Enhancing Course Revision: Introducing CoReaDa - an Advanced Reading Analytics Dashboard

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Abstract

Providing high-quality courses that facilitate successful learning outcomes is an imperative goal in education. To achieve this, course authors are tasked with the ongoing responsibility of continuously reviewing and revising their course content to meet the ever-evolving needs of learners. However, identifying and addressing the reading barriers that learners encounter, as well as determining how courses can be effectively improved, pose significant challenges for course authors. In this paper, we propose a novel learning analytics approach aimed at assisting course authors in overcoming these challenges and optimizing the course revision process. Our approach leverages the wealth of information captured in learners' activity logs to derive valuable insights into course reading activity. We compute a comprehensive set of indicators that specifically capture relevant aspects of learners' reading behavior, allowing us to detect potential issues and suggest targeted content revisions. The utilization of learning analytics provides course authors with valuable data-driven feedback, enabling them to make informed decisions in enhancing their courses to better meet the requirements of the learners. To facilitate the effective utilization of our proposed approach, we introduce CoReaDa—an advanced learning analytics dashboard that acts as a central hub for presenting the computed indicators, offering intuitive visualizations, and providing assistive features. CoReaDa empowers course authors with a holistic view of the course reading activity, enabling them to gain actionable insights into learners' engagement, comprehension, and potential difficulties. With its user-friendly interface and customizable functionalities, CoReaDa serves as a valuable tool in guiding course authors throughout the revision process. To validate the efficacy of our approach, we instantiate our proposals using the extensive logs gathered from a major European e-learning platform. We conduct a comprehensive study to assess the impact of our approach on course authors' decision-making processes and the overall improvement of courses. The study results reveal that our approach significantly enhances authors' awareness and guidance, leading to tangible improvements in course content and alignment with learners' evolving requirements. In summary, this paper introduces a pioneering learning analytics approach for supporting course authors in the continuous process of course revision. By utilizing learners' activity logs and presenting valuable insights through the CoReaDa dashboard, we empower course authors to detect reading barriers, identify areas for improvement, and optimize their courses to better meet the needs of the learners. The study validates the effectiveness of our approach, highlighting its potential to revolutionize course revision practices and foster enhanced learning experiences.

Keywords: Learning analytics, Course revision, Reading barriers, Learning dashboard, Learner engagement, Data-driven feedback

1. Introduction

Digital learning environments are nowadays recording very detailed information regarding learners' learning experience, resulting in a huge amount of data that is getting more and more voluminous. 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.

The use of analytics in education is relatively new, compared to other science disciplines such as physics and biology. According to Baker and Inventado [1], 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. In order to harness the vast amount of data made available, the field of *Learning Analytics* (LA) emerged as a middle ground between learning sciences and data analysis. The objective is to give education stakeholders the appropriate means to improve understanding of teaching and learning and, more specifically, to adapt education more effectively to learners. 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: "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* " [2].

The amount of learners traces being logged can scale up quickly, creating an abundance of information that needs to be analyzed and reported [3]. 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 [4].

2. Background & Related Research

2.1. Information visualization in education

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 [5]. 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).

Information visualization techniques are leveraged in learning analytics research to bring the resulting findings into the hands of human experts[6]. As stated by Duval [7], 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), they consist in visual tools that are easy to understand, ensuring an intuitive and straightforward insight into the learning process [8].

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 [9]. They provide interactive, historical, customized and analytical displays that are based on the results of analyzing learning data [10, 11]. 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 [7].

Learning dashboards have emerged as applications for visualizing and interacting with data collected in a learning environment in various forms [12]. Steiner et al. [13] referred to them as "visualizations of learning traces". For Yoo et al. [14], a learning dashboard is "a display which visualizes the results of educational data mining in a useful way". Schwendimann et al. [15] identified a lack of an agreed and shared definition and thus proposed the following: "*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.* " [15]

Learning dashboards are suitable for online, face-to-face, and blended learning [16]. 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

[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.

that prompt interventions [17, 18, 15]. Currently, they are increasingly deployed as a meaningful component in learning analysis systems. For instance, they are currently used in studying progression through courses [19], learners level of attainment [20], and learners' engagement from the cognitive and behavioral perspectives [21]. Despite being fairly recent educational tools, the research found many benefits of using learning dashboards to improve learning performance [22] and to increase learners' motivation [16, 23].

2.2.1. Design principles

Due to the recent emergence of learning analytics dashboards, there is still a scarcity of studies on their design principles [24]. Yoo et al. [14] 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.

For Verbert et al. [16], 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. Based on a number of theoretical principles in addition to his practical experience, Few [25] 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. [14] 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 [26], 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.

2.3. Discussion of the existing dashboards

One obstacle to the adoption of dashboards is the often existing gap between visual analyses and the objectives of the study [27]. 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” [7]. According to the survey reported in [28], 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 [29]. Bodily and Verbert [30] 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. [31] 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. [29] argued that the success of the dashboards depends on the degree to which its stakeholders have been involved in co-designing them.

Another limitation is related to the selection of both 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. [15], 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) [15].

A third major limitation of the existing dashboards is related their 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 [32, 33, 15]. 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 [34] 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 [22, 35, 36, 37, 15]. As stated by Kim et al. [11], 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 [10], 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. Towards a log-based reading analytics dashboard

3.1. Rationale

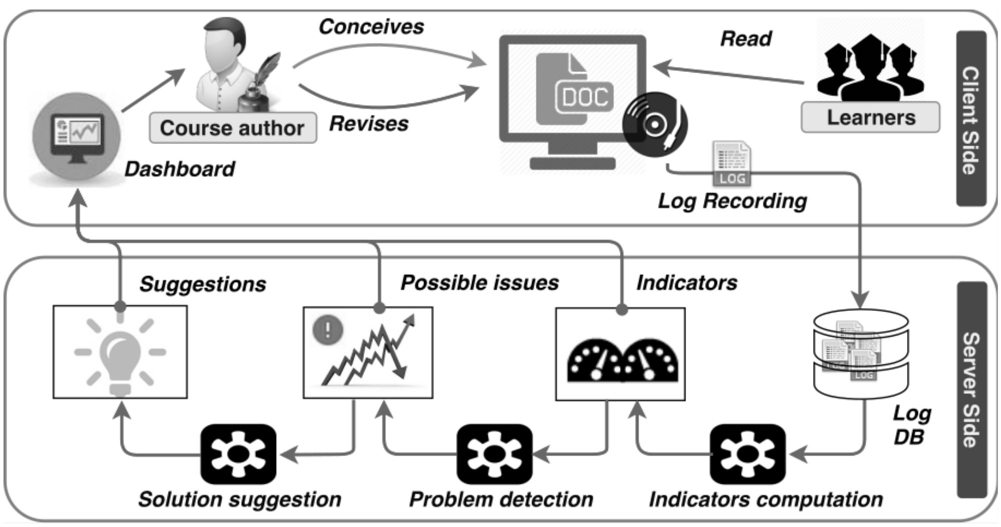

Figure 1: Author assistance approach

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 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 paper, the terms *revision* and *reengineering* refer to the same phenomena [38]. 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.

3.2. Course reading indicators, and related issues and suggestions

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. Behavioral indicators that are defined and measured using learners' behavioral 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 elements 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. 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.

We propose a set of behavioral indicators to describe reading from four 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.

3.2.1. 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 [39] and an indirect measure of the effectiveness, usability and organization of the site [40]. 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. Algorithm 1 provides the pseudocode algorithm for computing these indicators. 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.

Algorithm 1: 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
```
$VisitsRatio = Visits_{element} / Visits_{Course}$
$ReadersRatio = Readers_{element} / Readers_{Course}$
$RSRatio = RS_{element} / RS_{Course}$
$Speed = Size_{element} / Time_{element}$

Related issues and revision suggestions. Within this class, we identify three main types of reading issues:

- *Very few visits, readers, reading sessions, and/or interest*: the author is suggested to consider whether the content is worth being presented and to think about retitling it to better attract learners. Otherwise, he is asked to merge it with another element or merely delete it.
- *Very fast speed of reading*: the author is suggested to either explain, extend and/or deepen the content of the element; or merge the element with another; or delete it if its presence is not mandatory”
- *Very slow speed of reading*: the author is asked to rewrite the element by organizing, summarizing and/or illustrating its ideas. Verify, correct any possible error and update the outdated content.

3.2.2. 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 [41]. It is a strategy used spontaneously by struggling readers [42, 43] and thus it can predict potential user disorientation [42, 44].

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 Algorithm 2.

Algorithm 2: 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**

$RereadsRatio = RevisitsCount(element, session = all) / Visits(element)$
$WSRereadsRatio = RevisitsCount(element, session = within) / RevisitsCount(element, session = all)$
$BSRereadsRatio = RevisitsCount(element, session = between) / RevisitsCount(element, session = all)$

Related issues and revision suggestions. Within this class, we identify three main types of reading issues:

- Multiple rereads:“Simplify the writing of the content and/or reformulate, explain and illustrate its complex parts. Delete some links and replace them with short reminders.”

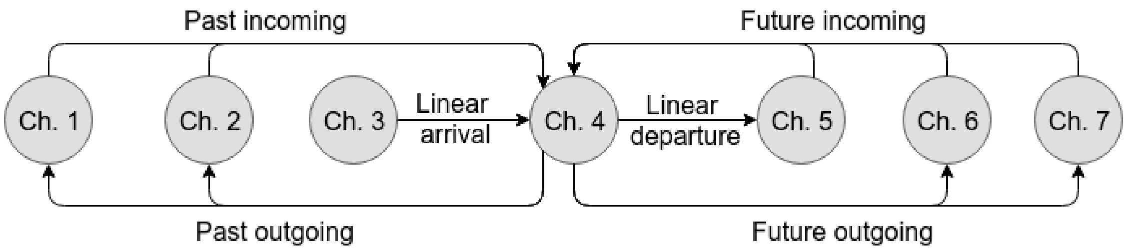

Figure 2: Transitions to and from a chapter of a course
The course is composed of 10 chapters, numbered according to their position in the course outline. The transitions are illustrated for Chapter 4

- *Multiple rereads within same sessions*: "Simplify the content and illustrate its main ideas. Rewrite the difficult parts of the content by reformulating and further explaining them."
- *Multiple rereads distributed between different sessions*: "Rewrite the content by explaining it to further enhance and facilitate its understanding. Delete some links and eventually replace them with short reminders."

3.2.3. 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 [45], 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 2 (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): (1) arrival from the preceding chapter (*linear arrival*); (2) arrival from a chapter situated far ahead (*past incoming*); (3) arrival from a chapter situated after (*future incoming*); (4) departure to the following chapter (*linear outgoing*); (5) departure to a chapter situated before (*past outgoing*); and (6) 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 Algorithm 3.

Algorithm 3: 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`

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

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

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

Related issues and revision suggestions. Within this class, we identify five main types of reading issues:

- *Low linearity of transitions, arrivals and/or departures*: "Simplify the writing of the content and/or reformulate, explain and illustrate its complex parts. Delete some links and replace them with short reminders."
- *Multiple arrivals from past elements*: "Move backwards the element to a more appropriate place or delete some of its links from elements located before."
- *Multiple arrivals from future elements*: "Reformulate and simplify the writing, and further explain and illustrate the ideas. Consider also moving the element to a more appropriate place."
- *Multiple departures to past elements*: "Either move this element to a more appropriate place, or add reminders of the main ideas and remove links to the container elements."
- *Multiple departures to future elements*: "Move the element forwards to a more appropriate place, or delete links to it from elements located ahead of it by replacing them with reminders."

3.2.4. 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 [46], 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 Algorithm 4.

Algorithm 4: 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**

$FinalReadingStops = ReadingSessionStops(at = element, resume = -) / ReadingSessionStops(at = any, resume = -)$

$ReadingHalts = ReadingSessionStops(at = element, resume = *) / ReadingSessionStops(at = any, resume = *)$

$ResumeLinearity = (ReadingSessionStops(at = element, resume = element) + ReadingSessionStops(at = element, resume = Following(element))) / ReadingSessionStops(at = element, resume = *)$

$ResumeToPast = ReadingSessionStops(at = element, resume = Past(element)) / ReadingSessionStops(at = element, resume = *)$

$ResumeToFuture = (ReadingSessionStops(at = element, resume = Future(element))$ - $ReadingSessionStops(at = element, resume = Following(element))) / ReadingSessionStops(at = element, resume = *)$

Related issues and revision suggestions. Within this class, we identify five main types of reading issues:

- *Multiple reading stops (final and/or not final)*: "Reformulate and simplify the writing, and further explain and illustrate the ideas. Verify, correct any possible error and update the outdated content. Add new elements to enrich the course and supply it with links."
- *Multiple non linear resumes*: "Simplify the writing of the element, reformulate and explain its difficult parts and illustrate its ideas. Also, consider moving it to a more appropriate place."

- *Multiple resumes on past elements*: "Move this element to a more appropriate place or add reminders of the presented ideas and delete links to the container elements."

- *Multiple resumes on future elements*: "Move forward the element to an appropriate place. Review the skipped elements and check whether it is more appropriate to move them elsewhere, merge them with the elements that are frequently read at resume, or totally remove them."

3.3. Indicator-based issue detection

The reading 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.

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 [47]. 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).

Algorithm 5: 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);
```

4. CoReaDa, the course reading analytics dashboard

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

4.1.1. 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 paper. 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.

4.1.2. 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. 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.

We have designed CoReaDa by conforming as closely as possible to the requirements identified in the field of visual analysis and dashboards (e.g. [17, 48]):

- 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 [48].

According to Dürsteler [49], 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 [50]: "*Overview first, Filter and zoom, Details on demand*". This mantra was recently adjusted by Keim et al. [51] 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 [52].

- 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 [53].
- *Contextual Cues* techniques augment the detail view with glyphs meant to help locate parts of interest that are outside the view area [54]. 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.

5. CoReaDa prototype

5.1. The development stack

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*[2], 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. In order to the Web application to communicate with R, we used *Rserve*[3], 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[4]. This package provides support of different types of data, plain text, and encrypted authentication.

5.2. Architecture

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.

3 presents 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.

[2] `https://www.r-project.org` (accessed on November 23th, 2018)
[3] `https://cran.r-project.org/web/packages/Rserve/index.html` (accessed on November 23th, 2018)
[4] `https://cran.r-project.org/web/packages/rio/index.html` (accessed on November 23th, 2018)

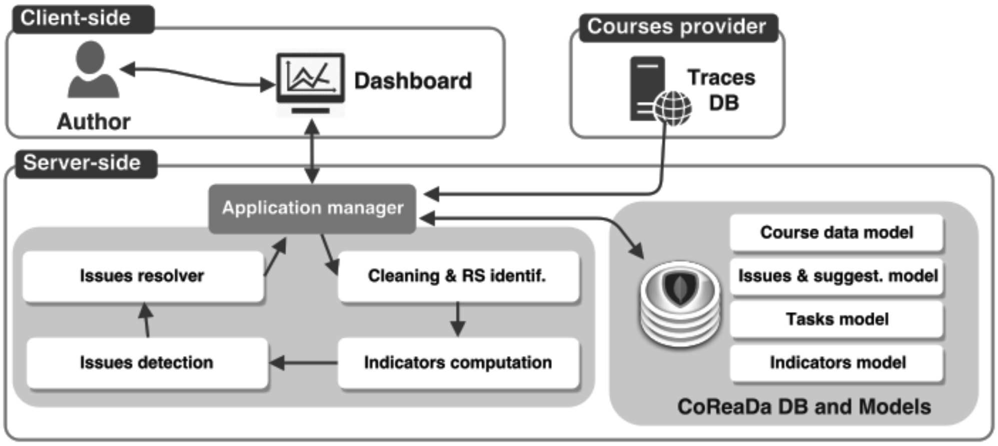

Figure 3: Architecture of CoReaDa

5.2.1. *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:

```
<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 4 presents an excerpt of a json document that provides the structure of a course from the platform provider used in the evaluation studies.

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*). 5 presents an excerpt of a document that provides the logs observed on a course.

5.2.2. *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:

```json
{
  "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": {
```


Figure 4: An excerpt of a *json* file providing the structure of a course

id	user_id	course_id	part_id	session_id	date
95	d9686458af021829d11a8104fe2b0b12	857447	850854	hd1rdhkjnlc7i39p80cdr59p67	2014-10-31 17:28:29
970	3fa0493d9ebcfaa3046ef425c87f7198	857447	850854	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 11:14:16
1131	3fa0493d9ebcfaa3046ef425c87f7198	857447	850854	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 11:47:23
1259	3fa0493d9ebcfaa3046ef425c87f7198	857447	850854	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 12:05:47
9415	3fa0493d9ebcfaa3046ef425c87f7198	857447	851033	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 11:47:32
20270	1580aa4853d58c559d30f90b8608f3b1	857447	851376	9449tskldh1j2h6vhi19qrbph0	2014-10-31 23:59:18
30842	3fa0493d9ebcfaa3046ef425c87f7198	857447	852634	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 12:11:34
38215	3fa0493d9ebcfaa3046ef425c87f7198	857447	853038	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 12:05:52
40525	3fa0493d9ebcfaa3046ef425c87f7198	857447	853038	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 12:16:16
43303	3fa0493d9ebcfaa3046ef425c87f7198	857447	853205	ck8ge0e9rnkkdp05mulebamis7	2014-10-31 11:47:38

Figure 5: An excerpt of a *csv* file describing the logged actions on a course

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 following the approach we described in [55, 56].
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* [57]. 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.

5.3. CoReaDa User Interface (front-end)

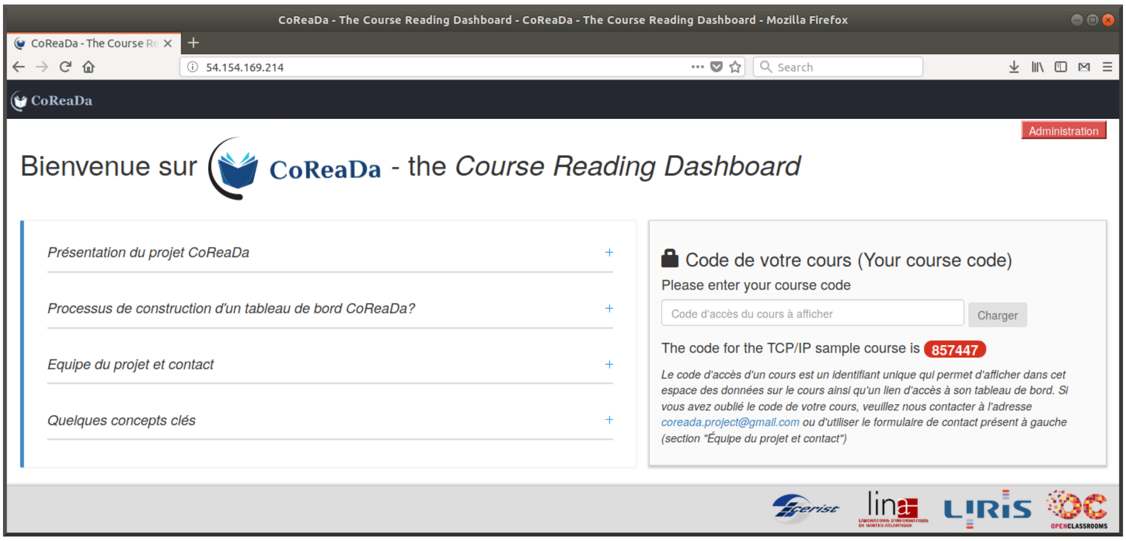

Figure 6: The Welcome screen of CoReaDa

We have designed the dashboard interface as a single-page application that does not require updating with each server request. 6 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. 5.3.3).

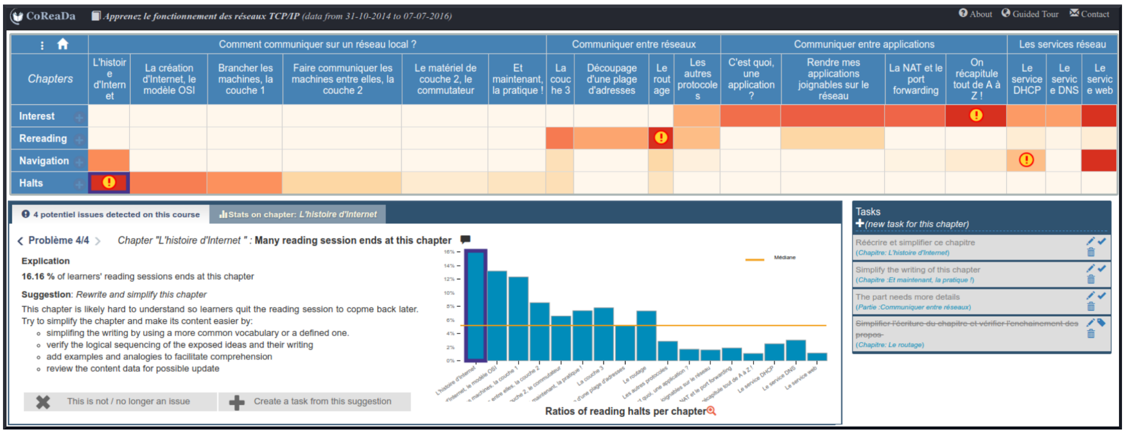

Figure 7: Screenshot of a CoReaDa instance

5.3.1. *Course analysis layout*

Figure 7 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.

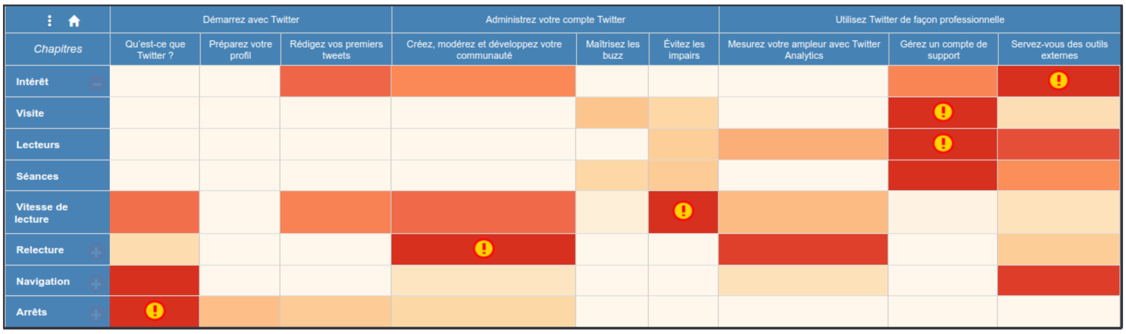

Figure 8: CoReaDa *heatmap* within the data grid area

Data grid area. This zone represents the values of the displayed indicators for each chapter as a two-dimensional matrix (8). The table representation of data allows to efficiently identify individual values [48]. 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 [48].

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 7, 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.

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* (9).

Figure 9: The *Stats tab* of the Inspector

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

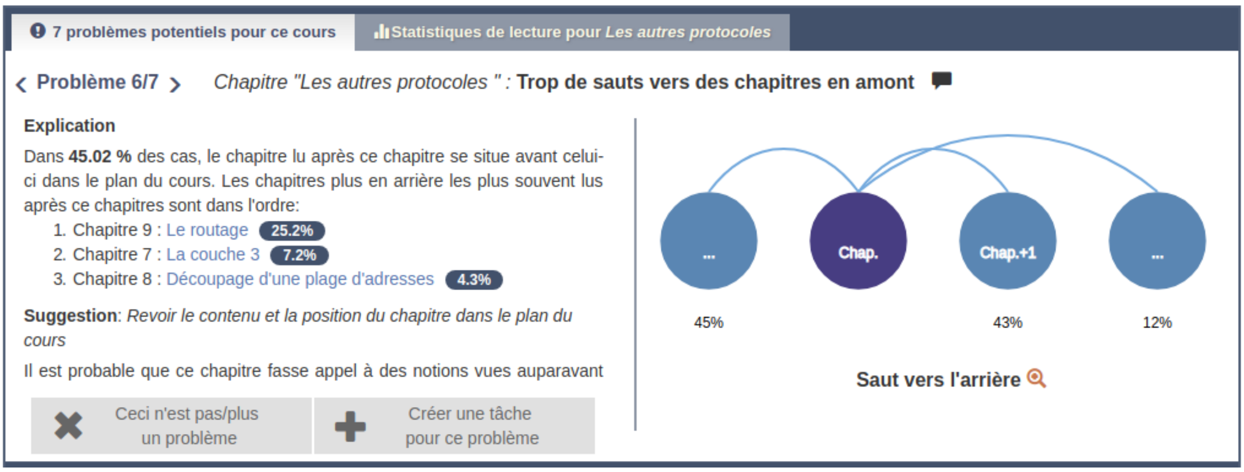

Figure 10: The *Issues tab* of the Inspector

Issues tab 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 (10); 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 7, 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.

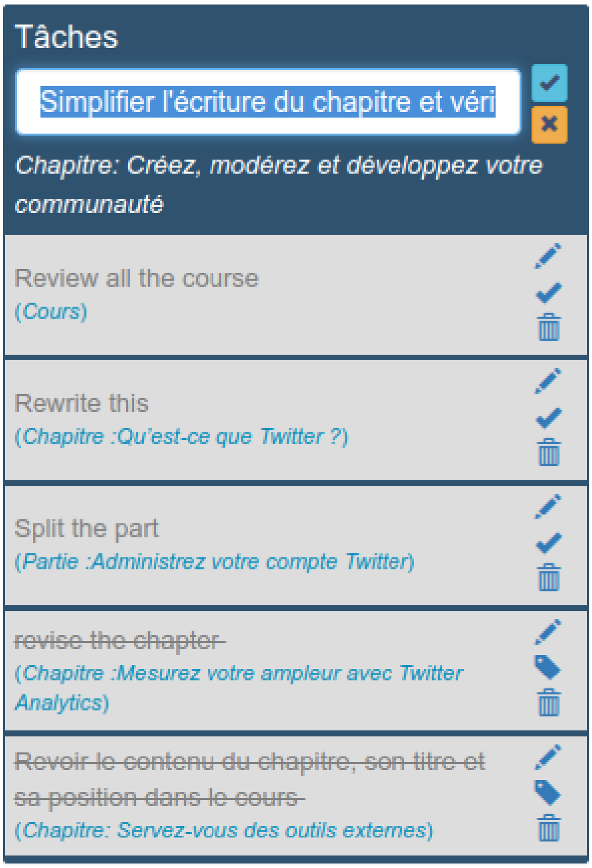

Figure 11: The *Tasks* area of CoReaDa

Task area. 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 11 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.

5.3.2. Help and assistance

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.

5.3.3. 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.

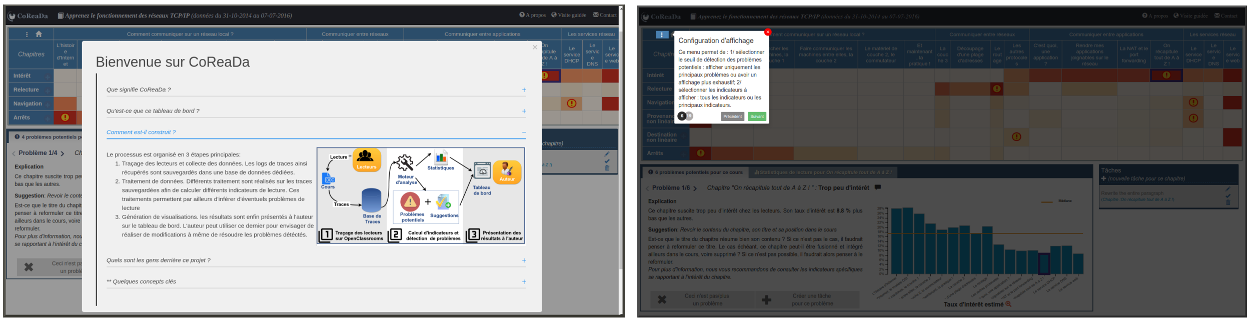

Figure 12: CoReaDa user help features

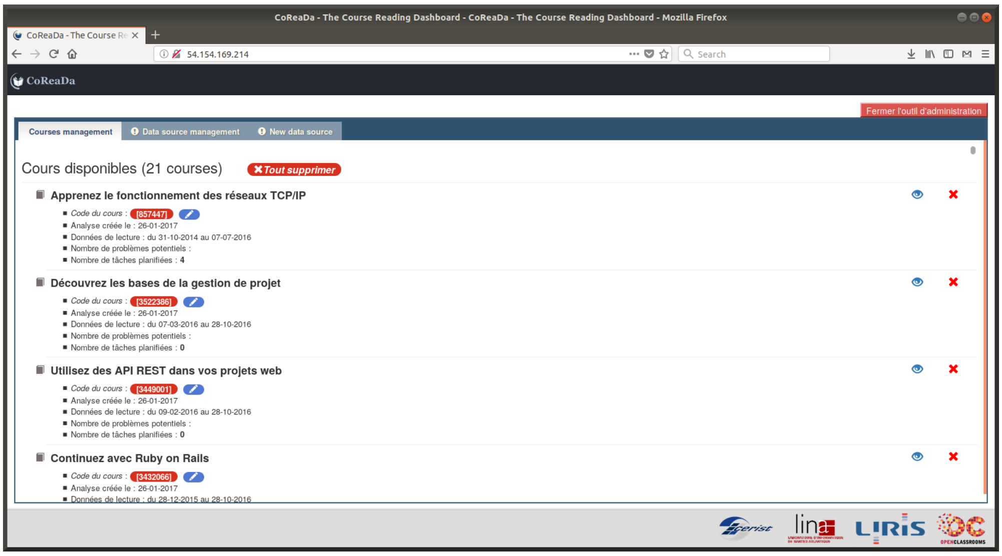

Figure 13: Managing the existing courses within CoReaDa

Courses management. 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 (13): 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.

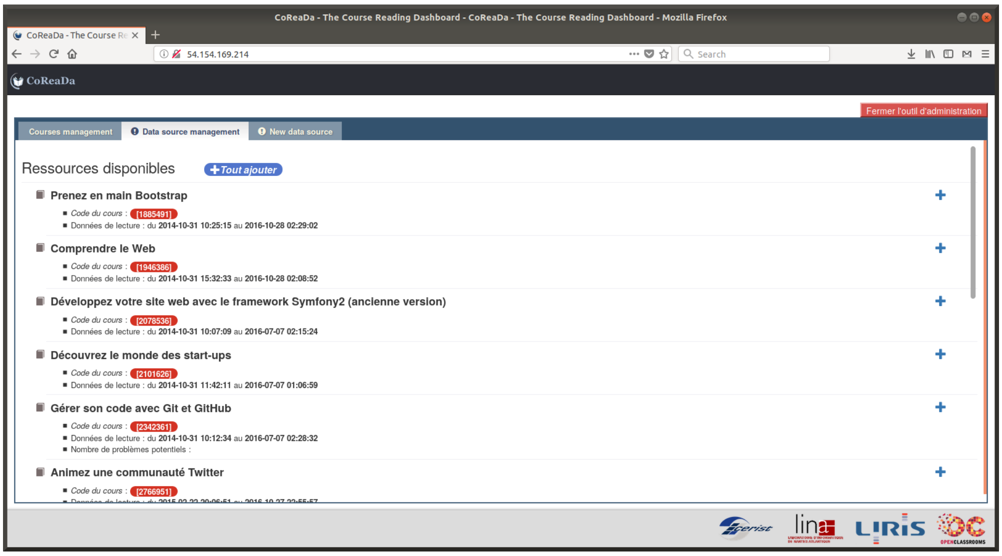

Figure 14: Managing CoReaDa data sources

Data source management. The data source management component (14) 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.

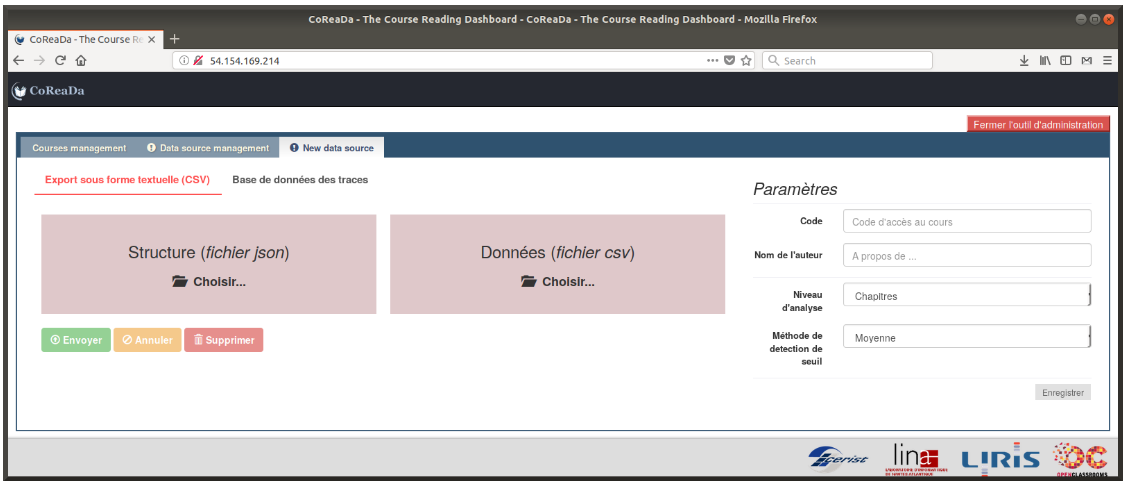

Figure 15: Adding an new data source to CoReaDa

New data source. 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 (15): a *json* file that contains the structure of the course, and 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.

6. Evaluation study

6.1. Protocol

This study, described in [58] and 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.

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 [59].

#	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 1: 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 1, 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.

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), [60], 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" [60, 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., [61]). A statistical meta-analysis of TAM applied to 88 published studies showed it to be valid and robust [62].

	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 2: 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 2), 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.

6.2. Results

6.2.1. Dashboard usability

Using the logs collected during the tasks-based experiment, we computed four performance metrics (results on Table 3):

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 3: 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

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 4: Results of the TAM questionnaire

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.

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 4 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.

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.

7. Conclusion

In this paper, we introduced CoReaDa, an innovative dashboard specifically designed to analyze online learners' reading behaviors, detect reading problems, and provide valuable suggestions for course revision and remediation actions. Our aim was to empower course authors with a comprehensive tool that enhances their ability to understand learners' reading experiences and make informed decisions for course improvement.

To begin, we elucidated the co-design process, which played a pivotal role in shaping the development of CoReaDa. By actively involving course authors, educational experts, and user experience designers, we ensured that the functional features of the dashboard were aligned with the specific needs and requirements of the target users. This collaborative approach allowed us to create a tool that seamlessly integrates into existing course revision workflows, optimizing the user experience and facilitating the adoption of CoReaDa in diverse educational contexts.

Furthermore, we outlined the key design choices that underpin the development of CoReaDa. These design choices were driven by the goal of providing a user-friendly, intuitive, and visually appealing interface that course authors can effortlessly navigate and utilize. By incorporating modern design principles and leveraging the advancements in web technologies, we were able to create a seamless and engaging user experience that facilitates efficient data analysis and interpretation.

The three-tier architecture of CoReaDa was presented, highlighting the logical framework that governs the functioning of the platform. We meticulously designed and implemented each layer, ensuring seamless communication and efficient data processing between the client-side and server-side components. The utilization of a modern stack of web technologies, complemented by a popular and free open-source analysis environment, further enhanced the scalability, reliability, and extensibility of CoReaDa.

In conclusion, this paper has provided a comprehensive overview of CoReaDa, an advanced dashboard designed to revolutionize the course revision process by harnessing the power of learning analytics. By leveraging learners' reading data and presenting actionable insights, CoReaDa equips course authors with a valuable tool for detecting reading barriers, making informed decisions, and improving their courses to better align with learners' needs. The detailed description of the co-design process, functional features, architecture, and implementation logics provides a solid foundation for further research and development in the field of learning analytics and course improvement. As future perspectives, we anticipate the continuous evolution of CoReaDa, with potential enhancements such as integration with other learning management systems, incorporation of advanced machine learning algorithms for predictive analysis, and the incorporation of real-time feedback mechanisms. With the rapid advancements in technology and the increasing importance of data-driven decision-making in education, CoReaDa stands as a promising tool that has the potential to shape the future of course revision and ultimately enhance the overall learning experience for students worldwide.

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