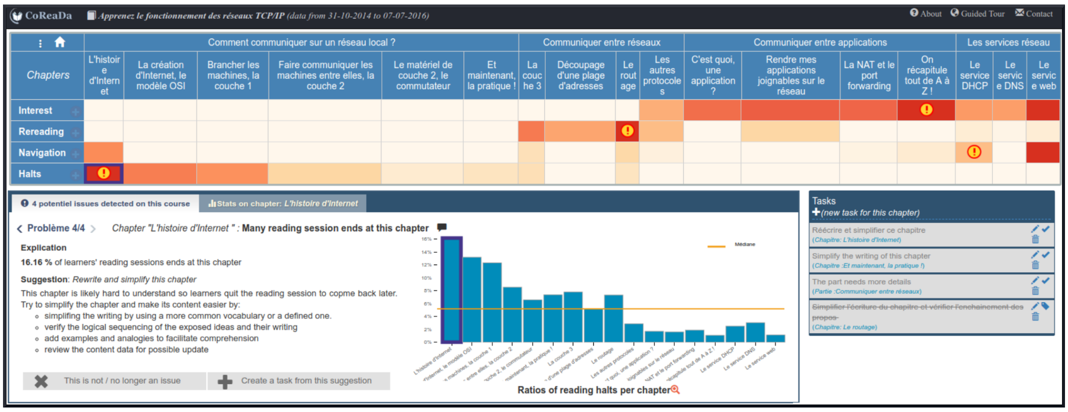


Fig. 7.9 Screenshot of a CoReaDa instance

Figure 7.9 illustrates the dashboard running on a course. The upper menu bar presents shortcuts to utility boxes (*about* and *contact* dialogs) and a launcher button for a *guided tour*. Three zones (or areas) constitute the main dashboard interface.

7.4.1.1 Data grid area

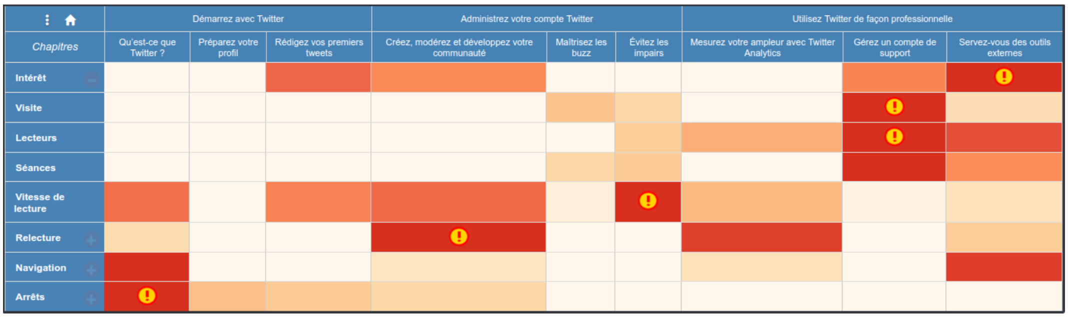


Fig. 7.10 CoReaDa *heatmap* within the data grid area

This zone represents the values of the displayed indicators for each chapter as a two-dimensional matrix (Figure 7.10). The table representation of data allows to efficiently identify individual values (Ganapati, 2011). The table column header represents the course plan (chapters and parts) and the row headers represent the class of indicators.

The *plus(+)/minus(-)* button allows the author to toggle the display of the indicators of a class. He can also display all the indicators by accessing the options menu from the vertical ellipsis. Selecting a given chapter header would highlight all the column and give an aggregated view of its statistics and detected issues in the *Inspector area*.

The values of an indicator for course elements are encoded into color shades within a heatmap, a representation not only meant to give an accurate reading but also to display the values side by side to easily spot patterns and give an overview of the data. The color of a cell represents the distance of the value of each chapter from the normal value (often the median or the mean one). It thus tends to turn red to depict abnormal values. The potential issues are indicated with a yellow exclamation icon, an artifact suitable to highlight alerts (Ganapati, 2011).

By clicking a cell, the *Inspector Area* is updated with information related to the selected indicator and the associated chapter. Looking at the example dashboard given in Figure 7.9, four of the red-colored cells are associated with exclamation marks to indicate that issues related to the associated chapter and indicator are detected. Actually, to not overwhelm the author, the dashboard shows by default only one issue per indicator, corresponding to the worst one. Once an issue is resolved, another issue may appear. The author can also display all the detected issues by activating the appropriate option using the vertical ellipsis.

7.4.1.2 Inspector area

The *Inspector area* displays contextual textual information and graphical visualizations concerning the selected element (course, part, chapter, cell, indicator, etc.). The zone is composed of two tabs: *Issue tab* and *Stats tab* (Figure 7.11).

A. Stats tab

Fig. 7.11 The *Stats tab* of the Inspector

When no issue is selected, *Stats tab* is active to display statistics related to the entire course or to the selected element.

B. Issues tab

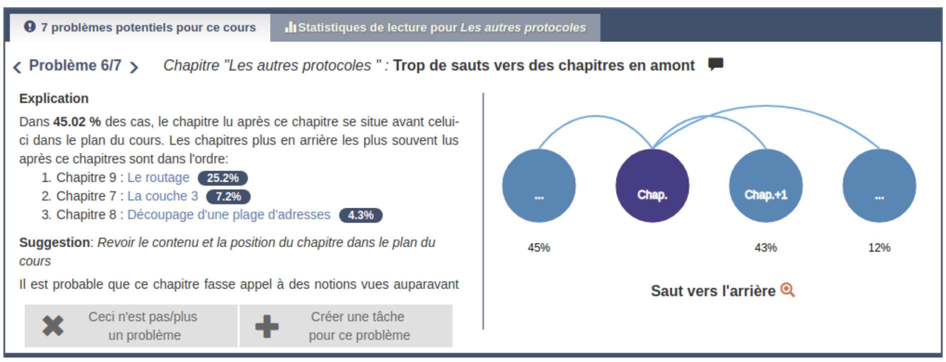


Fig. 7.12 The *Issues tab* of the Inspector

When the author selects an issue, for instance by clicking on its corresponding icon from the data grid area, the *Issue tab* displays a description and an explanation of the issue along with appropriate graphs. It also shows a revision suggestion for resolving it (Figure 7.12); the user can add the suggestion as a task or indicate that the detected issue is not really a problem. In this last case, this may indicate a detection error or an expected behavior. A navigational mechanism between issues is provided, in order for the author to focus on them.

In the example displayed on Figure 7.9, an issue related to reading session halts for the first chapter is selected and the author has an explanation illustrated by a chart, and a suggestion. Once the author reviews the provided information, he has the ability to mark the problem as not a real issue or as a fixed one, or to add the suggestion as a revision task.

7.4.1.3 Task area

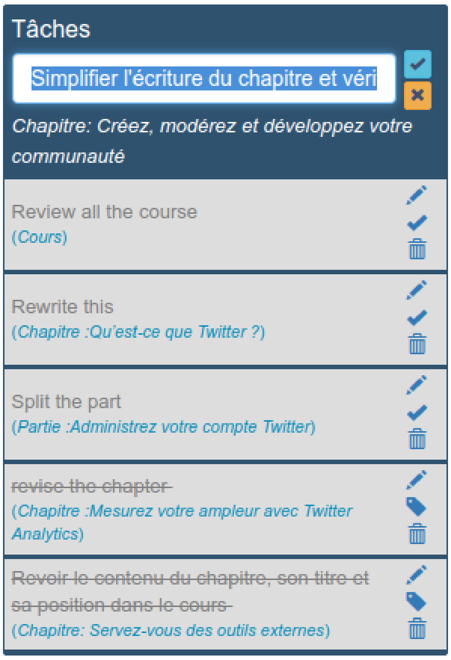


Fig. 7.13 The *Tasks* area of CoReaDa

The task area serves for the author in planning revision actions. A new task can target a specific issue, the context of the issue (the direct or indirect course element involved in the issue) or the whole course. The content of a task can come from the suggestions or introduced by the author. The example in Figure 7.13 shows four tasks among which one is marked as done (the one with strikethrough text). This is done using the buttons that accompanied each task. The two other buttons allow respectively to edit the associated task content and to delete it.

7.4.2 Help and assistance

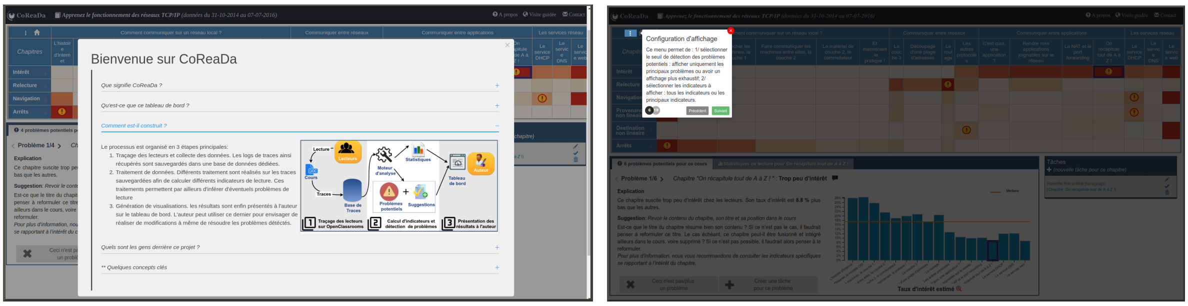


Fig. 7.14 CoReaDa user help features

Two complementary helping features are provided to the authors. When the dashboard is first launched, a welcome screen presents important information concerning the main functionalities of CoReaDa and defines different concepts used within it. This screen can be revisited at any time by clicking on the help button of the main interface. The second facility is a step-by-step guided visit through which the main components of the interface are reviewed one by one and their usage explained.

7.4.3 System administration

The system administration component provides an interface for the system administrator to manage the data used by the platform. It consists of three tabs that allow adding, editing and removing courses.

7.4.3.1 Courses management

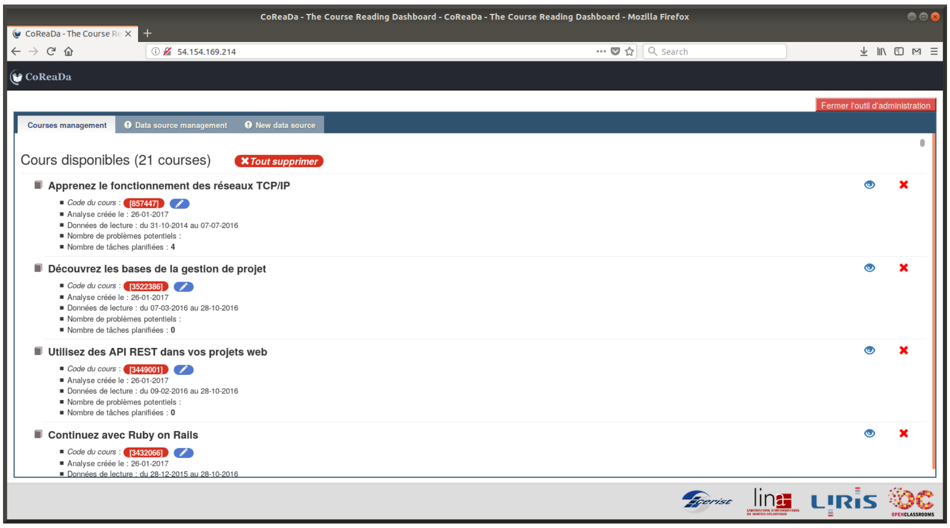


Fig. 7.15 Managing the existing courses within CoReaDa

The course management tool allows displaying the courses available and/or currently being analyzed within the platform. The courses are presented in the form of a list, with various information (Figure 7.15): the access code of the course, the date of creation of the analysis, temporal data on the analyzed logs, the number of critical problems as well as the number of tasks programmed by the author while using the dashboard. The tool allows also to withdraw a course and its data.

7.4.3.2 Data source management

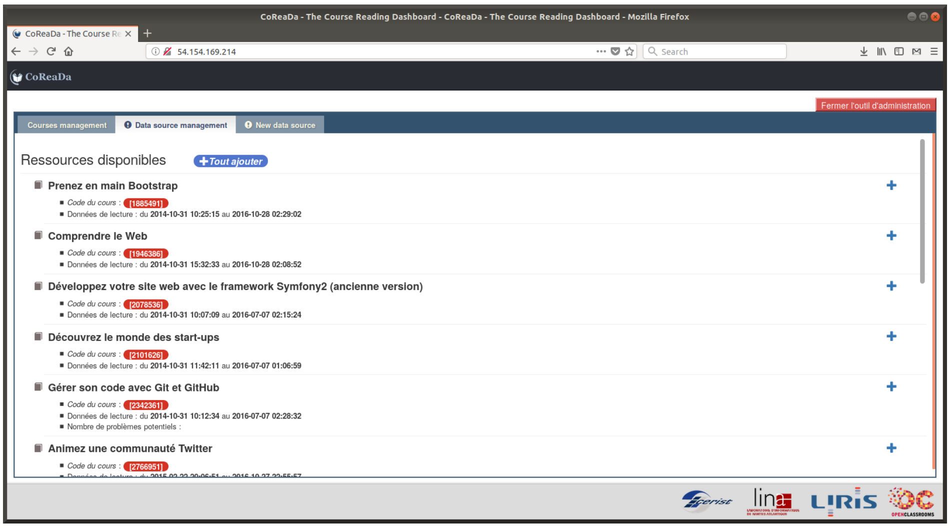


Fig. 7.16 Managing CoReaDa data sources

The data source management component (Figure 7.16) allows to bootstrap the analysis of new courses for which the required data (raw logs and course structure) are available within the database. To start the analysis of a new course and thus to generate an instance of the dashboard for that course, the system manager needs to activate the plus button.

7.4.3.3 New data source

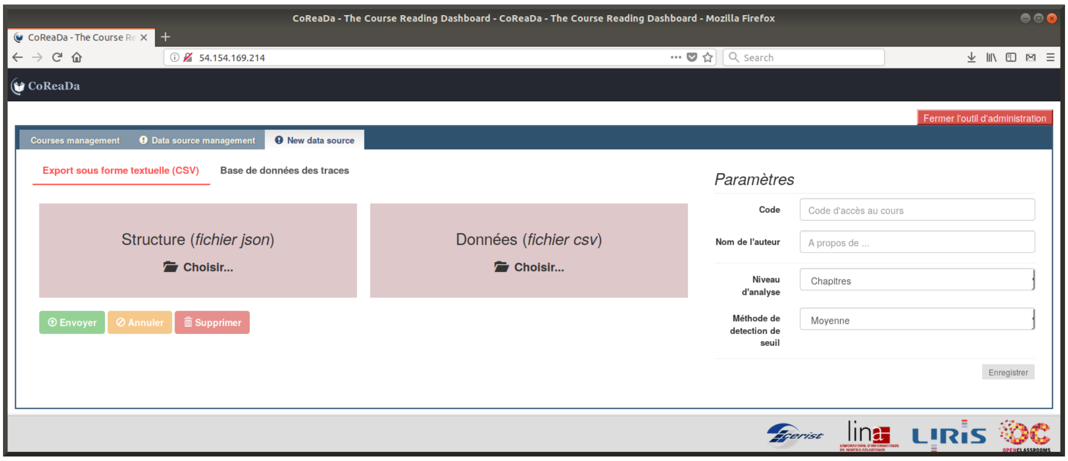


Fig. 7.17 Adding an new data source to CoReaDa

The new data source component is a tool that allows pouring new data into CoReaDa database. To upload and import data, two files need to be provided (Figure 7.17):

– A *json* file that contains the structure of the course

– A *csv* file containing the user logs of the course.

In addition to the course data, some parameters need to be provided

– A secret code of the course

– The name of the author

– The granularity level: whether the analysis will be done at *part-level*, *chapter-level* or *subchapter-level*.

– A method for detecting outliers. By default, the system used MAD, but the system manager may decide to use simply the mean or the median.

7.5 Summary

In this chapter, we presented an implementation of our different theoretical propositions. We described *CoReaDa*, a dashboard designed for analyzing online learners' reading, detecting their reading problems, and suggesting appropriate revision and remediation actions. The chapter firstly explained the co-design process, and outlined the functional features and the design choices for the development of the tool. It then provided the three-tier architecture of the platform and described the implementation logics using a modern stack of Web technologies, that make use of a popular and free open-source analysis environment. Finally, both the client-side and the server-side components of the tool were described in detail.

8
Evaluation and validation of the proposals

Research Questions and Objectives of the Chapter

(RQ5) What kind of systems and tools can effectively support authors for course improvement?

*RO*5.2: To validate the support methods and tools and to evaluate a functional prototype for analyzing course readings, detecting comprehension problems and taking corrective action.

In this chapter, we present the evaluation studies for validating our theoretical proposals and their implementation. First, we provide the evaluation context and purposes, as well as the participants and data used in the various studies conducted (§8.1). We then describe each of the different studies that make up our evaluation and validation process, in relation to the different objectives pursued: assessing the capabilities of the proposed session identification algorithm (§8.2); evaluating the relevance of the proposed set of indicators (§8.3); assessing the effectiveness of the issue detection and resolution mechanisms(§8.4); measuring the effectiveness of the issue detection mechanism for detecting real learners' issues (§8.5); and assessing the usability and acceptability of the dashboard (§8.6). The chapter concludes with a discussion of the main findings from these studies (§8.7)

8.1 Evaluation objectives and settings

8.1.1 Study context

Our proposals are evaluated using data from *OpenClassrooms*[1], a major French e-learning platform for vocational training, providing online courses, MOOCs, and learning paths on a freemium basis, and having for motto to make education more accessible by prioritizing a community-based, engaging learning experience. More than 1000 courses are available in English, French, and Spanish, focusing on in-demand skills that range from entrepreneurship, digital marketing to web development. Launched in 1999, *OpenClassrooms* now has 2.5 million users worldwide.

[1] htpp://fr.OpenClassrooms.com

8.1.2 Objectives

We conducted a series of studies using different methods, mostly with online course authors and learners. These studies had the following objectives::

Study 1 objective was to evaluate the capabilities of our session identification algorithm to identify reading sessions that were consistent with learners' actual sessions.

Study 2 goal was to assess with the course authors the perceived relevance of the proposed indicators for reading analysis and course revision.

Study 3 objective was to evaluate with the course authors the capabilities of the issue detection and resolution mechanisms

Study 4 purpose was to assess with learners the conformity of the problems identified with those they had actually encountered.

Study 5 objectives was to evaluate with the authors of the course the usability of the dashboard as well as its acceptability in terms of the readiness of course authors to adopt it.

We used a set of online questionnaires and a task-based experiment for the studies 2 to 5 (Appendix B presents the questionnaires used in studies 2 and 3)[2]. The face validity of the questionnaires was established by refereeing them by three independent researchers, and two course authors who are also members of the learning platform staff. The final questionnaires have been modified as per the received recommendations.

8.1.3 Participants and data used

We contacted 403 OpenClassrooms course authors by email inviting them to participate in the evaluation of an approach and tool intended to provide them with assistance in revising their courses (Cf. Appendix B for the template of the invitation). A total of 125 authors have agreed to take part in the first phase of the study. After the implementation of the dashboard[3], we selected a subset of twelve courses among those of participating authors, and asked their authors to participate in the remaining studies (*Studies 3* and *5*). The selection was based on two criteria: the *representativity* of the courses in terms of total number of chapters and its *popularity* in terms of number of visits and unique readers.

The courses had a different number of chapters ($Min = 3$, $Q1 = 7, Mean = 9$, $Median = 12$, $Q3 = 39$, $Max = 52$). We have identified those consisting of a number of chapters ranging from $Q1$ to $Q3$ chapters ($N = 62$). We sorted these courses according to the number of reading actions and the number of unique readers in descending order. Lastly, we selected the first twelve courses, for which we provide some statistical information in Table 8.1 (We refer to these courses using acronyms. The exact course titles according to these acronyms can be found in Appendix B).

[2] An aggregated version of the used material targeting a course about TCP/IP can be found here: http://bit.ly/coreada-eval

[3] The instance of CoReaDa used during the evaluation is hosted on an Amazon CE2 instance running Red Hat Enterprise Linux Server release 5.4.

The data used are learners' logs for the period starting from *31 October 2014* to *07 July 2016*.

Course	# chapters	# logs	# learners	# reading sessions
Bootstrap	7	229362	13045	94654
Web	18	240978	11793	53695
Twitter	9	17576	1560	5223
Adruino	14	66911	4864	26797
JavaScript	13	289153	12829	101614
Ionic	19	27283	2020	8663
Ruby	18	4895	706	2794
Project	14	49255	3156	14607
TCP	17	111026	7239	43392
Symfony	27	402039	9357	236635
Startups	21	11772	1223	3574
Github	19	109092	5826	29452
Median	17.5	88001.5	5345	28124.5
Mean	16.33	129945.2	6134.833	51758.33
SD	5.38	129909.1	4653.657	67299.6

Table 8.1 Basic statistics about the selected courses

Participants in *Study 4* were Algerian master's students in Computer Sciences and Information Systems who enrolled in an advanced training in Information Systems at the Algerian *Research Center on Scientific and Technical Information* (CERIST). A total of 26 master's students (10 female and 16 male, from 23 to 26 years old) took part in the study.

The courses with *OpenClassrooms* are organized as a series of interlinked *course elements* (corresponding to parts and chapters), each element being contained within a single web page. Learners' traces are automatically created and saved by the web server. Common cleaning and preprocessing steps are performed to obtain for each record a *timestamp* (datetime of the request) along with the *request identifier*, the *user* (empty if anonymous), the *server-side session*, the *course* and the *course element*. A record within the data has the following structure:

```
<request_id, user_id, course_id, element_id, server_session_id, timestamp>
```

8.2 Study 1 – capabilities of the session identification approach

8.2.1 Methodology

In the absence of a precise knowledge of the actual sessions that compose the navigation traces of the learners, it is in practice impossible to verify with confidence the conformance of the reconstructed sessions with the actual ones. A number of researchers have previously investigated the properties of users' real sessions and found that their size, expressed as the total number of pages visited, follows a *Power*

Law distribution (Berendt et al., 2001; Vázquez et al., 2006). More specifically, this law stipulates that most visits to a website are concentrated on a small number of pages, with the rest of the pages receiving relatively few visits. In light of these findings, we investigated the quality of our method by assessing the extent to which the distribution of the reconstructed sessions follows this empirical law. Such an approach to evaluation has also been used for the same purpose of analyzing the quality of session reconstruction by many authors (Arce et al., 2014; Román et al., 2014; Dell et al., 2008).

Assuming that complex course elements require more reading time, and in addition to evaluating session reconstruction quality, we also studied the conformity of the estimated action durations with the complexity of course elements. Complexity was quantified in terms of the size of the element, which is among the most significant factors in characterizing the complexity of a website (Butkiewicz et al., 2011).

We used the data of the twelve courses that were selected for the practical studies (Table 8.1). We first applied the session detection approach on the learners' traces on these courses, and then estimated the quality of the reconstruction. We also compared the results of our approach with popular web usage mining methods, in terms of quality of reconstruction, and compliance with course element complexity.

8.2.2 Results

8.2.2.1 Quality of the reconstruction

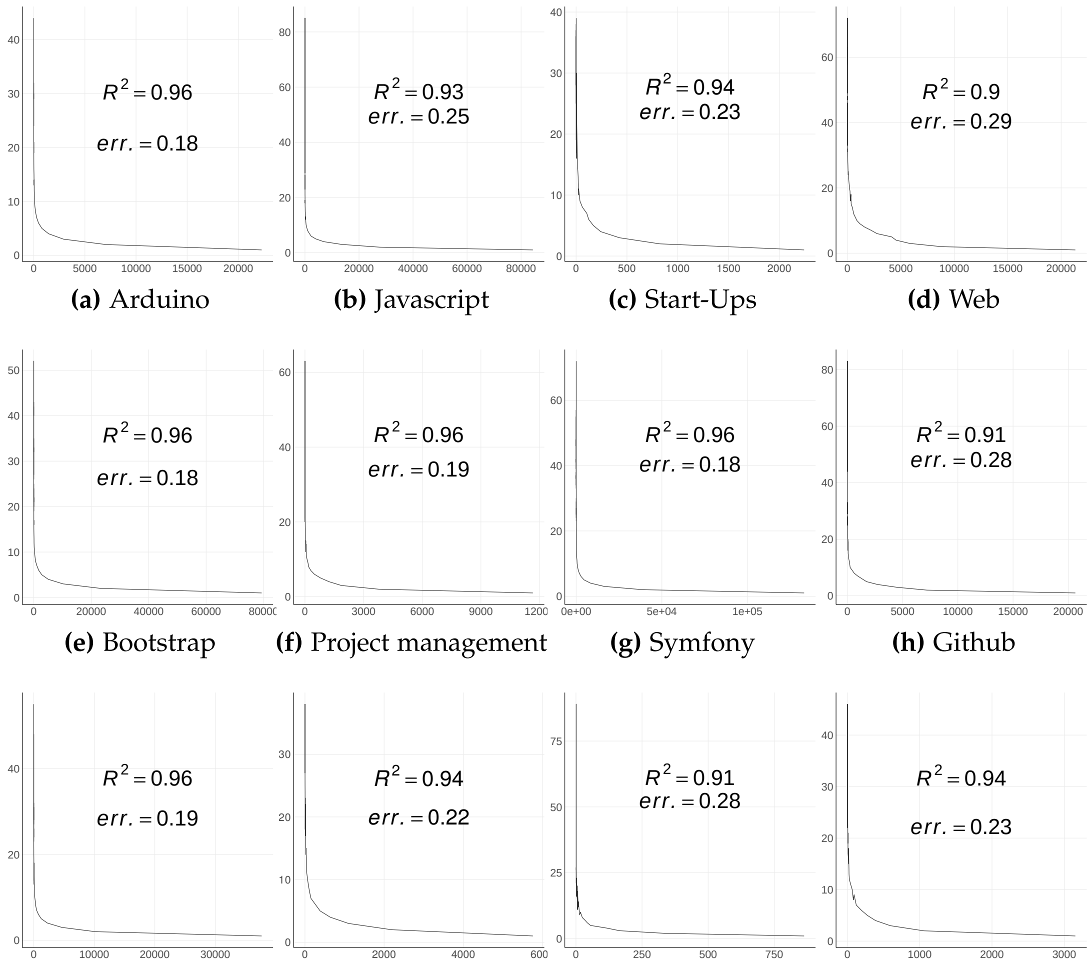
Evaluating the quality of reconstruction using the power law can be performed using a linear regression on the logarithm of the number of the distinct read elements and the logarithm of the total number of reading sessions. The quality measure is given by the regression correlation coefficient R^2 and the standard error *err*. The values of R^2 and *err* allow the evaluation of the degree of fit of the number of sessions versus the size of the sessions with the Power Law:

- When R^2, with $0 \leq R^2 \leq 1$, takes values close to 1, the model fits perfectly with the Power Law.
- The standard error of the model *err* measures the difference between the real value and the estimated value. The closer it is to 0, the better the model's fit is with real data.

The results represented on Figure 8.1 show that our approach has good capabilities for session identification, since it produces excellent fit results with good accuracy for all courses. Indeed, the values of the different regression correlation coefficients R^2 are all above or equal to 0.90 (mean value of 0.94). The different values of the standard error *err* are also acceptable (mean value of 0.22).

In order to reinforce our conclusions, we recalculated the learners' sessions on the twelve courses using two popular methods:

- using a fixed value of threshold on the *page stay time*; we chose *10 minutes*, given that it is the most used value for this class of approaches
- using a fixed value of threshold on *total session time*; we used *30 minutes* which is the widely used value for this class.



(a) Arduino **(b)** Javascript **(c)** Start-Ups **(d)** Web

(e) Bootstrap **(f)** Project management **(g)** Symfony **(h)** Github

(i) TCP **(j)** Ionic **(k)** Ruby on rails **(l)** Twitter

Fig. 8.1 Session size found by the power law distribution on the 12 courses

	Reading Session		*10-min Page Threshold*		*30-min Session Threshold*	
	R^2	*Err*	R^2	*Err*	R^2	*Err*
Bootstrap	**0.96**	**0.18**	0.95	0.22	**0.96**	0.21
Web	**0.90**	**0.29**	0.88	0.31	0.86	0.31
Twitter	**0.94**	**0.23**	**0.94**	0.24	0.91	0.25
Adruino	**0.96**	**0.18**	0.94	0.20	0.93	0.23
JavaScript	**0.93**	**0.25**	0.92	0.26	0.90	0.28
Ionic	**0.94**	0.22	0.93	**0.21**	0.92	0.24
Ruby	0.91	0.28	0.91	0.29	**0.93**	**0.26**
Project	**0.96**	**0.18**	0.92	0.24	0.92	0.23
TCP	**0.96**	**0.19**	0.95	0.20	0.95	0.20
Symfony	**0.96**	**0.29**	0.88	0.31	0.86	0.35
Startups	**0.94**	0.23	0.93	**0.22**	0.93	0.23
Github	0.91	0.28	**0.94**	**0.23**	0.93	0.25

Table 8.2 Constructed sessions using three methods : our proposal, fixed page threshold (10-min) and fixed session threshold (30-min).

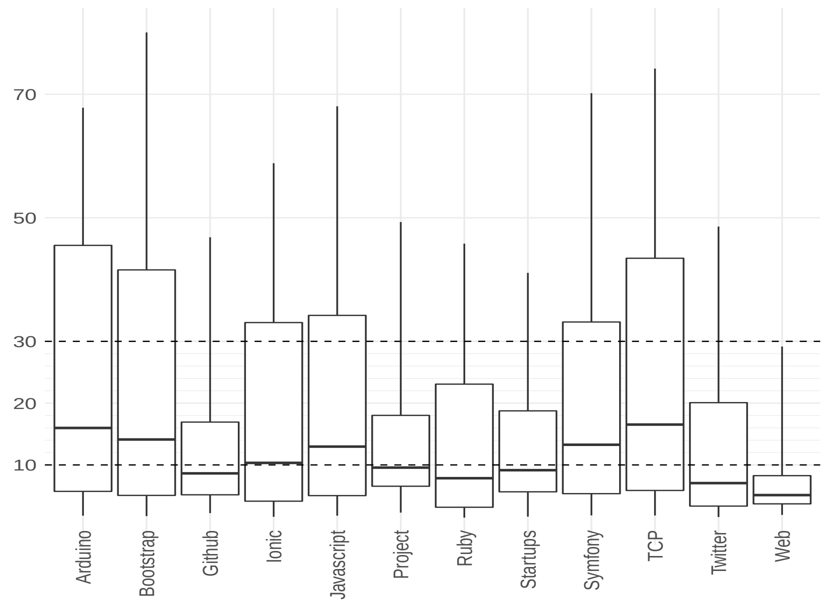


Fig. 8.2 Course chapters reading duration statistics

We estimated the quality of the reconstruction for each method using the same process, so that we could compare their results with ours. Results of the comparative study are given on Table 8.2, we emphasize in bold the best R^2 coefficient and *Err* error values. They show that the method we have proposed has given the best fit results for the majority of courses with an acceptable accuracy given by the error values. More precisely, they demonstrate that that our method ensured (1) best fit result for 75% of the courses (9 courses out of the 12); and (2) best values for the fitness and accuracy couple in 58% of cases (7 courses out of the 12). One side result of this study is that it appears that, at least for the context of the study, the use of thresholds on the stay time of a page (fixed or dynamic) appears more effective for the delimitation of reading sessions than the use of a fixed total duration.

8.2.2.2 Compliance with elements size and complexity

We used duration as an indicator of the element complexity. We estimated the size of each element of the courses by counting its significant words and in-line images (with each image considered as a short paragraph of 30 words). Figure 8.2 It indicates for each course the distribution of reading time for each of its elements (chapters). As shown by the evolution of the distribution, reflected by the size and shape of the boxplots, it is not possible to determine a single fixed threshold value that is appropriate either for all chapters of all the courses or even for chapters of the same course. Whatever the values selected, there will always be some elements that can be read in less time and others that may require much more time.

Defining dynamic thresholds per course elements can better reflect element complexity. Indeed, Pearson correlation coefficient between element size (computed as the words and figure count) and time threshold for that element is $r = 0.82$ ($p < 0.001$). This positive and significant correlation means that the method succeeds in assigning important durations for pages with significant content and, conversely, in associating reduced durations for relatively short pages. It is therefore fair to conclude that the approach is sufficiently generic and robust to take into account the size of the elements without having any further knowledge about them (and therefore without the need to calculate them). We can make the hypothesis that it is also the case for element complexity, even if element size does not directly indicate the complexity level of the content. This also confirms the need to take into account the characteristics of the elements for more accurate threshold values.

8.3 Study 2 – relevance of the indicators

8.3.1 Protocol

This study was carried out during one month (April 2016). A document presenting the project, its motivation, and its objectives was distributed to the 125 OpenClassrooms authors. Thereafter, the author received an online questionnaire titled *Indicators Relevance Survey* (the complete survey is presented in Appendix B) which is composed of four sections, one for each class of indicators. Each section explains the associated class and its indicators. The authors were asked to evaluate the relevance of each of the twenty indicators for course revision. The rating used a 5-point Likert scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). In average, the questionnaire needed 18 minutes to complete.

8.3.2 Results

To evaluate the perceived relevance of the indicators, we used the results from the *Indicators' relevance questionnaire*. There are two schools of thoughts on analyzing Likert-scale data: *ordinal vs. interval* (Carifio and Perla, 2007). A significant amount of empirical evidence exists supporting that Likert scales can be used as interval data (Carifio and Perla, 2007) or aggregated to create a new composite metric scale. Accordingly, we analyze the results both by individual indicators and by aggregating them into their corresponding classes.

The $Cronbach's\ \alpha$ coefficient obtained for the ratings is 0.82. The reliability coefficient for internal consistency if an individual indicator is removed from the scale gave values ranging from 0.78 to 0.91. This shows that the reliability of the results had appropriate internal consistency. No strong correlation between the ratings of the indicators was found (*Pearson correlation* coefficients ranging from -0.16 to 0.62). This suggests that the authors considered these indicators to cover relatively distinct aspects of reading behavior.

We conducted a series of $ANOVA$ (analysis of variance) to study the influence of each independent demographic variable (gender, age, and level of education) on the author ratings (the significance level was set at 0.05). The demographic data (gender, age, and education level) of the 125 course authors are provided in Table 8.3. The results showed no significant effect of the gender and level of education on the ratings ($p > 0.05$). However a tangible effect of the age on the results was found for two classes: stickiness ($F(2,125) = 3.83,\ p = 0.024$) and navigation ($F(2,125) = 3.41,\ p = 0.036$). The variable age can have three values ($N = 125, Min = 19, Max = 58, Mean = 29.48, Median = 27, SD = 8.12$), as indicated

Variable	*Category*	*Frequency*	*Percentage*
Gender	Female	57	45.6%
	Male	68	54.4%
Age	19-25	48	38.4%
	26-40	66	52.8%
	41-58	11	8.8%
Level of education	Bachelor	11	8.8%
	Master	degree	49%
	Doctorate	degree	65%

Table 8.3 Demographic description of the participating authors

in Table 8.3, allowing to split the participants into three groups. A *Tukey* post hoc test revealed that the ratings of the stickiness and navigation indicators were statistically different ($p < 0.05$) between the three groups of participants. In addition, they showed that the ratings of young participants were higher, while those of older participants were the lowest.

	Descriptive statistics			Student t-test*			Inter-correlations (Spearman)		
	Mean	*SD*	*Median*	*t*	*df*	*p*	*Navigation*	*Rereading*	*Stops*
Stickiness	3.66	0.53	3.71	0.41	105	0.67	0.01	0.16	0.13
Navigation	3.44	0.54	3.33	0.47	105	0.64		−0.01	−0.04
Rereading	3.67	0.59	3.67	−0.04	105	0.96			0.01
Stops	3.55	0.60	3.67	−0.89	105	0.33			

$^{*}group\ 1 : female\ participants(n = 42); group\ 2 : male\ participants(n = 63)$

Table 8.4 Statistics about authors' ratings

In order to investigate for possible differences between the genders, we ran an independent *t-test* for each class of indicators (the significance level for the mean variation was set at $p < 0.05$). The results, shown on Table 8.4 (columns 5, 6 and 7), revealed no significant difference for all the classes of indicators. Associations between the ratings of the different classes of indicators were examined using *Pearson's correlation coefficients*. As reported in the table, no significant correlation was found.

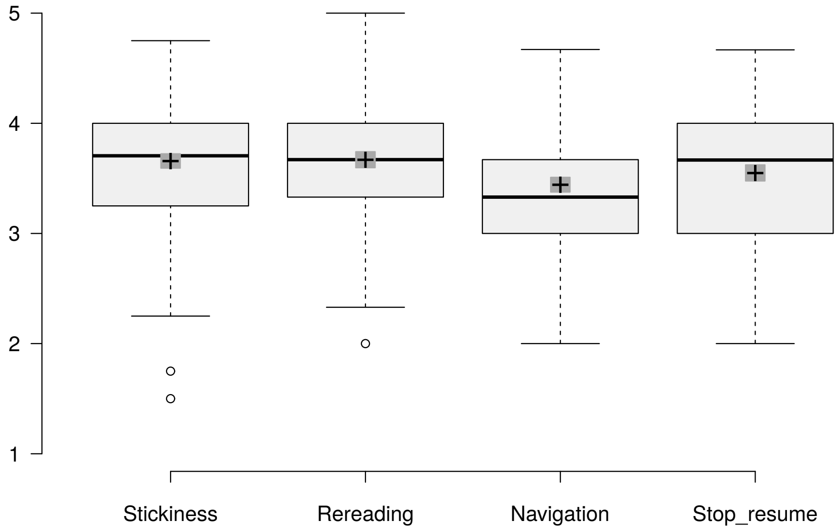
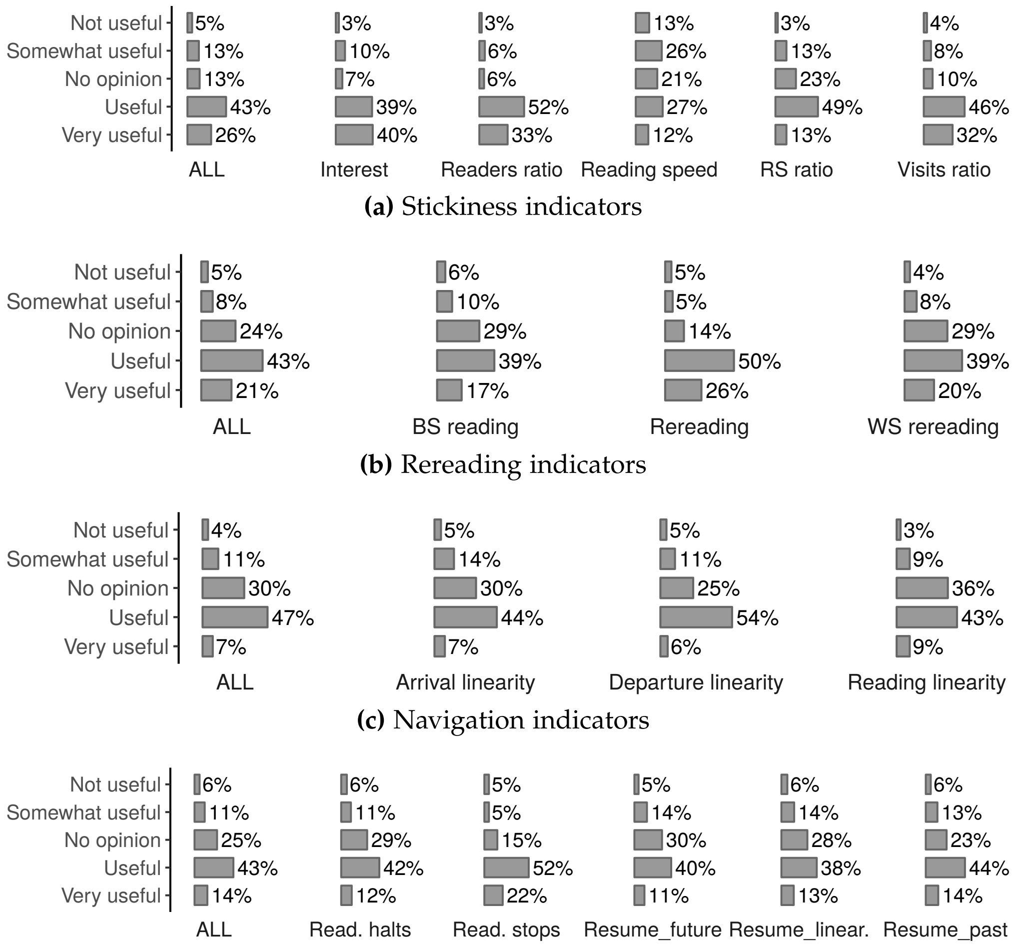


Fig. 8.3 Authors' rating of the indicators, aggregated by classes

The descriptive statistics of the aggregated results are presented on the first three columns of Table 8.4 and the boxplots represented on Figure 8.3. The boxplots are relatively short, suggesting that the participants had a high-level agreement with each other. The results show that participants mostly agreed that the classes of indicators are relevant for analyzing course reading. All the proposed classes of indicators were highly rated; indeed, the median and mean points were all above the neutral point of 3 (corresponding to the mention "neither agree nor disagree"). In other words, globally the four classes of indicators were deemed useful.

The authors' rating of the reading indicators is given on Figure 8.4. We define as *positive rating* any rating that is either *useful* or *very useful*, while a *negative rating* corresponds to either *somewhat useful* or *not useful*. According to the results, the indicators were found globally suitable for analyzing reading and performing revisions, as reflected by the generally positive rating of each of them, the aggregated results for all the classes being 61% positive, 23% no opinion and 16% negative. The stickiness class was perceived as the most relevant (average of 69% of positive rating). Indeed, authors were very interested in the popularity of their courses given that the most highly rated indicators were *readers ratio*, *interest* and *visits ratio* (resp. 85%, 79% and 78% of positive ratings). The authors recognized the importance of the indicators related to rereading (average of 64% of positive rating for this class). Yet, while the rereading ratio indicator is highly rated (76% of positive rating), the indicators related to within and between sessions rereading seem too technical and complicated for some authors, as reported in their comments and ratings (less than 60% of positive rating and 30% of no opinion).



(a) Stickiness indicators

(b) Rereading indicators

(c) Navigation indicators

(d) Stops and resume indicators

Fig. 8.4 The relevance of the reading indicators, rated by 125 authors

Indicators related to navigation are those rated the less useful (54% of positive rating). About 30% of authors responses on these indicators have no opinion, while 15% have a negative rating. Two authors argued that they do not expect their courses to be read in a totally linear way, and another pointed out that his course could be read in any order. The relatively low-rated indicators are related to reading speed (about. 39% is negative and 21% no opinion). According to their feedbacks, many authors did not pay much attention to the speed of reading since learners differ in background and learning styles. One common suggestion of three authors is to combine some indicators into higher level ones, to lower the number of indicators and to provide aggregated results.

Comments and opinions

Many authors think that these indicators are numerous enough and judicious to give a good idea of the way learners read courses. The following sample quotes illustrate some authors' opinion:

– "What is interesting is this opportunity given to the authors of online courses and their learning to communicate, in a direct and indirect way."

– "Why not include direct exchanges between authors and learners through comments and forums?"

– "These are important metrics about course consumption, they could help me understand how to rethink my course material."
– "While they seem interesting, I think you would have to select the more important indicators to present to authors. The other ones can serve for deeper analysis."
– "Be careful not to abuse the personal data of users. The reader should actually be informed that his reading is logged and analyzed."

The authors recognize that the interaction with readers is essential to create interesting and productive courses. While more than 60 authors found the list of indicators to be comprehensive enough to analyze reading, five of them considered that there were too many indicators: without a meaningful presentation to the authors, this would be counterproductive. The fact that readers' usages logs allow considering the end-user perspective on consuming the course is deemed interesting.

All participating authors valued the usefulness of using reading traces to detect parts or aspects of the course that necessitate review. Many among them have appreciated the definition of indicators that result from aggregating data, since this may better reflect recurrent reading problems. For one authors, the approach seemed complicated to implement technically and therefore may generate some unreliable results. Similarly, another author felt that we would need a good level of abstraction so that authors would not have to consult many tables and endless statistics. Several authors proposed to consider the supplementation of computed indicators with explicit readers feedback (courses ratings, comments and annotations, etc.) that would help them to better understand readers needs. A last aspect reported by two authors was related to privacy: they suggested to ask learners before logging them.

8.4 Study 3 – capabilities of the issue detection and resolution mechanisms

8.4.1 Protocol

This study was conducted from January 13th to January 26th, 2017. Each author received a pre-filled version of an online questionnaire with data specific to his course. Titled *Issues and Suggestions Survey* (cf. Appendix B), the questionnaire contained two sequential parts. The first part was a blank list that the author had to complete with his predictions on the possible problems encountered by learners related to each of the indicator classes. The second part consists of a listing of the issues detected and the revision suggestions generated. Using five-point Likert scales, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*), the author was asked to estimate the plausibility of each issue and then to evaluate the usefulness of the related revision suggestion. The questionnaire took an average of 34 minutes to complete.

8.4.2 Results

8.4.2.1 Effectiveness of the detected issues for enhancing authors' awareness

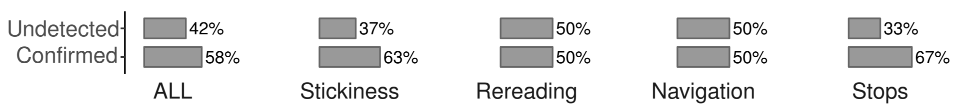
To evaluate the quality of the issue detection, we used the gathered data about authors' expectations of possible issues that may exist on their courses. In order to quantify and qualify the gain in awareness provided by the detection tool, we classified the set of issues (provided by the author and/or by the tool) based on three criteria: whether they were expected or not, whether they were detected or not, and whether they were rated useful for revision or not. We transposed this classification into classes of knowledge as follows:

– In terms of detection of the expected issues: the *undetected knowledge* reflects the set of issues expected by the author but not detected by the tool; and the *confirmed knowledge* results from the set of issues expected by the author and detected by the tool.

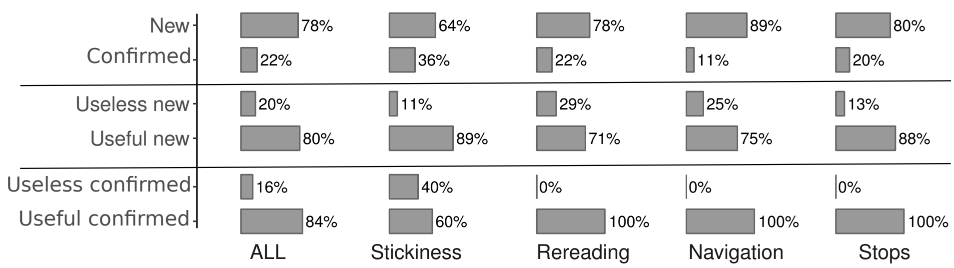
– In terms of expectation of the detected issues: the *confirmed knowledge* (the same above-defined class) reflects the set of issues expected by the author and detected by the tool; and the *new knowledge* is the set of issues that were not expected by the author but detected by the tool.

– In terms of usefulness for revision of the expected and detected issues: the *useless confirmed knowledge* results from the set of issues that were expected by the author and detected by the tool, but were nor rated useful for revision; and the *useful confirmed knowledge* reflects the set of issues that were expected by the author, detected by the tool and rated useful for revision.

– In terms of usefulness for revision of the detected but not expected issues: the *useless new knowledge* reflects the issues that were detected by the tool but neither expected nor rated useful for revision; and the *useful new knowledge* reflects the set of issues that were not expected by the author but were detected by the tool and rated useful for revision.



(a) Distribution of the knowledge expected by the authors with regards to its detection by the tool



(b) Authors' expectation and relevance for revision rating, of the knowledge detected

Fig. 8.5 Distribution of the knowledge expected and the knowledge provided

Figure 8.5 represents (a) the distribution of the expected knowledge in terms of confirmed/undetected classes; (b) the distribution of the detected knowledge in terms of authors expectation and relevance for revision. Slightly more than half of the knowledge expected by the authors was discovered by the tool. The authors had particularly good guesses about the issues related to reading stops and reading stickiness and interest. The undetected knowledge likely corresponds to false expectations and beliefs and is more related to rereading and navigation. About 78% of the detected knowledge was new for authors, of which 80% was found relevant for triggering revision actions. 22% of the knowledge provided by the tool was expected, of which 84% was deemed useful. On the stickiness class, some issues were expected and detected but were not considered relevant for revision (*useless expected knowledge* class). According to some authors, these problems were predictable; for example, chapters containing only additional information do not attract much interest.

8.4.2.2 Usefulness of the suggestions for guiding authors in course revision

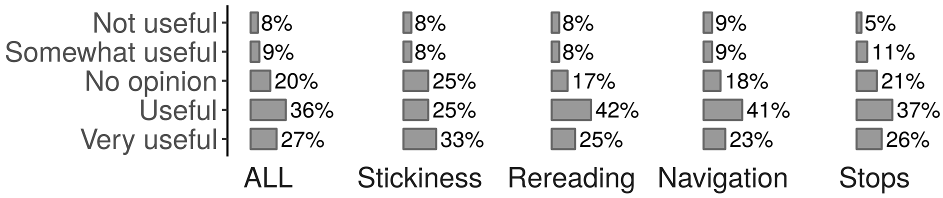


Fig. 8.6 Relevance of the suggestions

Figure 8.6 presents the results of the *Issues and suggestions questionnaire* related to the authors' ratings of the usefulness of the suggestions. 63% of these suggestions were rated either useful or very useful, i.e. found to provide hints and guidance for revising the course so as to resolve the associated issues. In one-fifth of cases, the authors were not sure whether the proposed solutions could effectively be the best revision to undertake; they found the suggestions too broad and they noted that deeper analysis was first needed. The suggestions marked as not relevant (17%) were mostly related to issues not highly rated as needing revisions, in more than 90% of cases. For the remaining cases, authors suggested reformulations that took more into account the context of the provided suggestions without calling into question the primitives used for generating the suggestions.

8.5 Study 4 – conformance of the detected issues with learners' problems

8.5.1 Description

Among the twelve courses used is *Study 3* (Table 8.1), the students selected four courses that they indicated having already followed on the platform during the first and/or the second semester of the year 2017 (*TCP*, *JavaScript*,*Bootstrap* and *Symfony*). The reading logs of these courses, provided by *OpenClassrooms*, were used to compute the values of the different indicators. We examined the statistical distribution of the values of these indicators for each course, to assess possible reading issues. In order to not overwhelm the learners, we considered some major problems that can be encountered by learners and detected by our tool. The rules we followed for marking a given value of a specific indicator as reflecting a potential reading issue are provided on Table 8.5. The numerical results of the issue detection on the four courses are shown on Table 8.6.

Class	Issue triggering	Issue description
Stickiness	Low values of: visits, readers, reading session; High reading speed	(SI_1) Low popularity due to low attractiveness of the chapter and/or its low readability
	Low reading speed	(SI_2) Low stickiness due to the complexity of the content
Navigation	Low linearity of reading (arrivals and/or departures); High ratios of navigation to distant chapters	(NI_1) Disorientation due to bad structuring
		(NI_2) Non linear reading due to low memorability
		(NI_3) Non linear reading due to low content complexity
Rereading	High values of rereads and/or within-session rereads	(RRI_1) Many consecutive rereading due to content complexity
	High values of between-session rereads	(RRI_2) Many distant rereading,due to low memorability
Stop & resume	High values of final reading stops	(SRI_1) Permanently stop reading the course because of loss of interest, poor readability and/or high complexity
	High values of reading halts (non final stops)	(SRI_2) Reading halts due to content complexity
	High values of nonlinear resume; High values of resume on distant chapters	(SRI_3) Resuming on previous on future distant chapters due to content complexity, low memorability and/or bad structuring

Table 8.5 Issue detection using indicator value

	Stickiness		*Navigation*			*Rereading*		*Stop & resume*			*ALL*
Cours	SI_1	SI_2	NI_1	NI_2	NI_3	RRI_1	RRI_2	SRI_1	SRI_2	SRI_3	
TCP	3	1	2	3	0	1	2	1	0	1	14
Javascript	1	1	1	1	0	1	0	1	0	2	8
Symfony	3	1	2	1	1	2	1	2	1	1	15
Bootstrap	1	1	1	2	1	2	2	0	1	2	13

Table 8.6 Main reading issues detected on four courses

After gathering basic demographic characteristics of the students, we presented them a paper-based questionnaire that listed for each class of indicators the issues we assessed, supplemented with summary explanations. We asked the students to carefully examine the marked issues and to rate their effectiveness using five-points *Likert scales* (1=absolutely disagree, 5=absolutely agree).

8.5.2 Results

	Descriptive statistics*			Student t-test** results		
	Mean	*SD*	*Median*	*t*	*df*	*p*
Stickiness issues						
SI_1	4.04	0.96	4.00	−0.57	24	0.57
SI_2	3.15	1.26	3.00	−0.81	24	0.43
Navigation issues						
NI_1	3.58	0.86	4.00	−1.32	24	0.20
NI_2	3.50	1.03	4.00	−1.18	24	0.25
NI_3	3.42	1.03	4.00	−1.28	24	0.21
Rereading issues						
RRI_1	3.96	1.04	4.00	−1.88	24	0.07
RRI_2	3.39	1.02	3.50	−0.33	24	0.75
Stop & resume issues						
SRI_1	3.73	1.00	4.00	−1.35	24	0.19
SRI_2	3.46	0.95	4.00	−1.54	24	0.13
SRI_3	3.31	1.12	3.00	−0.74	24	0.47

$^{*}Scales : 1 = very\ low\ to\ 5 = very\ high$
$^{**}group\ 1 : female\ participants\ (n = 10); group\ 2 : male\ participants (n = 16)$

Table 8.7 Statistics about learners' rating of the effectiveness of the issues, and *t-test* results based on gender difference

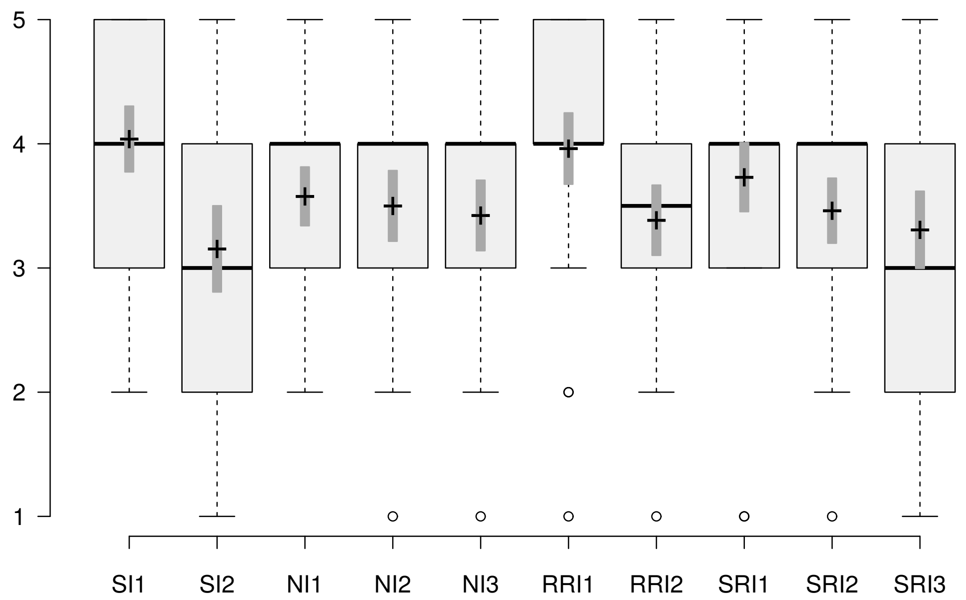


Fig. 8.7 Learners' rating of the effectiveness of the issues (1 = very low, 5 = very high)

The descriptive statistics of the results are shown on Table 8.7 and Figure 8.7. To examine the difference in ratings between male and female participants, we conducted an independent-samples *t-test* analysis (with the significance level for the mean variation set at $p < 0.05$). The results (the last three columns of Table 8.7) show no statistically significant difference between the two groups (female vs. male). There is a clear difference in the rating distribution for the different indicators in terms of skewness.

All the issues had good rating values, with a median that is superior to the neutral point of 3 except for SRI_3 which median is equal to the neutral point. This suggests that the participating students acknowledged that most of the detected issues correspond to real problems within the course that may hamper easily reading it and understanding its ideas. Issues related to course element popularity ($SI1$) and content complexity (RRI_1, SRI_1 and NI_1) were the most highly rated.

	SI_2	NI_1	NI_2	NI_3	RRI_1	RRI_2	SRI_1	SRI_2	SRI_3
SI_1	-0.30	-0.13	-0.02	0.23	0.01	-0.18	-0.19	0.16	-0.46^{*}
SI_2		0.04	0.28	0.08	-0.18	-0.17	-0.09	-0.50^{**}	0.08
NI_1			0.52^{**}	0.21	0.30	0.24	0.37	0.15	0.39^{*}
NI_2				0.48^{*}	0.35	0.38	0.36	0.20	0.31
NI_3					0.20	0.22	-0.01	0.24	0.02
RRI_1						0.70^{***}	0.64^{***}	0.55^{**}	0.42^{*}
RRI_2							0.57^{**}	0.51	0.24
SRI_1								0.64^{***}	0.54^{**}
SRI_2									0.35

Note. $^{*}p < .05,^{**}p < .01,^{***}p < .001$

Table 8.8 Inter-correlations (Spearman) among learners' ratings of the detected issues

To further investigate the results, we used Pearson correlations between the issue ratings to determine if any association existed between them. The results that are shown on Table 8.8 reveal many significant relations. There are moderate negative correlations between score of stickiness issues and issues related to reading halts and nonlinear resumes (SI_1 and SRI_3 with $r = -0.46, p < .05$; SI_2 and SRI_2 with $r = -0.50, p < .01$). This suggests that the failure to attract learners' interest is also reflected by the tendency of learners to stop or to momentously interrupt reading. There are also moderate to strong positive correlations between rereading and reading stops and nonlinear resume issues (RRI_1 and SRI_2 with $r = 0.64, p < .001$; RRI_1 and SRI_2 with $r = 0.55, p < .01$; RRI_1 and SRI_3 with $r = 0.64, p < .05$; and RRI_2 and SRI_1 with $r = 0.57, p < .001$). The majority of these issues reflect the difficulty for learners to grasp the meaning. Positive moderate inter-correlations within class issues exist: issues related to stops and resume (SRI_1 and SRI_2 with $r = 0.64, p < .001$; SRI_1 and SRI_3 with $r = 0.54, p < .01$), navigation issues (NI_1 and NI_2 with $r = 0.52, p < .01$; NI_2 and NI_3 with $r = 0.47, p < .05$), and rereading issues (RRI_1 and RRI_2 with $r = 0.69, p < .001$). Finally, we found a weak correlation between two issues (NI_1 and SRI_3 with $r = 0.39, p < .05$), both of them reflect possible disorientation due to the course structuring.

8.6 Study 5 – evaluation of the dashboard

8.6.1 Protocol

This study, conducted from April 5th to April 11th, 2017, aimed to evaluate the dashboard interface in terms of usability and acceptance. The authors first received their personal credentials for accessing the tool running on their courses. They were then instructed to access the interface, to complete the usability experiment and then to fill an acceptance questionnaire.

8.6.1.1 Usability experiment

Usability assessment is a means of ensuring that an interactive system is adapted to users and their tasks and that there are no negative consequences of its use. Evaluating interactive system usability is a fundamental step in the user-centered design process. Its goal is to assess the degree to which the system is effective (i.e., how well the system's performances meet the tasks for which it was designed), efficient (i.e., how much resources such as time or effort is required to use the system in order to achieve tasks for which the system was design), and favors positive attitudes and responses from the intended users (Bevan, 2001).

#	Task
T1	Follow the guided tour
T2	Find a specific indicator value for a given chapter
T3	Find a specific issue, review it and mark it as not an actual problem.
T4	Select an issue, add the suggestion as a task, modify the task and then mark it as done.
T5	Display all the available indicators and issues to find chapters with the most issues.

Table 8.9 Authors' tasks

In this study, we aimed at evaluating the usability of the dashboard using a task-based experiment. The authors were asked to accomplish the set of tasks, described on Table 8.9, on their course dashboard. The task $T1$ consisted in obtaining assistance with the use of the tool. The tasks $T2$, $T3$ and $T4$ were related to performing diverse instructional design activities, by using features such as visualizing data, interpreting the analysis results, and taking relevant decisions. To perform the task $T2$, the author must scan the available data looking for a specific information. In the task $T3$, the author had to examine the source of a detected problem and then decide whether an intervention is appropriate. During the task $T4$, the author had to consider the suggestions provided before using them for designing and implementing appropriate corrective actions. The last task $T5$ involved some of the tool's advanced features to plan and execute complex pedagogical decisions.

The task list was integrated into the dashboard as a non-modal floating window that displays the tasks one-by-one in sequence and that collects the authors' answers. All the authors' actions were recorded. The experiment took an average time of 11 minutes.

8.6.1.2 Acceptance evaluation

At the end of their task-based sessions, authors were invited to describe their willingness to adopt the dashboard in their revision work by answering an online questionnaire. We relied on the *Technology Acceptance Model* (TAM) (Davis 1989), Davis (1989), a theoretical model that helps to predict user adoption of information technology. Two measures of acceptance are posited by TAM: *Perceived Usefulness*

(*PU*), and *Perceived Ease of use* (PE). Perceived usefulness is "the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organizational context", and perceived ease of use reflects "the degree to which the prospective user expects the target system to be free of effort" (Davis, 1989, p. 985). This model is among the most widely used in investigating technology acceptance, and has been validated by many empirical studies in the context of e-learning, and in educational research (e.g., (Cheung and Vogel, 2013)). A statistical meta-analysis of TAM applied to 88 published studies showed it to be valid and robust (King and He, 2006).

	Perceived Ease of Use (PE)
Q1	Learning to use CoReaDa would be easy for me
Q2	I would find it easy to get CoReaDa to revise my course
Q3	My interaction with CoReaDa would be clear and understandable
Q4	I would find CoReaDa to be flexible to interact with
Q5	It would be easy for me to become skillful at using CoReaDa
Q6	I would find CoReaDa easy to use
	Perceived Usefulness (PU)
Q7	Using CoReaDa to revise my course would enable me to accomplish tasks more quick
Q8	Using CoReaDa would improve my revision performance
Q9	Using CoReaDa to revise my courses would increase my productivity
Q10	Using CoReaDa would enhance my effectiveness on course revision
Q11	Using CoReaDa would make it easier to revise my courses
Q12	I would find CoReaDa useful in revising my courses

Table 8.10 TAM questionnaire items

Being correlated to predicted future usage, these two measures can reflect the authors' attitudes towards adopting the dashboard in their work. Consequently, based on TAM, we designed the Acceptance Questionnaire (Table 8.10), the online version of which was provided to the authors for completion. They were asked to assess their level of agreement with each of the statements, using a 7-point Likert scale, ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The questionnaire necessitated an average time of 6 minutes to complete.

8.6.2 Results

8.6.2.1 Dashboard usability

Using the logs collected during the tasks-based experiment, we computed four performance metrics (results on Table 8.11):

1. the *success ratio* gives the ratio of tasks that were achieved successfully;
2. the *average clicks* metric gives the average number of clicks that were performed to accomplish the task;
3. the *average erroneous clicks* is the number of clicks that cannot help the author successfully do the task; and

4. the *average time in seconds* is the mean time spent by authors doing the task.

Different successful paths (in terms of click sequences and associated times) can be followed to achieve a given task. Instead of using reference values, we analyzed the results in absolute terms regardless the underlying paths, since our objective is to evaluate whether or not authors were able to quickly and effectively use the dashboard from the first attempt.

	Success ratio	Average #clicks	Average #erroneous clicks	Average time (sec.)
T1	100%	20	0	171
T2	100%	6	0.7	36
T3	100%	4.3	1.1	27
T4	87%	7	1.6	43
T5	75%	13	3.1	89

Used metrics: Success ratio, Average number of clicks (*avg. #clicks*), Average number of erroneous clicks (*avg. #err.clicks*) and Average time spent in seconds (*avg. time (sec.)*)

Table 8.11 Performance metrics computed from the tasks results

The results show that the tasks that involve options available by default on the interface ($T1$, $T2$, and $T3$) are performed easily, quickly and successfully. The guided visit ($T1$) contains 18 mini-pages organized in sequence, and thus requires a significant amount of time with an average of 8.5 seconds per mini-page. The authors pointed out the capital gain of this stage for rapidly learning to use the dashboard, which comforts our choice to prompt the guided visit automatically at the dashboard load. Tasks $T2$ and $T3$ are related to the use of the main features of the tool and require an average time of about half a minute to be accomplished, with an average of one erroneous manipulation click. The task $T4$ implies the use of the task manager and takes less than one minute to completion, with one failure (an author deleted a task instead of marking it as *done*). The task $T5$ required the use of advanced/hidden features of the tool (activating an advanced view) since the authors needed to figure out and locate the corresponding options. Two authors were not able to correctly find the chapter with more issues, they both provided chapters with fewer issues than the expected one. This task, despite its complexity, took an average of less than one minute and a half to be accomplished.

8.6.2.2 Dashboard acceptance

The TAM scale ranges from 1 (strongly disagree) to 7 (strongly agree), with 4 (neither agree nor disagree) as the neutral midpoint. A score above 4 indicates that the respondent agrees to some extent with the corresponding statement. The descriptive statistics of the results on Table 8.12 show that the mean scores for PE were between 4.38 and 5.25, suggesting that a significant number of respondents had no major technical concerns when using the tool. They also reveal that the respondents were not very dispersed around their mean scores on individual statements (standard deviations between 1.49 and 1.92). The mean scores of the statements used to measure PU were between 4.75 and 5.50 with a standard deviation ranging from 1.31 to 1.83. This shows that most respondents tend to perceive the dashboard as having a rather positive impact in terms of effort, time and performance in conducting course reading analysis and revision tasks.

Perceived Ease of Use			Perceived Usefulness		
Item	*Mean**	*SD*	*Item*	*Mean**	*SD*
Q1	4.38	1.92	*Q7*	4.75	1.83
Q2	5.00	1.60	*Q8*	5.00	1.69
Q3	5.00	1.51	*Q9*	4.75	1.67
Q4	4.88	1.55	*Q10*	5.13	1.81
Q5	5.00	1.51	*Q11*	5.25	1.49
Q6	5.25	1.49	*Q12*	5.50	1.31
PE	4.91	1.62	*PU*	5.06	1.49

**Scale: 1=Strongly disagree to 7=Strongly agree*

Table 8.12 Results of the TAM questionnaire

Items related to the perceived usefulness were combined into a composite variable PU ($mean = 5.06, std = 1.62$) and the items related to the perceived ease of use were combined into a composite variable PE ($mean = 4.91, std = 1.49$). A one-sample t-test (with the midpoint 4 as test value) for each of these variables indicated that the mean was significantly higher than the neutral midpoint (PU: $t = 1.736, df = 7, p = .125; PE : t = 1.736, df = 7, p = .125$).

These results reflect a good authors' opinion about the studied aspects. Indeed, 77% of the responses on the perceived usefulness of the dashboard were positive. This indicates that the dashboard is found convenient by authors for easily, quickly and effectively planning the revision of their courses. Moreover, 72% of the responses expressed a positive level of agreement of the perceived ease of use. This indicates that: (1) they found the tool easy to learn, to master and to use in a concise and convenient way; (2) using the tool could contribute to improving their performances since they have to deploy little effort to use it.

Within the comment section, five authors expressed their willingness to see such functionalities within their private space on the platform. An author said that this would help authors integrate course revision to their agenda as a routine. Another author, although having done successfully the experiments, suggested simplifying the interface even more, for a better user experience.

8.7 Discussion

The proposed method for delimiting learners' reading sessions by computing page per page thresholds is grounded on data that represent learners' interactions with course elements and that take into account each page characteristics. The resulting thresholds are dynamic since their values are recalculated each time new reading actions are logged. This allows their automatic updating to (1) adjust their values to incoming reading data, and to (2) take into account any evolution of the courses like pages restructuring and content update. According to the evaluation results, the proposed method allows to better represent learners reading, and to fit the expected statistical behavior of real sessions. The results also consolidated our statement that the use of fixed-value methods (for session duration or for page stay time) may not be appropriate for educational websites. Indeed, unique threshold values are not suitable for considering neither the specificity of the courses nor the content of their different pages. Nevertheless, it would be interesting to (1) further verify the method capabilities by defining more accurate metrics related to element complexity, and (2) to compare the deduced sessions compliance with the learners real ones.

Modeling reading activity using sessions allowed us to define indicators that describe the underlying process from behavioral perspectives. We used reading indicators not only to describe the reading behavior of learners but also as clues to alert about the comprehension problems that these learners might encounter. The list of reading indicators that have been evaluated with course authors were found quite relevant and expressive (more than 60% of positive ratings). The choice of these indicators is motivated by their robustness and popularity in online behavior analysis. Nevertheless, it is far from exhaustive: other metrics need to be tested and evaluated. It is important to identify a robust methodology to elucidate all factors of behavior that can be observed and/or calculated, and which can provide information on the level of understanding, or more directly, the quality of the content read.

These indicators serve to detect reading issues for which revision actions are associated. This process empowers authors with a valuable amount of knowledge related to course improvement possibilities. Sometimes, this knowledge confirms their expectations (more than 50% of the expected issues were indeed detected); other times, it invalidates some beliefs (about 50% of authors' expectations were not real). Often, this makes authors acquire new insights (almost 80% of the detected issues were not expected). Moreover, 63% of the provided suggestions were found useful and capable to resolve the reported issues. Not surprisingly, the majority of the cases where authors found the suggestion inappropriate are related to issues that were not found relevant. The study we conducted with learners showed that this approach and its subsequent implementations offer an effective way of reflecting possible reading problems related to the structure and content of the course. Such information can make the author aware of the difficulties of comprehension encountered by their learners, and encourage them to think about how to adjust their courses to make them easier to read and understand.

The dashboard was found quite intuitive and relatively easy to use by the participating authors. This is reflected experimentally by the task-based study where the authors succeeded in using it from the very first attempt. This is also supported by the acceptance study. The TAM model posits that both perceived usefulness and ease of use are good predictors to the user attitude and desirability towards using the system. This attitude is also a major predictor of whether or not the user will actually use it. Based on the study results and authors' comments, the authors not only present a good attitude towards the use of the dashboard, but also intend to use it. Yet, as stated by Park and Jo (2015), a visualization tool is only useful when it generates the intended changes in the users. Although learning analytics dashboards are gaining in popularity in recent years and that their concept is intuitively attractive, there have numerous studies pointing out their limitations and possible pitfalls when it comes to the complex set of skills that are part of learning (e.g. (Corrin and de Barba, 2015; Teasley, 2017)). More globally, for the adoption of such tools as part of a common educational toolbox, it is necessary to conduct more studies to assess the long-term impact of LA dashboards. Moreover, in order to design these dashboards in accordance with practices of educational psychology, more large-scale empirical studies are required to provide more precise design principles (Klerkx et al., 2014; Verbert et al., 2014).

Despite this encouraging direct and indirect feedback, we must stress out that this study has some limits. It only involved courses in informal settings, delivered through a self-directed learning platform. Moreover, the first part related to the relevance of the indicators involved 125 authors among which only 8 authors participated in the subsequent stages of the experiment. Nielsen (2000) argues that five users are enough for reliable usability testing. However, to be able to generalize our findings, we think that broader studies that involve more course authors from different learning settings - formal, informal and blended are mandatory.

Conclusion

It is important to remember that educational software, like textbooks, is only one tool in the learning process. Neither can be a substitute for well-trained teachers, leadership, and parental involvement.

Keith Krueger

9 General conclusion

The research we presented in this thesis aimed to provide means and tools for exploiting reading traces in the perspective of providing a better understanding of learners' reading behavior, and unveiling a knowledge that would improve the authors' awareness about their course consumption. Our main research goal was:

Research aim

To investigate the use of reading analysis on learners' traces in order to identify their comprehension issues and to assist authors in improving their contents accordingly.

In this chapter, we look back at the presented contributions and tie them together before concluding and providing some perspectives for the research presented in the thesis.

9.1 Summary of the contributions

In line with our research objective, we have formulated a number of proposals aimed at helping to answer our various research questions.

1. Generic usage-based document reengineering model

Research question answered: (*RQ*1) — *What is the general conceptual framework for supporting authors to improve their courses and solve learners' understanding issues?*

Related research objective:

(*RO*1.1) *To define a methodology for analyzing reading usages in order to identify understanding problems and support authors in solving those problems.*

The model proposed (§5.1.2) aims to conceptualize the process of instrumenting digital usage data to operate reengineering tasks on the documents, which corresponds to the first research objective (*RO*1.1). The model provides a high-level framework to describe methodological processes that help authors collect feedback from readers and use it as a means for evolving their documents.

2. Factors of document structures that impact the level of comprehension, and the associated issues

Research question answered: *RQ*2 – *What are those understanding issues?*

Related research objectives:

(*RO*2.1) *Identify the most important document properties that contribute to the level of ease of understanding afforded by these documents.*

(*RO*2.2) *To identify the reading issues that may arise from these properties.*

The comprehension factors that fall within the scope of this thesis are related to the different structures that make up a document. Therefore, we first presented a document model that allowed us to study its surface and conceptual structures (§5.1.3). From the surface structure, we identified the factors originated from the physical and logical level of document representation. From the conceptual structure, we investigated the important factors for comprehension related to the readability and meaning levels (from resp. the microstructure and macrostructure perspective) of the document. We have studied these different factors of document structures in order to identify the problems that readers may encounter in relation to these factors.

3. A model of revision, and a taxonomy of revision actions associated to the reading issues related to the document structures

Research question answered: *RQ*3 – *According to those understanding issues, what remediation can be proposed to authors?*

Related research objectives:

(*RO*3.1) *To design appropriate suggestions for solving these understanding issues.*

(*RO*3.2) *To design appropriate suggestions based on the revision actions for answering the comprehension issues.*

We described a model of the revision activity and elaborated a taxonomy of revision primitives that include the various enrichment, editing, and restructuring actions that an author can operate on his document (§5.2.2). We then used these primitives to associate different revision actions with understanding problems that have their roots in the document's structures. From these actions, we have produced revision suggestions that aim to facilitate the author's attempts to improve both the parts and the aspects of the document that are causing difficulties for readers to have a more complete and correct understanding (§5.3).

4. Reading analytics approach for course revision

Research question answered: (*RQ*4) — *How is it possible to detect those issues and associate suitable remediation actions?*

Related research objective:

(*RO*4.1) *To elaborate a reading analytics approach for reengineering courses based on learners' usages.*

The proposed course revision approach instantiates the reengineering model for educational context (§6.1.2). It makes use of learners' reading data as recorded in their traces to provide authors with insight into their documents consumption by computing *reading indicators* and detecting *reading issues*; as well as guidance to make informed decisions on how to improve their documents - from slight clarifications to profound rewriting, through *revision suggestions*.

The reading analytics approach is data-driven, using the tracked data of learners. It is non-intrusive as it does not interfere with the learner's activity and fully based on applying analytics on the data collected from the learning environment. One inconvenient of such an approach is that only indirect feedback from learners is used in the analysis. The integration of learners' opinions and comments could be very effective in better identifying learners' needs and expectations. A more holistic approach to user data analysis is to design multi-source collection mechanisms and to associate them with triangulation and inference methods that would produce much more accurate data.

5. Reading sessions and their computation algorithm

Research question answered: *RQ*4 – *How is it possible to detect understanding issues from learners' traces and associate them appropriate remediation actions?*

Related research objective:

(*RO*4.2) *To conceive a reading activity model allowing the analysis of learners' traces.*

The concept of reading session (§6.2) allows modeling reading activity by denoting learners active reading periods. We proposed a new method for delimiting learners' activity sessions by computing page per page thresholds. The proposed method is grounded on data that represent learners' interactions with course elements and that take into account each page characteristics. The resulting thresholds are dynamic since their values are recalculated each time new reading actions are logged. This allows their automatic updating to (1) adjust their values to incoming reading data, and to (2) take into account any evolution of the courses like pages restructuring and content update.

According to the evaluation results (§8.2), the method allows to better simulate learners reading, and to fit the expected statistical behavior of real sessions. The results also consolidated our statement that the use of fixed-value methods (for session duration or for page stay time) may not be appropriate for educational websites. Indeed, unique threshold values are not suitable for considering neither the specificity of the courses nor the content of their different pages.

6. A taxonomy of session-based reading indicators

Research question answered: *RQ4 – How is it possible to detect those issues and associate suitable remediation actions?*

Related research objective:

(*RO4.3*) *To build an informed synthesis of reading activities using indicators.*

Modeling reading activity using sessions allowed us to define indicators that describe the underlying process from behavioral perspectives. We have proposed several reading indicators (§6.3) that are constructed and calculated using data about learners' reading sessions. Their aim was to better represent and explain how learners consume and assimilate the content offered on the learning platform.

The relevance of these indicators for document reengineering was evaluated with course authors. The results show that participants mostly agreed that the classes of indicators are relevant for analyzing course reading. Globally the four classes of indicators were deemed useful: the authors acknowledged the usefulness of the proposed indicators and confirmed their relevance to guide them in improving their courses.

7. Indicator-based detection of comprehension issues, and revision suggestions

Research question answered: *RQ4 – How is it possible to detect those issues and associate suitable remediation actions?*

Related research objectives:

(*RO4.4*) *To build a strategy based on these indicators to detect the reading issues and to suggest remediation actions.*

We used reading indicators not only to describe the reading behavior of learners, but also to alert about the comprehension problems that these learners might encounter.

We introduced a mechanism to analyze the different values of each indicator on the different document elements and to detect the outliers values (§6.4). The element on which abnormal behavior has been observed is considered to have a construction imbalance induced by factors, related to the different structures of the document, that have an impact on the level of comprehension. For each reading issue that can be caused by a specific indicator, we associate the corresponding reengineering actions (§§6.4.3 to 6.4.6). We translate the set of actions using a more human understandable suggestion.

The study we conducted with learners (§8.5) showed that this approach and its subsequent implementations offer an effective way of reflecting possible reading problems related to the structure and content of the course. It can make the author aware of the difficulties of comprehension encountered by their learners, and encourage them to think about how to adjust their courses to make them easier to read and understand.

8. CoReaDa, an analytics and assistance learning dashboard

> **Research question answered**: *RQ*5 – *What kind of systems and tools can effectively support authors for course improvement?*
>
> **Related research objective**:
>
> (*RO*5.1) *To identify functional and design requirements for implementing assistive systems that present the information timely and appropriately.*
>
> (*RO*5.2) *To implement these requirements through a functional prototype for course reading analysis, comprehension issues detection and remediation actions taking.*

CoReaDa, the "Course Reading Dashboard", is an implementation of our different proposals for the analysis and the revision of online courses reading (chapter 7). For its conception, we have drawn on the existing literature to identify the requirements to which such a tool must respond, in terms of functionality and design. We then co-designed with course authors the user interface, implemented the functionalities and instantiated the dashboard for courses delivered on a major European e-learning platform.

As reflected by the task-based experiment (§8.6.1.1), the dashboard was found quite intuitive and easy to use, and the authors managed to use it correctly from the very first attempt. This is also supported by the acceptance study (§8.6.1.2). According to the results and authors' comment, not only the authors expose a good attitude to use the dashboard but also, they actually plan to use it.

9. A set of evaluation and validation studies

> **Research question answered**: *RQ*5 – *What kind of systems and tools can effectively support authors for course improvement?*
>
> **Related research objective**:
>
> (*RO*5.1) *To validate the support methods and tools and to evaluate a functional prototype for analyzing course readings, detecting comprehension problems and taking corrective action.*

We evaluated and validated our proposals through a series of studies conducted with online course authors. Working on popular course provider offers the opportunity to conduct these studies in "life-size" configuration. The questions examined were:

- the capabilities of the session identification approach;
- the relevance of the set of indicators for course revision;
- the capabilities of the issues detection and resolution mechanisms;
- the conformance of the detected issues with actual learners' reading ones; and

– the usability and acceptance of the dashboard

The results corroborate the effectiveness of using analytics on learners' logs to provide authors with appropriate dashboards that support them in analyzing reading behavior, detecting improvement opportunities, and performing relevant revisions. The studies we carried, notwithstanding their limits, reveal the deep interest of course authors' to disclose some of the least accessible aspects of learning, related to learners' comprehension while reading and its relation to course quality. The studies results demonstrate at some extent the effectiveness and usefulness of such an approach to support course authors understanding learners' behavior, detecting improvements opportunities and performing the appropriate corrective actions. More broadly, these findings provide confirmatory evidence that the authors feel confident towards being assisted to gain awareness on how to improve their courses to maximize their comprehension.

9.2 Outlook & final reflections

Assuming that relevant and good-quality contents highly impact the success of learning, we elaborated a learning analytics approach and LA tools that exploit logs of learners' reading activity to assist course authors improving the delivered contents. This approach was afterward instantiated upon a major European e-learning platform. Our proposals were based on theoretical background originated from research on document engineering, reading comprehension and content revision, that we apply to the learning analytics field. At the best of our knowledge, the findings of the work previously done in these fields were not explicitly brought to e-learning.

It is important for the learning analytics field to draw on educational research and theories when building applications (Wise et al., 2014). Within the learning community, aligning learning design with learning analysis tools is a key issue that requires a collective effort (Bakharia et al., 2016; Lockyer et al., 2013; Echeverria et al., 2018). This research is a starting point to pave part of the way for further investigation on how reading analytics and learning dashboards can impact course authors in the long run to improve the quality of the learning contents.

There are many potential areas of future work as a follow up of the results achieved during this dissertation. Our first perspective is to carry out large-scale studies in different educational settings, in order to better refine our proposals and confirm our findings. The concept of a session could be further refined by taking into account learner-related aspects, such as the background and the reading pace. This ensures that traces are represented in a way that better reflects the behavior of different categories of learners. Subsequently, we plan to integrate traces of other learning activities (such as video lecture, exercises, etc.), learners profile and assessments data. This would offer a framework that gives awareness and assistance for enhancing not only the quality of course content but also the quality of all the learning pedagogical scenarios and activities.

Regarding reading indicators, we would like to work on defining more elaborated metrics, or even define several levels of indicators, where some would be based on the combination of others. This would allow learners' reading to be more effectively characterized and more data on their needs to be derived. To this end, further experiments with both authors and learners must be carried out, including pre-tests and post-tests to better estimate which indicators are most appropriate and correlated with the learners' level of understanding and even their actual learning performance.

In the sense of visual reading analytics with CoReaDa, a possible future step would be to design and implement different and customizable visualizations for a more in-depth analysis of reading activity. We would also like to integrate editing tools to offer authors the opportunity to redesign their courses within the platform. This would allow the fourth level of assistance to be integrated, namely the automatic generation of revised versions of the course based on the results of the analysis. A highly interesting initiative would be to develop a modular and common framework of indicators and visualization that could be easily adapted to different courses and platforms, thereby significantly improving interoperability.

Technology is fundamentally changing the educational environment for today's learners. Ultimately, the goal of education and any training is to provide the skills and knowledge that learners are able to mobilize in the right situations. One of the key questions raised by the use of technology concerns the quality of teaching and its effectiveness in terms of outcome improvement. We strongly believe that when a technology fails to improve the learning experience and its outcomes, then that technology can be regarded as a change, but not as a pedagogical innovation. For it to be effective, investing in technology is not enough: we must also help teachers, instructors, and course authors to be and do better.

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A
Description of the technological stack

R is a language and environment for statistical computing and graphics... R provides a wide variety of statistical (linear and nonlinear modeling, classical statistical tests, time-series analysis, classification, clustering, ...) and graphical techniques, and is highly extensible.

NODE.JS is an open-source, cross-platform JavaScript run-time environment that executes JavaScript code server-side. It uses V8 –a high-performance JavaScript engine designed by Google–as its JavaScript engine, and a C library called LibUV as a platform-independent abstraction layer for handling asynchronous I/O operations. The V8 engine uses an event-driven and non-blocking model to handle concurrency. Its server applications can be created and executed from a command line or Unix Shell. Node.js has a modular-oriented structure. Modules are blocks of code built to accomplish certain tasks. Their functionalities could be standalone or combined with each other in order to achieve many sophisticated operations. In addition to core modules, a lot of third-party modules exist that extend the functionalities of Node.js. Node.js' package ecosystem, *npm*, is the largest ecosystem of open source libraries in the world.

EXPRESS.JS (or simply *Express*) is a free and open-source web framework under the MIT License. Express is a minimal and flexible Node.js web application framework that provides a robust set of features for APIs, web and mobile applications. Express is responsible for passing data from the backend to the front-end and vice versa. It provides a host of powerful features to efficiently control the state of an application by managing and using routes, requests, views, templates, partials and more.

ANGULAR is an open-source JavaScript framework that exclusively runs client-side and is supported on all modern web browsers. Like Node.js, Angular is originally developed by Google in 2010; Angular 2.0 was released in 2014. It uses the MVC programming paradigm to isolate the application logics from the user interface. One of its purposes is to move some responsibilities from the server-side to the client-side, to where they are actually better suited. It uses Plain Old JavaScript Objects (POO) which improves the usage of an Object and makes it easier to add or change properties. Angular is feature-rich, with built-in solutions for tasks like two-way data-binding (the model updates the view on changes, automatically, and vice versa), form validation and much more. In addition, a module system and a mechanism for dependency injection are integrated. There is no additional template engine utilized, rather HTML itself is extended to perform templating. Due to favoring declarative code over an imperative code, the framework has a very high level of abstraction.

MongoDB is an open-source, cross-platform, NoSQL, non-relational, and document-oriented database management system. Considering the huge datasets, we selected this database system which is one of the most popular for Big Data, providing high-performance queries and supports spatial query from very large datasets. It uses JSON like documents instead of a table based architecture. Due to its scalability and flexibility in a structural format for storage, MongoDB is suitable for storing educational data.

D3.js (or just D3 for Data-Driven Documents) is a powerful JavaScript library for producing dynamic and interactive data visualizations. It makes use of the widely implemented SVG, HTML5, and CSS standards. It allows generating visualizations by taking advantage of imperative programming style and easily integrating them with other JavaScript libraries. D3 makes it also possible to bind a large amount of data to a complex visualization. It allows great control over the final visual result with compatibility, debugging and performance benefits.

JSON is an open-standard file format well suited to data that needs to be both human and machine readable. It is presented as a low-overhead alternative to `XML`, `OGDL`, `YAML` and `CSV` formats that support creation, reading and decoding in the real-world contexts in which they are commonly used. It is a language-independent data format derived from `JavaScript`. `JSON` data objects consist of attribute-value pairs and array data types (or any other serializable value).

B

Courses and questionnaires used in studies 2 & 3

Invitation and demographic information

Instructions

Dear Author,
Thank you for agreeing to participate in this evaluation of the CoReaDa project. This evaluation aims to validate theoretical foundations and the functional aspects of the application. During this experiment, you will be asked to answer a set of questions and make some manipulations on the CoReadDa platform. Do not worry if you have not yet had the time or the opportunity to know the platform, we will start by introducing you.
Therefore, please access the dashboard of your course "TCP" on another window (or tab) of your browser as explained in our previous mail.

Consent

By participating in this study, you accept that anonymous statistics on the data collected on this platform can be used in various scientific works (communications, theses, etc.).

Personal Information

GENDER – What is your gender?

- ◯ Male
- ◯ Female

AGE – What is your age?

- ◯ Under 19 years old
- ◯ 19 - 25
- ◯ 25 - 40
- ◯ 41 - 59
- ◯ 60 years old or older

EDUCATION – What is the highest degree or level of school you have completed? (If you're currently enrolled in school, please indicate the highest degree you have received.)

- ◯ Less than a high school degree
- ◯ High school degree or equivalent

◯ Bachelor's degree or equivalent
◯ Master's degree or equivalent
◯ Professional degree or equivalent
◯ Doctorate degree or equivalent

Indicators Relevance Survey

Class of indicators: Stickiness

This class contains indicators that can be used to judge the ability of each course chapter to attract and hold learners interest.

VISITS RATIO this indicator gives for each chapter the percent of the visits from the total that were captured on that chapter.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

READERS RATIO this indicator gives for each chapter the percent of the distinct readers from the total that visited this chapter.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

READING SESSIONS RATIO this indicator gives the ratio of the observed reading sessions of all the readers that contain this chapter.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

READING SPEED this indicator gives for each chapter the average reading speed that the readers use when reading the chapter, expressed in words per minute.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

INTEREST this is a proxy indicator that summarizes the stickiness class indicators.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Class of indicators: Rereading

This class contains indicators that describe how the learners revisit the course chapters.

REREADS RATIO This indicator gives the percent of the returning visits (of the same reader) to the chapter and corresponds to the percent of visits that are actually revisits .
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

WITHIN-SESSION RATIO this indicator gives the percent of the returning visits (of the same reader) to the chapter that occurs within the same reading sessions .
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

BETWEEN-SESSION RATIO this indicator gives the percent of the returning visits (of the same reader) to the chapter that occur in different reading sessions.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Class of indicators: Navigation

This class describes the order of visits of the course chapters. The learner navigation corresponds to his reading path which results from the transitions he made between the visited course chapters (arrivals and departures). A transition is linear when the arrival chapter is located just after the departure chapter in the course outline.

Navigation linearity percent of the navigation cases (from/to this chapter) from/to the previous/next chapter, in a linear way. This corresponds to reading the chapter in a linear way.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Arrival linearity percent of arrivals to this chapter originated from the chapters situated just before this chapter in the structure of the course. The non linearity arrivals correspond thus to arrivals from chapters different than those situated just before this chapter.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Departure linearity percent of departures from this chapter to chapters situated just after this chapter in the structure of the course. The non linearity departures correspond thus to departures to chapters different than those situated just after this chapter.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Future incoming percent of arrivals to this chapter originated from chapters situated after this chapter in the structure of the course.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Past incoming percent of arrivals to this chapter originated from chapters situated before this chapter and the chapter that just precedes in the structure of the course.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Future outgoing percent of departures from this chapter to chapters situated after this chapter in the structure of the course.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Past outgoing percent of departures from this chapter to chapters situated before this chapter and the chapter that just precedes in the structure of the course.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Class of indicators: Stop & resume

This class describes how learners stop the reading activity and how they resume reading the course. The indicators that belong to this class allow to quantify: the interruptions occurred on an element, with or without resumes.

Reading halts percent of the reading sessions terminations that occur on this chapter.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Final stops percent of reading final stops (without resumes) occurred on the chapter
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Resume linearity percent of resumes after reading halt on the chapter that occur on elements different from this one and the following one.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Resume to past after stopping reading on this chapter, this gives the percent of reading resumes that occur on previous chapters.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Resume to future after stopping reading on this chapter, this gives percent of reading resumes that occur on elements far ahead from the current element and

its direct following one.
`Not useful` ◯ ◯ ◯ ◯ ◯ `Very useful`

Titles of the twelve courses of the participating authors

Acronym	*Complete title*
Bootstrap	Prenez en main Bootstrap
Web	Comprendre le Web
Twitter	Animez une communauté Twitter
Adruino	Programmez vos premiers montages avec Arduino
JavaScript	Apprenez à coder avec JavaScript
Ionic	Développez une application mobile multi-plateforme avec Ionic
Ruby	Continuez avec Ruby on Rails
Project	Découvrez les bases de la gestion de projet
TCP	Apprenez le fonctionnement des réseaux TCP/IP
Symfony	Développez votre site web avec le framework Symfony
Startups	Découvrez le monde des start-ups
Github	Gérer son code avec Git et GitHub

Table B.1 Course titles of participating authors

Issues and Suggestions Survey

Part I – Your expectations of existing reading issues

Please enumerate the possible reading issues that you expect on your course, for the different classes of indicators.

STICKINESS according to you, what are the chapters that may present issues related to interest and stickiness (readers count, visit count, reading speed, etc.) ?
....
....

REREADING according to you, what are the chapters that may be often reread, within a single learning session, and through different sessions?
....
....

NAVIGATION according to you, what are the chapters that may be read in a non-linear way? Can detail this in terms of non-linear arrivals and non-linear departures?
....
....

STOP & RESUME according to you, what are the chapters that may cause the reading to stop momentously? definitively? imply non-linear resumes?
....
....

OTHER POSSIBLE READING ISSUES? ....

Part II – Relevance of the detected issues and usefulness of the provided suggestions

In this section, you're invited to discover the detected issues on the course. Please rate the relevance of each of these issues and the usefulness of the associated suggestions. **Important**: please rate the usefulness of the suggestion regardless your rating of the associated issue

Issue 1/14 > Chapter "On récapitule tout de A à Z! ": Very low interest

Explanation This chapter attracts too little interest among readers. The computed normal value of interest computed on this chapter is 9% lower than the others.
This issue is interesting and may trigger revision actions:
`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

Suggestion Review the content of the chapter, its title and its position in the course Does the title of the chapter summarize its content well? If this is not the case, you should think of reformulating this title. If so, can this chapter be merged and integrated elsewhere in the course, or deleted? If that is not possible, you may consider reformulating it. For more information, we recommend that you consult the other indicators related to the chapter's stickiness.
The suggestion is useful for course revision:
`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

A comment or a better revision suggestion? ....

Issue 2/14 > Chapter "On récapitule tout de A à Z ! " : Very few visits

Explanation This chapter is visited 3.3% less than the others.
This issue is interesting and may trigger revision actions:
`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

Suggestion Does the title of the chapter summarize its content well? If this is not the case, you should think of reformulating this title. If so, is this chapter really interesting to the course? If so, can it be merged with another chapter of the course? Otherwise, it may be necessary to delete it and review the course plan.
The suggestion is useful for course revision:
`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

A comment or a better revision suggestion? ....

Issue 3/14 > Chapter "Le service web " : Very few reading sessions contain it

Explanation This chapter is read in 15.5% less reading sessions than the other chapters.
This issue is interesting and may trigger revision actions:
`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

Suggestion Does the title of the chapter summarize its content well? If yes: Is this chapter really interesting in relation to the course? If so, can it be reformulated, or even integrated elsewhere in the course? If not, delete it and review the chapter and course plan. If so, it should be reworded.
The suggestion is useful for course revision:
`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

A comment or a better revision suggestion? ....

Issue 4/14 > Chapter "Le routage " : Too many rereads

Explanation This chapter is on average reread 12% more than the others

This issue is interesting and may trigger revision actions:

`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

Suggestion This chapter should be simpler to read, understand and memorize. You may need to simplify it for example by using a more common or directly defined vocabulary in the content, avoiding dispersion by going to the essential. Please verify the logical sequence of exposed ideas and add examples/analogies to facilitate understanding of the content. You may need also to revise the content for possible updates and corrections. Finally, try to avoid the use of references to this chapter from other ones. You can replace them by reminders.

The suggestion is useful for course revision:

`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

A comment or a better revision suggestion? ....

Issue 5/14 > Chapter "La couche 3 " : Too many within-session rereads

Explanation There are 4.6% more joint readings on this chapter than on the others. Joint re-readings are rereadings made during the same reading session.

This issue is interesting and may trigger revision actions:

`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

Suggestion This chapter should be simpler to read, understand and memorize. You may need to simplify it for example by using a more common or directly defined vocabulary in the content, avoiding dispersion by going to the essential. Please verify the logical sequence of exposed ideas and add examples/analogies to facilitate understanding of the content. You may need also to revise the content for possible updates and corrections. Finally, try to avoid the use of references to this chapter from other ones. You can replace them by reminders.

The suggestion is useful for course revision:

`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

A comment or a better revision suggestion? ....

Issue 6/14 > Chapter "Le routage " : Too many between-session rereads

Explanation There is 5.6% more rereads in different sessions on this chapter than on the others.

This issue is interesting and may trigger revision actions:

`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

Suggestion This chapter is probably difficult to memorize or contains elements that are prerequisites to reading other chapter (s). If so, you may need to restructure the course to avoid phenomenon these between-session rereads. For example, you can consider moving the chapter to a more appropriate place in the plan. Try to avoid the use of references to this chapter from other ones. You can replace them by reminders.

The suggestion is useful for course revision:
Strongly disagree ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strongly agree

A comment or a better revision suggestion? ....

Issue 7/14 > Chapter "Le service DHCP " : Too many non linear navigation to/from this chapter

Explanation 35.55% of the chapters read just before / after are not those provided in the course plan (they are not direct neighbors).
This issue is interesting and may trigger revision actions:
Strongly disagree ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strongly agree

Suggestion This non-linear reading of a chapter typically occurs when the chapter is poorly positioned in the course structure. It may also be due to the fact that this chapter is a prerequisite for other chapters and/or that other chapters are prerequisites for it. In the two cases, consider moving the chapter to a more appropriate place. Also, think to delete some references to/from distant chapters from/to this chapter and replace them with quick reminders. For more information, we recommend that you refer to the specific indicators for repeat readings.
The suggestion is useful for course revision:
Strongly disagree ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strongly agree

A comment or a better revision suggestion? ....

Issue 8/14 > Chapter "Le service DHCP " : Too many non linear arrivals

Explanation In 63.34% of the cases, the chapter read before it is not the chapter that precedes it directly in the course plan. The Top3 of the chapters most often read before this one is:
1. Chapter 14: On récapitule tout de A à Z! 36.7%
2. Chapter 16: Le service DNS 16.3%
3. Chapter 17: Le service web 9.7%
This issue is interesting and may trigger revision actions:
Strongly disagree ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strongly agree

Suggestion This chapter may be an important prerequisite for several other remote chapters. If so, please consider restructuring the course to reflect this (moving this chapter, bringing other chapters in the direct vicinity of this chapter)? It is also possible that there are several references in non-neighboring chapters to this chapter, and/or this chapter contains references to non-neighboring chapters. In any case, it may be worthwhile to include reminders.
The suggestion is useful for course revision:
Strongly disagree ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strongly agree

A comment or a better revision suggestion? ....

Issue 9/14 > Chapter "Le service DHCP " : Too many non linear arrivals from past

Explanation In 37.34% of the cases, the chapter read before this one is upstream of the previous chapter in the course plan. The *Top3* of the chapters read just

before this chapter is:
1. Chapter 11: C'est quoi, une application ? 6.4%
2. Chapter 9 : Le routage 6.3%
3. Chapter 13: La NAT et le port forwarding 5.9%
This issue is interesting and may trigger revision actions:
`Strongly disagree` ○ ○ ○ ○ ○ ○ ○ `Strongly agree`

Suggestion This type of navigation typically occurs when the chapter is poorly positioned in the course structure. It is probably due to the fact that this chapter is a prerequisite for other chapters. Consider moving the chapter to a more appropriate place. Also, think to delete some references to/from distant chapters from/to this chapter and replace them with quick reminders. For more information, we recommend that you refer to the specific indicators for repeat readings.
The suggestion is useful for course revision:
`Strongly disagree` ○ ○ ○ ○ ○ ○ ○ `Strongly agree`

A comment or a better revision suggestion? ....

Issue 10/14 > Chapter "Les autres protocoles" : Too many non linear departures

Explanation In 56.53% of cases, the chapter read after this chapter is not the one that follows it in the course plan. The chapters most often read after this chapter are in order:
1. Chapter 11: C'est quoi, une application ? 43.5%
2. Chapter 9 : Le routage 25.2%
3. Chapter 7 : La couche 3 7.2%
This issue is interesting and may trigger revision actions:
`Strongly disagree` ○ ○ ○ ○ ○ ○ ○ `Strongly agree`

Suggestion This phenomenon can occur when the understanding of this chapter requires information located on distant chapters. In this case, the course needs to be restructured (moving this chapter, bringing other chapters in the direct vicinity of this chapter)? If this chapter contains several references to remote chapters, can these chapters be partly or not deleted by adding a reminder of the necessary notions? For more information, we recommend that you refer to the specific indicators related to repeat playback.
The suggestion is useful for course revision:
`Strongly disagree` ○ ○ ○ ○ ○ ○ ○ `Strongly agree`

A comment or a better revision suggestion? ....

Issue 11/14 > Chapter "Les autres protocoles" : Too many non departures to past

Explanation In 45.02% of the cases, the chapter read after this chapter is placed before this one in the course plan. The Top3 of the chapters read just after this chapters are:
1. Chapter 9 : Le routage 25.2%
2. Chapter 7 : La couche 3 7.2%
3. Chapter 8 : Découpage d' une plage d'adresses 4.3%

This issue is interesting and may trigger revision actions:
Strongly disagree ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strongly agree

Suggestion Probably this chapter makes use of notions previously seen but not fully understood. If so, you can rewrite the chapters containing these concepts by:
- simplifying it for example by using a more common or directly defined vocabulary in the content, and avoiding dispersion by going to the essential
- verifying the logical sequence of the remarks
- adding examples / analogies to facilitate understanding
- reviewing its contents for possible updating, possible corrections.
There may also be references in chapters to this chapter. If so, it should be considered to remove some of them. In all cases, it may be worthwhile to include reminders.
The suggestion is useful for course revision:
Strongly disagree ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strongly agree

A comment or a better revision suggestion? ....

Issue 12/14 > Chapter "L'histoire d'Internet ": too many reading session stops

Explanation 16.16% of reading sessions end on this chapter.
This issue is interesting and may trigger revision actions:
Strongly disagree ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strongly agree

Suggestion This chapter is likely difficult to read and to understand. You may need to further simplify it for example by using a more common or directly defined vocabulary in the content, avoiding dispersion by going to the essential. You need also to verify the logical sequence of the exposed ideas, and to add examples/analogies to facilitate understanding. Please review the content for possible updates and corrections Add references to other chapters and links to external resources to facilitate the understanding of the chapter.
The suggestion is useful for course revision:
Strongly disagree ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strongly agree

A comment or a better revision suggestion? ....

Issue 13/14 > Chapter "L'histoire d'Internet ": too many final reading stops

Explanation 21.08% of final stops of reading (leaving the course) occurred on this chapter.
This issue is interesting and may trigger revision actions:
Strongly disagree ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strongly agree

Suggestion This chapter is likely difficult to read and to understand. You may need to further simplify it for example by using a more common or directly defined vocabulary in the content, avoiding dispersion by going to the essential. You need also to verify the logical sequence of the exposed ideas, and to add examples/analogies to facilitate understanding. Please review the content for possible updates and corrections Add references to other chapters and links to external resources to facilitate the understanding of the chapter.
The suggestion is useful for course revision:
Strongly disagree ◯ ◯ ◯ ◯ ◯ ◯ ◯ Strongly agree

A comment or a better revision suggestion? ....

Issue 14/14 > Chapter "Le service DHCP ": too many resumes after stops on this chapter occur to the past

Explanation After stopping on this chapter, 33.23% of the repeats are done on previous chapters.
This issue is interesting and may trigger revision actions:
`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

Suggestion This chapter is likely difficult to read and to understand. You may need to further simplify it for example by using a more common or directly defined vocabulary in the content, avoiding dispersion by going to the essential. You need also to verify the logical sequence of the exposed ideas, and to add examples/analogies to facilitate understanding. Please review the content for possible updates and corrections Add references to other chapters and links to external resources to facilitate the understanding of the chapter.
The suggestion is useful for course revision:
`Strongly disagree` ◯ ◯ ◯ ◯ ◯ ◯ ◯ `Strongly agree`

A comment or a better revision suggestion? ....

Abstract. Providing high-quality content is of utmost importance to drive successful reading. Besides, designing documents that are received the way the author wishes has always been difficult, and the digital world increases this difficulty by multiplying the possibilities related to mixed medias and interactivity. This compels authors to continuously review the delivered content to meet readers' needs. Yet it remains challenging for them to detect the comprehension barriers that may exist within their documents, and to identify how these latter can be improved accordingly. This compels authors to continuously review the delivered content to meet readers' needs. Yet it remains challenging for them to detect the comprehension barriers that may exist within their documents, and to identify how these latter can be improved accordingly. In this thesis, we focus on an educational context, where reading is a fundamental activity and the basis of many other learning activities. We propose a learning analytics approach for assisting course authors to maintain their courses to sustain learning. The proposals are based on theoretical background originated from research on learning analytics, reading comprehension and content revision. We advocate \usage-based document reengineering", a process defined as a kind of reengineering that changes document content and structures based on the analysis of readers' usages as recorded in their reading traces. We model reading activity using the concept of reading-session and propose a new session identification method. Using learners' reading sessions, a set of indicators related to different aspects of the reading process are computed and used to detect comprehension issues and to suggest corrective content revisions. The results of the analytics process are presented to authors through a dashboard empowered with assistive features. We instantiate our proposals using the logs of a major e-learning platform, and validate it through a series of studies. The results show the effectiveness of the approach and dashboards in providing authors with guidance in improving their courses accordingly.
Keywords. Document reengineering; e-Learning; Learning analytics; Learning dashboard; Reading monitoring; Reading indicators; Comprehension; Document Revision; Web log mining; Reading session

Résumé. Dans le contexte éducatif la qualité des contenus offerts est d'une importance capitale pour la réussite de l'acte d'apprentissage moyennant des ressources écrites. Les auteurs sont donc appelés à veiller sur la qualité de leurs contenus, et à les réviser en permanence, pour mieux répondre aux besoins des lecteurs. Cependant, il est difficile de détecter les obstacles à la compréhension inhérents aux documents et d'identifier comment ces derniers peuvent être améliorés en conséquence. Dans cette thèse, une approche basée sur l'analyse de l'apprentissage est proposée pour assister les auteurs dans la révision de leurs dans le but de faciliter l'apprentissage. Cette approche s'appuie sur une base théorique issue de la recherche en *learning analytics*, la compréhension de la lecture et la révision de contenus. Elle introduit un processus de réingénierie documentaire basée sur les usages dans le but de modifier le contenu et les structures documentaires en fonction du comportement des lecteurs. Un algorithme de détection de séance de lecture à partir des traces des apprenants est introduit. À partir de ces séances, un ensemble d'indicateurs liés aux différents aspects du processus de lecture sont calculés et utilisés pour identifier les problèmes de compréhension et proposer des suggestions pour des modifications au contenu. Les résultats sont présentés aux auteurs moyennant des tableaux de bord dotés de fonctions d'assistance. Les propositions sont implémentées à l'aide des traces collectées sur une importante plateforme européenne d'e-learning. Les propositions sont évaluées à travers une série d'études dont les résultats montrent l'efficacité de l'approche et des tableaux de bord associés pour fournir aux auteurs un plus grand niveau de connaissance leur permettant d'entreprendre des actions de révision à même d'améliorer leurs cours et de de répondre aux besoins des apprenants.
Mot-clés. Réingénierie documentaire ; Apprentissage en ligne ; Analyse de l'apprentissage ; Tableau de bord ; Suivi de la lecture ; Compréhension ; Indicateur de lecture ; Révision documentaire ; Extraction de logs Web ; Session de lecture

ملخص: تعتبر جودة المحتوى الوثائقي عاملاً حاسماً يسمح بنجاح أو فشل فعل القراءة ونتائجه من حيث الفهم. بالإضافة إلى ذلك ، لا يعد تصميم المستندات التي تلبي احتياجات القراء مهمة سهلة. يزيد الرقمنة من حدة هذا التحدي من خلال زيادة إمكانيات الوسائط المتعددة والتفاعلية. وهذا يتطلب من المؤلفين مراجعة وثائقهم بصفة دورية على أساس دائم من أجل تحديد العوائق المحتملة للفهم التي قد تكون موجودة في المحتوى ، وتحديد كيفية تحسين هذه المستندات وفقًا لذلك. هذه الأطروحة هي جزء من السياق التعليمي عبر الإنترنت ، وتقترح نهج تحليل القراءة لمساعدة مؤلفي الدورة التدريبية على أداء مهام المراجعة الضرورية. نحن نؤيد "إعادة هندسة المستند إلى الاستخدام" التي نحددها كعملية تهدف إلى تعديل بنية المحتوى والتوثيق اعتمادًا على تحليل سجلات المتعلمين الملحوظة على خادم منصة القراءة. نقترح وضع نموذج لنشاط القراءة باستخدام مفهوم جلسات القراءة ونقترح طريقة مبتكرة لتحديدها. بناءً على هذه الجلسات ، يتم تعريف مجموعة من المؤشرات المتعلقة بالجوانب المختلفة لعملية القراءة ويتم استخدامها للكشف عن مشاكل الفهم واقتراح إجراءات المراجعة. يتم تقديم نتائج العملية التحليلية للمؤلفين من خلال لوحة أجهزة القياس مع وظائف مساعدة. لقد قمنا بتنفيذ مقترحاتنا على واحدة من أكبر منصات التعليم الإلكتروني الأوروبية. لإثبات صحتها ، قمنا بسلسلة من الدراسات مع المؤلفين المعنيين. تظهر النتائج فعالية النهج ولوحات المعلومات لتزويد المؤلفين بمستوى أعلى من المعرفة تمكنهم من اتخاذ إجراءات المراجعة لتحسين دوراتهم وتلبية احتياجات المتعلمين.
لكلمات المفتاحية: تفاعل الإنسان والحاسوب؛ إعادة هندسة الوثائق التعلم الإلكتروني؛ تحليلات التعلم لوحة القيادة التعلم؛ مراقبة القراءة؛ مؤشرات القراءة؛ استيعاب؛ مراجعة الوثيقة