



Towards fine-grained reading dashboards for online course revision

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Abstract

Providing high-quality courses is of utmost importance to drive successful learning. This compels course authors to continuously review their contents to meet learners' needs. However, it is challenging for them to detect the reading barriers that learners face with content, and to identify how their courses can be improved accordingly. In this paper, we propose a learning analytics approach for assisting course authors performing these tasks. Using logs of learners' activity, a set of indicators related to course reading activity are computed and used to detect issues and to suggest content revisions. The results are presented to authors through CoReaDa, a learning dashboard empowered with assistive features. We instantiate our proposals using the logs of a major European e-learning platform, and validate them through a study. Study results show the effectiveness of our approach providing authors with more awareness and guidance in improving their courses, to better suit learners' requirements.

Keywords Learning analytics · Learning dashboards · Web-based interaction · Information visualization · Reading indicators · Content revision

Introduction

Reading is a common learning strategy that is widely used in education (Al Madi and Khan 2015). During reading, the learner constructs an interpretation of the text that reflects his level of understanding (Sullivan and Puntambekar 2015). Amongst the factors that shape this level, “course quality” plays a decisive role (McNamara and Magliano 2009). Authors are therefore required to continually review their courses to meet learners' needs and expectations. However, it is difficult for them to determine which

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aspects of a course need improvement, and to decide on appropriate changes (MacArthur 2012; McGahan 2018). Consequently, authors often revise their courses infrequently and superficially, unless they receive guidance on assessing learners' needs and revising their contents accordingly (Hayes 2004; MacArthur 2012).

Through the use of learning platforms with logging capabilities, data on learners' activities are being captured and studied. "Reading logs" are the time-stamped events recorded on such platforms, related to learners' reading activity. The application of appropriate analytics methods on these logs allows investigating learners' reading behavior. When returned in a timely and appropriate manner, the results can serve authors as a formative assessment tool for improving their courses (Tempelaar et al. 2013).

In this article, we present an analytical approach that uses learners' reading logs to assist authors in revising their courses. To instantiate this approach, we elaborate a set of indicators capturing learners' reading behavior, used to identify their potential problems, and to generate suggestions for corrective revision actions. We also present CoReaDa, a learning dashboard that implements these proposals. Finally, we describe a study that evaluates: the relevance of the reading indicators, the effectiveness of the detection tool, the usefulness of the provided suggestions, and the usability and authors' acceptance of the dashboard.

The remainder of this paper begins with a review of relevant research. The analytics approach for course revision and its implementation are then presented. Next, the evaluation methods are described and their results are presented and discussed before concluding.

Related research

Course quality assessment and content revision

Learners' level of understanding is a key outcome measure of learning by reading (Bloom et al. 1956). This level depends on both the characteristics of the reader (e. g., reading skills and strategies), and the quality of the course (Gray 1935). The latter is related to course readability, which reflects the ease with which a reader can understand its content. Readability depends largely on the course format (e.g., layout), organization (e.g., headings), style (e.g., language structure) and content (e.g., nature of the subject). It is often evaluated using specific formulas such as Flesch Reading Ease Score, Flesch-Kincaid Grade Level, and SMOG Index (Zamanian and Heydari 2012). However, these formulas do not relate to any theory of reading comprehension and are criticized for their low validity from the perspective of psycholinguistic theories, and their low effectiveness in predicting readers' judgments about the complexity of the text (Crossley et al. 2017).

Assessing the quality of a course can highlight areas for appropriate revisions. Some revisions change the course information (*text-based changes*), while others preserve the original information (*surface changes*) (Faigley and Witte 1981). In practice, revision is a complex process that involves reconsidering ideas, reorganizing them, rewriting content, and detecting further enhancements (Hayes 2004). Consequently, many authors revise their contents infrequently and superficially, unless they are guided in identifying and implementing the necessary changes (Hayes 2004; MacArthur 2012).

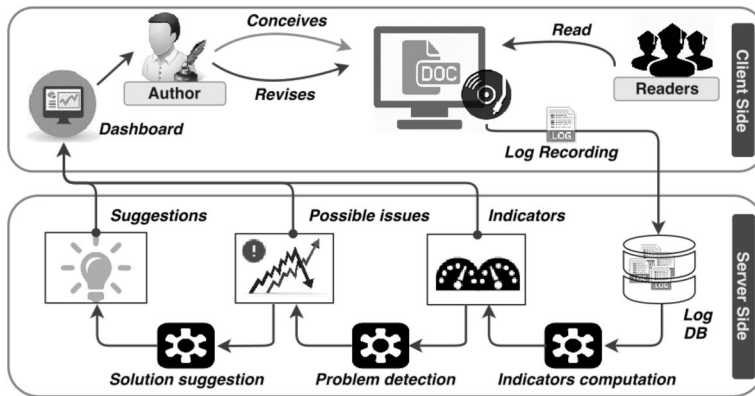


Fig. 1 Author assistance approach based on reading logs analysis

Monitoring learning and assisting authors for course revision

Improving contents from the readers' perspective is an effective strategy for ensuring a better level of understanding (Cho and MacArthur 2011). However, in e-learning and apart from some attempts to use learners' explicit feedback (e.g., Pattanasri et al. 2012), little attention has been devoted to assessing what learners actually understand (Zamanian and Heydari 2012). This is in part due to the difficulty to monitor learning, which requires sensitive observation skills and an active learning environment (Pattanasri et al. 2012).

Widespread use of educational platforms with logging capabilities promoted the field of *learning analytics*, which uses the logged data to understand and optimize learning (Siemens and Gašević 2012). Applying analytics methods on reading logs can provide a good insight into learners' level of understanding (Huang and Liang 2015). However, these methods require technical skills that course authors often lack (Peerani 2013; Spector et al. 2016). It is therefore necessary to design tools that mask the technical complexity of analytical methods, while providing knowledge that can be easily understood and properly used by authors. Such assistive tools could also motivate authors to revise their courses more frequently.

An increasingly popular option consists of using information visualization techniques to accurately represent the results of analyses. Different visualizations can be used, ranging from plain text to more elaborate display media such as tables and graphs; they are often embedded within single displays called *learning dashboards* (Duval 2011). In order to trigger authors' reactions, these dashboards need to integrate decision-making options (e.g., alerts and suggestions), features that the majority of the existing dashboards lack (Schwendimann et al. 2017).

Using reading analytics to assist authors in course revision

A log-based approach for course revision

We propose a log-based approach for assisting authors throughout the revision process (Fig. 1). Once the author conceives and delivers his course, the reading logs are

captured and processed on the server-side. Various indicators are computed from these logs and used for identifying learners' comprehension issues. For each issue, an assistance mechanism provides remediation suggestions. The server sends the results to the client-side to be displayed through a dashboard. The author is thus empowered with three types of data: (1) the *indicators* give hints on how the course was read; (2) the *issues* highlight unexpected values of the indicators; and (3) the *suggestions* propose actions to resolve these issues.

This approach can be adapted to different learning contexts (formal, informal, vocational or lifelong learning). We have instantiated it for the revision of courses delivered on an e-learning platform.

Course and log models

A *course* is a document composed with *blocks of contents* that we call "course elements". A course element can refer to a chapter or a subchapter; it may also contain other elements (e.g., a chapter that contains subchapters). These elements are arranged to define the course outline (or plan) with possible navigation links between them.

The *log* of a learner is the set of events representing his activity, recorded by the server during a given period. Each log record is timestamped and contains information to identify the learner, the course, and the accessed element.

A taxonomy of course edition actions

A revision consists in performing a set of *edition actions* that targets a particular course element. An edition action can impact the *style*, the *structure*, the *content*, or the *links* of its target, resulting on four classes:

- *Restyling actions* change the element layout and presentation style on the user interface.
- *Restructuring actions* update the element organization within the course plan.
- *Rewriting actions* change the element content. They are derived from the Bloom taxonomy which identifies various levels for classifying educational goals (Bloom et al. 1956); each level being associated with a list of action verbs. From the "comprehension" level, we selected verbs relevant to our context.
- *Linking actions* impact the navigational links contained in the element.

Applying an edition action on an element results on an *addition*, *modification* or *suppression* effect. Table 1 presents the actions associated to each class, grouped according to their effect on the element.

Reading indicators and issues, and associated revision actions

We use the four classes of indicators that we have introduced and discussed in (Sadallah et al. 2015): *Stickiness*, *Rereading*, *Navigation*, and *Stops & Resume*. The *reading issues*

Table 1 Classes of revision actions and their effects on the target elements

Class	Action effect	Action title
Restyling	Addition	Add style
	Modification	Alter style
	Deletion	Delete style
Restructuring	Addition	Add element
	Modification	Retitle; Move; Merge; Split
	Deletion	Delete element
Rewriting	Addition	Insert; Explain; Illustrate; Remind
	Modification	Organize; Reformulate; Extend; Summarize; Deepen; Simplify; Correct; Update
	Deletion	Delete content
Linking	Addition	Add link
	Modification	Alter link
	Deletion	Delete link

Table 2 Issues and revision suggestions associated to *Stickiness*

Issue	Revision suggestion
Very few visits, readers, reading sessions, and/or interest	“If the element is worth being presented, <i>retitle</i> it to better attract learners. Otherwise, <i>merge</i> it with another element or merely <i>delete</i> it”
Very fast speed of reading	“Either <i>explain</i> , <i>extend</i> and/or <i>deepen</i> the content; or <i>merge</i> the element with another; or <i>delete</i> it if its presence is not mandatory”
Very slow speed of reading	“Rewrite the element by <i>organizing</i> , <i>summarizing</i> and/or <i>illustrating</i> its ideas. Verify, <i>correct</i> any possible error and <i>update</i> the outdated content”

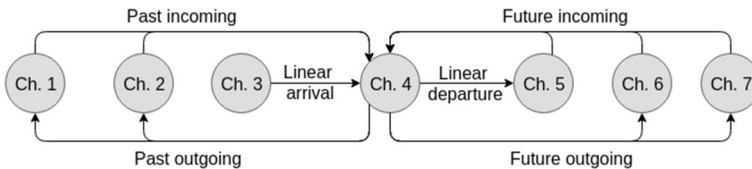
highlight unexpected values of each indicator. For each type of issues, we associate a revision suggestion composed from a set of edition actions.

Stickiness

This class reflects the ability of a course element to attract and hold learners' interest. We quantify stickiness in terms of: *visits* that are observed on the element; unique *readers* who visited the element; *reading sessions* that contain the element; and learners' *reading speed*. The *reading speed* can reflect the level of processing afforded by the content: a complex content is generally read at a slower rate (Walczyk 2000), and a high reading rate can be associated with poor reading performance (Rayner et al. 2016). The indicator *interest*, computed as the mean value of the other indicators, summarizes this class. Table 2 provides the associated reading issues and revision suggestions.

Table 3 Issues and revision suggestions associated to *Rereading*

Issue	Revision suggestion
Multiple <i>rereads</i>	“Simplify the writing and/or reformulate, explain and illustrate its complex parts. Delete some links and replace them with short reminders”
Multiple <i>rereads within same sessions</i>	“Simplify the writing and illustrate its main ideas. Rewrite the difficult parts by reformulating and further explaining them”
Multiple <i>rereads distributed between different sessions</i>	“Rewrite the content by explaining it to further enhance its understandability. Delete some links and replace them with short reminders”

**Fig. 2** Transitions to and from chapter 4 (the course is composed of 10 chapters, numbered according to their position in the course outline)

Rereading

Rereading is a widely used strategy in reading for learning, especially by struggling readers. We quantify rereading in terms of: returning visits from the same readers (*rereads*); rereads that occurred within the same reading session (*within-session rereads*); and rereads that occurred across different sessions (*between-session rereads*). Rereading indicators can provide significant information on the learners' level of understanding (Wise et al. 2012). Table 3 presents the associated reading issues and revision suggestions.

Navigation

The learner navigation corresponds to his reading path which results from the transitions (*arrivals* and *departures*) he made between the visited elements. We can distinguish six types of transitions (Fig. 2): arrival from the preceding chapter (*linear arrival*), from a chapter situated far before (*past incoming*), and from a chapter situated after (*future incoming*); and departure to the following chapter (*linear outgoing*), to a chapter situated before (*past outgoing*), and to a chapter situated far after (*future outgoing*). A *linear* transition reflects a reading that follows the course plan. All transitions (arrivals or departures) that involve an element are recorded. Thus, each element visited by a learner (except the first and the last elements) is involved in at least two transitions: an arrival and a departure.

Based on this categorization, we quantify navigation in terms of: the *linearity of the transitions*, the *linearity of the arrivals* and the *linearity of the departures*. We also compute the percent of *future incoming* and *past incoming* related to the total number of arrivals, and the percent of *future outgoing* and *past outgoing* from the total number of

Table 4 Issues and revision suggestions associated to *Navigation*

Issue	Revision suggestion
Low linearity of transitions, arrivals and/or departures	“ <i>Simplify the writing and/or reformulate, explain and illustrate the complex parts. Delete some links and replace them with short reminders</i> ”
Multiple arrivals from past elements	“ <i>Move the element to an appropriate backwards location; Or, delete some links coming from elements located before</i> ”
Multiple arrivals from future elements	“ <i>Reformulate and simplify the writing, and further explain and illustrate the ideas. Consider moving the element to an appropriate forward location</i> ”
Multiple departures to past elements	“ <i>Move this element to a more appropriate place; Or, remove links to the previous elements and replace them with reminders</i> ”
Multiple departures to future elements	“ <i>Move the element to a forwards appropriate location; Or delete links coming from elements located ahead and replace them with reminders</i> ”

Table 5 Issues and revision suggestions associated to *Stop & Resume*

Issue	Revision suggestion
Multiple reading stops (final and/or not final)	“ <i>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</i> ”
Multiple nonlinear resumes	“ <i>Simplify the writing, reformulate and explain its difficult parts and illustrate its ideas. Consider moving it to a more appropriate location</i> ”
Multiple resumes on past elements	“ <i>Move this element to an appropriate backward location; Or delete links to previous elements and replace them with reminders</i> ”
Multiple resumes on future elements	“ <i>Move the element to an appropriate forward location. 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</i> ”

departures. These indicators can help diagnose reading difficulties such as disorientation and cognitive overload (Nakayama et al. 2000), which may be due to the complexity of the content or its poor structuring (Blom et al. 2018). Table 4 presents the reading issues and revision suggestions associated to this class.

Stop & resume

Learners often stop reading contents that no longer attract their interest and keep them motivated (Bushman and Hans 2005), or that exceed their reading capabilities (Grimshaw et al. 2007). When a course is complex or poorly structured, resumes tend to be nonlinear (Blom et al. 2018). To investigate how learners interrupt and resume their reading activity, we define indicators to quantify: the interruptions on an element, with or without resumes (resp. *reading halts* and *reading stops*); the halts on an element with resumes on this element or on the

following one (*resume linearity*); the halts on an element with resumes on previous elements (*past resume*); the halts on an element with resumes on elements far ahead (*future resume*). Table 5 provides the associated reading issues and revision suggestions.

The Course READING Dashboard

We implemented the analytical approach through a web-based learning dashboard. The Course Reading Dashboard (*CoReaDa*) is constructed around two components: data analysis and data visualization.

Data analysis process

This process begins once the learners' logs are retrieved from the course provider and pre-processed to identify the reading sessions, as described in Sadallah et al. (2015). The indicators are then computed using the methods presented with a simplistic notation in Table 6. Thereafter, the values of each indicator are analyzed to identify possible reading issues. These indicators being univariate numeric variables, the issue detection consists in searching possible outliers within their values. For this task, we use the *Median Absolute Deviation* (MAD) method (Leys et al. 2013). An outlier does not necessarily represent an issue (e.g., a high value of interest). Depending on the indicator, an outlier reflects an issue when it is within the *sample maximum* (extremely high values), the *sample minimum* (extremely low values), or both, as indicated in Table 6 (third column). Finally, revision suggestions are generated for the issues identified using the appropriate edition actions.

CoReaDa interface description

Figure 3 illustrates the dashboard running on a course. Three zones constitute the user interface. The upper zone (*Data grid area*) presents the indicators' values, encoded into color shades (forming a *heatmap*). The white color of a cell tends to turn red to depict an abnormal value. The issues are indicated with yellow exclamation icons. To avoid overwhelming the author, only the most critical issue is displayed for each indicator. Once this issue is resolved, another issue may appear. The vertical ellipse allows configuring which indicators and how many issues to display.

The bottom left zone (*Inspector area*) is intended to inspect contextual information about the selected element (chapter, cell, indicator, etc.) in textual mode or using a graphical visualization. Depending on his goals, the author can obtain either basic statistics, or a detailed report that examines for instance a specific reading issue or a given revision suggestion.

The bottom right zone (*Task area*) allows planning and managing revision tasks. A task may target a specific issue or its context (elements involved in the issue). Its specification can be derived from the suggestions or introduced by the author.

Table 6 Indicators computation and issue detection

Indicator	Computation for each course element p^*	Issues
Visits	$Visits_count(p)/Visits_count(course)$	Min values
Readers	$Unique_readers_count(p)/Unique_readers_count(course)$	Min values
Reading session	$Reading_session_count(p)/Reading_session_count(course)$	Min/Max values
Reading speed	$Size_in_words(p)/Average(Reading_time(p))$	Min values
Interest	$Mean(Visits, Readers, Read_session, Reading_speed)$	Max values
Reread	$Revisits_count(p)/Visits_count(p)$	
With.-sess. reread	$Same_session_visits_count(p)/Revisits_count(p)$	
Betw.-sess. reread	$Between_session_visits_count(p)/Revisits_count(p)$	
Navigation linearity	$(Arrivals_count(from = p-1, to = p) + Departures_count(from = p, to = p+1))/Transitions_count(p);$	Min values
Arrival linearity	$Arrivals_count(from = p-1, to = p)/Arrivals_count(from = "any", to = p)$	
Departure linearity	$Departures_count(from = p, to = p+1)/Departures_count(from = "any", to = p)$	
Future arrivals	$Arrivals_count(from = "future", to = p)/Arrivals_count(from = "any", to = p)$	Max values
Past arrivals	$Arrivals_count(from = "past", to = p)/Arrivals_count(from = "any", to = p)$	
Future departures	$Departures_count(from = p, to = "future")/Departures_count(from = p, to = "any")$	
Past departures	$Departures_count(from = p, to = "past")/Departures_count(from = p, to = "any")$	
Reading stop	$Count(Reading_session_end(at = p, resume = "no"))/Count(Reading_session_end(at = "any", resume = "no"))$	
Reading halt	$Count(Reading_session_end(at = p, resume = "yes"))/Count(Reading_session_end(at = "any", resume = "any"))$	
Resume linearity	$(Count(Reading_session_end(at = p, resume = "p")) + Count(Reading_session_end(at = p, resume = p+1)))/Count(Reading_session_end(at = "p", resume = "yes"))$	
Future resume	$Count(Reading_session_end(at = p, resume = "future"))/Count(Reading_session_end(at = p, resume = "yes"))$	
Past Resume	$Count(Reading_session_end(at = p, resume = "past"))/Count(Reading_session_end(at = p, resume = "yes"))$	

* p : the studied element; $p-1$ and $p+1$: the element that resp. precedes and follows p in the course outline. "any": any value; "past" and "future": elements located resp. before and after p in the course outline



Fig. 3 Screenshot of the user interface of CoReaDa

Table 7 Demographic description of the participating authors (N = 125)

Variable	Category	Statistics ^a
Gender	Female	$n = 57, f = 45.6\%$
	Male	$n = 68, f = 54.4\%$
Age	19–25	$n = 48, f = 38.4\%, M = 22.6, sd = 1.9$
	26–40	$n = 66, f = 52.8\%, M = 31.36, sd = 4.33$
	41–58	$n = 11, f = 8.8\%, M = 48.45, sd = 5.35$
Level of education	Bachelor	$n = 11, f = 8.8\%$
	Master degree	$n = 49, f = 39.2\%$
	Doctorate degree	$n = 65, f = 52.0\%$

^aFor each group: number of participants (n), frequency (f), mean (M), and standard deviation (sd)

Methods

Objectives and study design

To validate our proposals, we conducted a three-phase study (we refer to each phase as “sub-study”): *Sub-study 1* addressed the relevance of the indicators for course revision; *Sub-study 2* investigated the effectiveness of the detection and resolution tool; and *Sub-study 3* evaluated the CoReaDa dashboard.

The study was performed using data provided by *OpenClassrooms*,¹ a major European e-learning platform. We used questionnaires and a task-based study.² The face validity of the questionnaires was established by refereeing them by three independent researchers, and two course authors. The final questionnaires have been modified as per the received recommendations.

¹ <https://openclassrooms.com>.

² An aggregated version of the used material can be found here: <https://bit.ly/coreada-eval>.

Table 8 Description of the used courses

Course	#chapters	#logs	#learners	#detected issues
Bootstrap	7	229,362	13,045	11
Javascript	13	289,153	12,829	8
Ruby on Rails	18	40,895	306	13
Web	18	240,978	11,793	9
TCP/IP	17	111,026	7239	14
Symfony	27	402,039	9357	15
Git	19	109,092	5826	11
Python	38	263,847	13,116	13

Participants and data used

The participants were authors of courses available on *OpenClassrooms*. These courses were provided for informal learning, i.e. they were not part of a curriculum offered by a specific formal educational institution or program. We contacted 403 authors by email, explained the rationale and objective of our project, and invited them to participate in evaluating the indicators (*Sub-study 1*). One hundred twenty-five authors, all instructors of their respective courses, agreed to participate. Table 7 shows some of their demographic data (gender, age and education level).

Sub-studies 2 and 3 required the use of actual reading data. Therefore, from the courses of the authors who participated in *Sub-study 1*, we selected a sample of eight courses. The selection was made in two stages. The first stage aimed to identify typical cases by selecting representative courses in terms of size, measured by the number of chapters. Since the courses consisted of a different number of chapters ($Min=3$, $Q1=7$, $Mean=9$, $Median=12$, $Q3=39$, $Max=52$), those with a number of chapters contained between $Q1$ and $Q3$ were selected ($N=62$). In the second stage, we refined the first set by selecting the most popular courses among learners. We thus sorted in descending order the 62 courses according to both *numbers of visits* and *unique readers*, and then selected the first eight ones.

The authors of the eight courses were invited by email to evaluate the tool (*Sub-studies 2 and 3*) using data related to their courses. All authors agreed to participate. The data used were anonymized reading logs of learners observed on the selected courses for the period from 31 October 2014 to 7 July 2016. A course element corresponded to a chapter and was displayed on a separate webpage. The learners' logs of each course were analyzed and the data integrated into the dashboard (Table 8).

Procedure and tools

Sub-study 1: indicators relevance

This sub-study was carried out during one month (April 2016). An electronic document outlining the rationale and objectives of the project was first sent by email to the 125 authors. The authors were then asked to access an online questionnaire titled *Indicators Relevance Survey* to gather their opinions on the relevance of the indicators for course

revision. This questionnaire consisted of four sections, one for each class of indicator. Each class was described and its indicators defined. The authors were instructed to assess the relevance of each indicator using a 5-point Likert scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). In average, the questionnaire needed 18 min to complete.

Sub-study 2: issue detection and resolution

This sub-study was conducted after the implementation of the tool, from January 13th to January 26th, 2017. An online questionnaire titled *Issues and Suggestions Survey* was sent to each of the eight authors, prefilled with data specific to their respective courses. This questionnaire was divided into two parts. The first part contained a blank list to be filled by the author with predictions on the problems that learners might encounter. The second part presented the list of issues detected with associated revision suggestions. Using five-point Likert scales ranging from 1 (*strongly disagree*) to 5 (*strongly agree*), the author was asked to estimate the usefulness of each issue for triggering revision actions, and then to evaluate the usefulness of the related revision suggestion. The questionnaire took an average of 34 min to complete.

Sub-study 3: the CoReaDa dashboard

This study, conducted from April 5th to April 11th, 2017, aimed to evaluate CoReaDa 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 a *Usability Study* and then to fill an *Acceptance Questionnaire*.

Usability study This study included a series of tasks (T1 to T5) designed to assess the authors' ability to use CoReaDa effectively and easily (Table 9). T1 consisted of obtaining assistance in using CoReaDa. T2, T3 and T4 focused on using basic features such as visualizing data, interpreting results, and taking decisions. To perform T2, the author had to scan the available data looking for specific information. In T3, the author needed to identify the source of a given issue and decide whether an intervention was appropriate. During T4, the author had to examine the suggestions provided before using them to design and implement revision actions. T5 required the use of advanced tool functionality to plan and execute complex operations. The task list was integrated into the dashboard as an auxiliary window that displays the tasks one-by-one and collects the authors' answers. All authors' actions were automatically recorded. The study took an average time of 11 min.

Acceptance questionnaire To investigate authors' attitude towards the adoption of CoReaDa, we used the *Technology Acceptance Model* (TAM) (Davis 1989). This model is widely used in investigating technology acceptance, and has been validated by many empirical studies in educational research (e.g., Cheung and Vogel 2013). A statistical meta-analysis of TAM applied to numerous studies showed it to be valid and robust (King and He 2006). Two measures of acceptance are posited by TAM: *Perceived Usefulness*, which reflects the user's belief that using a system would increase his performance, and *Perceived Ease of use* which assesses the user's belief of how easy a system is to learn and use.

Using the items proposed by Davis (1989) to measure the perceived usefulness and ease of use of professional software, we designed the *Acceptance Questionnaire* (Table 10). The authors received by email the questionnaire and were asked to assess their level of

Table 9 List of authors' tasks

#	Task purpose	Task content
T1	Getting help	Follow the guided tour
T2	Analyzing the computed indicators	Find a specific indicator value for a given chapter
T3	Analyzing the detected issues	Find a specific issue, review it and mark it as not being an actual problem
T4	Performing basic revision tasks	Select an issue, add the associated suggestion as a task, modify the task and then mark it as done
T5	Performing complex operations	Show all available indicators and issues to find the chapter(s) with the greatest number of issues

Table 10 Statements of the TAM questionnaire (translated from French)

Perceived ease of use	Perceived usefulness
- Learning to use CoReaDa would be easy for me	- Using CoReaDa would enable me to revise my course more quickly
- I would find it easy to get CoReaDa to revise my course	- Using CoReaDa would improve my revision performance
- My interaction with CoReaDa would be clear and understandable	- Using CoReaDa to revise my courses would increase my productivity
- I would find CoReaDa to be flexible to interact with	- Using CoReaDa would enhance my effectiveness on course revision
- It would be easy for me to become skillful at using CoReaDa	- Using CoReaDa would make it easier for me to revise my courses
- I would find CoReaDa easy to use	- I would find CoReaDa useful in revising my courses

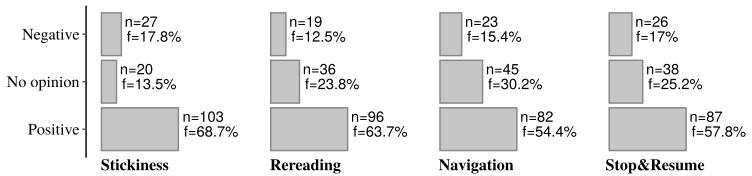


Fig. 4 Ratings of the relevance of the indicators (aggregated by class) by course authors (N = 125)

agreement with each of the statements using a 7-point Likert scale, ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The questionnaire took an average time of 6 min to complete.

Results

Results of sub-study 1

This sub-study aimed to evaluate the relevance for course revision of the set of indicators grouped under the four classes (Stickiness, Rereading, Navigation, and Stop & Resume). The ratings of the participating 125 authors were collected using the *Indicators Relevance Survey*. Table 11 provides descriptive statistics of the results and Fig. 4 represents the ratings aggregated by indicator class.

The Cronbach’s alpha coefficients obtained for the ratings of each indicator gave values ranging from .78 to .91. This shows that the reliability of the results had appropriate internal consistency. We used Spearman’s rank correlation coefficient to assess the correlations between the ratings of the indicators. While some low to medium correlations existed (correlation coefficients between $-.12$ and $.50$), no strong correlation was found. This suggests that authors considered these indicators to cover relatively distinct aspects of reading behavior.

To study the influence of each independent demographic variable (gender, age and level of education) on the ratings, a three-way ANOVA was used. It revealed a significant main effect of age ($F = 281.33, p < .0001$), but not gender ($F = .65, p = .419$), or level

Table 11 Rating of the relevance of the indicators by authors (N = 125)

Indicator	Positive rating		Neither agree nor disagree	Negative rating	
	Strongly agree	Agree		Disagree	Strongly disagree
Visits	<i>n</i> = 40 <i>f</i> = 32%	<i>n</i> = 58 <i>f</i> = 46%	<i>n</i> = 12 <i>f</i> = 10%	<i>n</i> = 10 <i>f</i> = 8%	<i>n</i> = 5 <i>f</i> = 4%
Readers	<i>n</i> = 41 <i>f</i> = 33%	<i>n</i> = 65 <i>f</i> = 52%	<i>n</i> = 8 <i>f</i> = 6%	<i>n</i> = 8 <i>f</i> = 6%	<i>n</i> = 2 <i>f</i> = 3%
Reading session	<i>n</i> = 16 <i>f</i> = 13%	<i>n</i> = 61 <i>f</i> = 49%	<i>n</i> = 29 <i>f</i> = 23%	<i>n</i> = 15 <i>f</i> = 12%	<i>n</i> = 4 <i>f</i> = 3%
Reading speed	<i>n</i> = 15 <i>f</i> = 12%	<i>n</i> = 34 <i>f</i> = 27%	<i>n</i> = 27 <i>f</i> = 22%	<i>n</i> = 33 <i>f</i> = 26%	<i>n</i> = 16 <i>f</i> = 13%
Interest	<i>n</i> = 50 <i>f</i> = 40%	<i>n</i> = 49 <i>f</i> = 39%	<i>n</i> = 9 <i>f</i> = 7%	<i>n</i> = 12 <i>f</i> = 10%	<i>n</i> = 5 <i>f</i> = 4%
Reread	<i>n</i> = 32 <i>f</i> = 26%	<i>n</i> = 62 <i>f</i> = 50%	<i>n</i> = 17 <i>f</i> = 14%	<i>n</i> = 10 <i>f</i> = 5%	<i>n</i> = 7 <i>f</i> = 5%
With.-sess. reread	<i>n</i> = 25 <i>f</i> = 20%	<i>n</i> = 49 <i>f</i> = 39%	<i>n</i> = 36 <i>f</i> = 29%	<i>n</i> = 10 <i>f</i> = 8%	<i>n</i> = 5 <i>f</i> = 4%
Betw.-sess. reread	<i>n</i> = 21 <i>f</i> = 17%	<i>n</i> = 49 <i>f</i> = 39%	<i>n</i> = 36 <i>f</i> = 29%	<i>n</i> = 11 <i>f</i> = 9%	<i>n</i> = 8 <i>f</i> = 6%
Reading linearity	<i>n</i> = 11 <i>f</i> = 9%	<i>n</i> = 54 <i>f</i> = 43%	<i>n</i> = 45 <i>f</i> = 36%	<i>n</i> = 11 <i>f</i> = 9%	<i>n</i> = 4 <i>f</i> = 3%
Arrival linearity	<i>n</i> = 9 <i>f</i> = 7%	<i>n</i> = 55 <i>f</i> = 44%	<i>n</i> = 37 <i>f</i> = 30%	<i>n</i> = 18 <i>f</i> = 14%	<i>n</i> = 6 <i>f</i> = 5%
Departure linearity	<i>n</i> = 8 <i>f</i> = 6%	<i>n</i> = 66 <i>f</i> = 53%	<i>n</i> = 31 <i>f</i> = 25%	<i>n</i> = 14 <i>f</i> = 11%	<i>n</i> = 6 <i>f</i> = 5%
Reading stop	<i>n</i> = 28 <i>f</i> = 22%	<i>n</i> = 65 <i>f</i> = 52%	<i>n</i> = 19 <i>f</i> = 15%	<i>n</i> = 7 <i>f</i> = 6%	<i>n</i> = 6 <i>f</i> = 5%
Reading halt	<i>n</i> = 15 <i>f</i> = 12%	<i>n</i> = 52 <i>f</i> = 42%	<i>n</i> = 36 <i>f</i> = 29%	<i>n</i> = 14 <i>f</i> = 11%	<i>n</i> = 8 <i>f</i> = 6%
Resume linearity	<i>n</i> = 16 <i>f</i> = 13%	<i>n</i> = 48 <i>f</i> = 38%	<i>n</i> = 35 <i>f</i> = 28%	<i>n</i> = 18 <i>f</i> = 14%	<i>n</i> = 8 <i>f</i> = 6%
Future resume	<i>n</i> = 14 <i>f</i> = 11%	<i>n</i> = 50 <i>f</i> = 40%	<i>n</i> = 37 <i>f</i> = 30%	<i>n</i> = 17 <i>f</i> = 13%	<i>n</i> = 7 <i>f</i> = 6%
Past resume	<i>n</i> = 17 <i>f</i> = 14%	<i>n</i> = 55 <i>f</i> = 44%	<i>n</i> = 29 <i>f</i> = 23%	<i>n</i> = 16 <i>f</i> = 13%	<i>n</i> = 8 <i>f</i> = 6%

Number (*n*) and percentage (*f*) of authors who rated the indicator (in row) using the category (in column)

of education ($F = .463$, $p = .496$) on the results. No significant interaction among these variables was found. A Tukey HSD post-test between the three groups of age (defined in Table 7) showed that the means differed significantly from each other ($p < .01$). The ratings of young participants were higher than those of other participants, while those of older participants were the lowest. To determine how the indicator classes were related to the variable *age*, we calculated Spearman's correlation coefficients between *age* and authors' ratings, aggregated by indicator class. This revealed a moderate relation for the stickiness ($r_s = -.48$, $p < .0001$) and navigation ($r_s = -.52$, $p < .001$) classes, but no significant correlation for the rereading ($r_s = -.18$, $p < .001$) and stop & resume ($r_s = -.28$, $p < .0001$) classes.

As shown in Table 11, we defined as *positive rating* any rating that is either *useful* or *very useful*, while a *negative rating* corresponded to either *not really useful* or *not useful*.

Table 12 Number of issues detected and issues expected for each indicator class

	Issues expected by authors		Issues detected by the tool	
	#	Detected	#	Expected
Stickiness	11	7	27	9
Rereading	8	4	18	4
Navigation	14	7	26	3
Stop and resume	12	8	23	5
Total	45	$n=26, f=58\%$	94	$n=21, f=22\%$

Detected issues detected among those expected, *Expected* issues expected among those detected, n number of the issues in the category, f frequency of the issues in the category

Table 13 Rating of the usefulness of the detected issues by the eight authors

	All the detected issues		Issues detected that were expected		Issues detected that were not expected	
	#	Useful	#	Useful	#	Useful
Stickiness	27	21	9	6	17	15
Rereading	18	14	4	4	14	10
Navigation	26	21	3	3	23	17
Stop and Res	23	21	5	5	18	16
Total	94	$n=77 (f=82\%)$	21	$n=18 (f=86\%)$	73	$n=58 (f=80\%)$

Number (n) and percentage (f) of the issues that were rated useful in the category

The most highly rated indicators were *readers*, *interest* and *visits* (resp. 85%, 79% and 78% of positive rating), while the *reading speed* was the lowest rated one (39% of negative rating and 21% of no opinion). The aggregated results (Fig. 4) show that on average, stickiness indicators were perceived as the most relevant (68.7% of positive rating), followed by rereading then stop & resume indicators (resp. 63.7% and 57.8 of positive rating). Navigation indicators were perceived as the least relevant (54.4% of positive rating, 15.4% of negative rating, and 30.2% of no opinion).

Results of sub-study 2

This sub-study was conducted with the authors of the eight courses using the *Issues and Suggestions Survey*.

The authors first listed the issues they expected, and assessed the relevance of the issues that were detected. They then rated the usefulness of the provided suggestions for course revision.

Table 12 presents statistics on the issues expected by the authors and those detected by the tool. The total number of issues detected ($N=94$) was slightly more than double the number of issues expected ($N=45$). About 58% of the expected issues were also detected, with the expected ones related to stickiness and reading stops being the most detected (resp. 7 out of 11, and 8 out of 12). In contrast, only 22% of the issues

Table 14 Ratings by eight authors of the relevance of the provided suggestions (N=76)

	#	Positive ratings		Neither agree nor disagree	Negative ratings	
		Strongly agree	Agree		Disagree	Strongly disagree
Stickiness	24	8	6	6	2	2
Rereading	12	3	5	2	1	1
Navigation	21	5	9	3	2	2
Stop and Res	19	5	7	4	2	1
Total	76	$n=48, f=63\%$		$n=15, f=20\%$	$n=13, f=17\%$	

Number (n) and frequency of the rating (f) in each category

Table 15 Performance metrics computed from the tasks results ($n=8$)

	Success ratio (%)	Clicks		Erroneous clicks		Time (in sec.)	
		Range	Average	Range	Average	Range	Average
T1	100	11–32	20	0	0	86–230	171
T2	100	5–6	6	0–2	.7	10–103	36
T3	100	4–7	4.3	0–4	1.1	5–41	27
T4	87	4–10	7	0–6	1.6	24–78	43
T5	75	9–20	13	1–8	3.1	39–184	89

Tasks: *T1*: Getting help; *T2*: Analyzing the computed indicators; *T3*: Analyzing the detected issues; *T4*: Performing basic revision tasks; *T5*: Performing complex operations. Metrics: *Success ratio*: percent of participants that achieved the task successfully; *Clicks*: number of clicks performed to accomplish the task; *Erroneous clicks*: number of erroneous clicks; *Time*: time needed to do the task

detected were expected. The undetected issues were more related to rereading and navigation (resp. 4 out of 18, and 3 out of 26).

Table 13 summarizes the authors' ratings of the relevance of the detected issues. Of the issues detected (expected or not), 82% were found useful for initiating revision actions. Interestingly, 80% of the issues that were detected but not expected (representing 78% of the detected issues as shown in Table 12) were deemed useful. All the expected issues among those detected were rated positively, with the exception of three issues related to stickiness. According to some authors, such issues were predictable; for example, chapters containing only supplementary material do not attract much interest.

The authors' ratings of the relevance of the provided suggestions (N=76) for resolving the detected issues are presented in Table 14. About 63% of these suggestions (48 out of 76) were deemed relevant. Specifically, the authors rated positively 58% of the suggestions related to stickiness (14 out of 24), 66% of those related to rereading (8 out of 12), 66% of those related to navigation (14 out of 21), and 63% of those related to stop & resume (12 out of 19). While 17% of the suggestions received a negative rating (13 out of 76), 20% of them had a neutral score (15 out of 76), suggesting that they were considered to be very general and need further elaboration.

Table 16 Descriptive statistics of the *Acceptance Questionnaire* results (N = 8)

Questionnaire items	Results	
	Mean ^a	SD
Perceived ease of use		
Learning to use CoReaDa would be easy for me	4.38	1.92
I would find it easy to get CoReaDa to revise my course	5.00	1.60
My interaction with CoReaDa would be clear and understandable	5.00	1.51
I would find CoReaDa to be flexible to interact with	4.88	1.55
It would be easy for me to become skillful at using CoReaDa	5.00	1.51
I would find CoReaDa easy to use	5.25	1.49
Perceived usefulness		
Using CoReaDa would enable me to revise my course more quickly	4.75	1.83
Using CoReaDa would improve my revision performance	5.00	1.69
Using CoReaDa to revise my courses would increase my productivity	4.75	1.67
Using CoReaDa would enhance my effectiveness on course revision	5.13	1.81
Using CoReaDa would make it easier for me to revise my courses	5.25	1.49
I would find CoReaDa useful in revising my courses	5.50	1.31

^aScale: 1 = Strongly disagree to 7 = Strongly agree

Results of sub-study 3

Usability study

Using the authors' logs that were automatically collected while they were performing the tasks-based study, we computed four performance metrics: (1) *success ratio* is the percent of authors that achieved the task successfully; (2) *average clicks* gives the average number of clicks performed by authors to accomplish the task; (3) *average erroneous clicks* is the number of clicks that do not correspond to those required to complete the task; (4) *average time* is the mean time (in seconds) spent by authors doing the task.

The results (Table 15) show that the tasks involving the main functionalities of CoReaDa (T1, T2 and T3) were performed easily, quickly and successfully. T1 (getting help) consisted of following a guided visit (18 sequential mini-pages) and required the significant time of about 8.5 s per mini-page. T2 (analyzing the computed indicators) and T3 (analyzing the detected issues) consisted of scanning the available data and looking for specific information. Both tasks required about half a minute to complete, with an average of one erroneous manipulation click. T4 (performing basic revision tasks) implied the use of the task manager to design and implement revision actions. It took less than one minute to complete, with one failure (one author deleted a task instead of marking it "done"). T5 (performing complex actions) required the use of advanced features and resulted in two failures. It needed about one minute and a half to complete.

Acceptance study

The *Acceptance Questionnaire* used a scale that ranged 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 with the statement. Table 16 shows descriptive statistics of the responses.

The mean scores of the statements used to measure the *Perceived ease of use* ranged from 4.38 to 5.25, suggesting that most authors had no major technical concerns when using CoReaDa. 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 the *Perceived usefulness* ranged from 4.75 to 5.50 (standard deviation between 1.31 and 1.83). This indicates that, overall, the authors perceived CoReaDa as having a rather positive impact in terms of effort, time and performance in reading analysis and course revision.

Discussion

Course design is an iterative process that involves a constant loop of writing, evaluation and revision (Park and Kim 2014). Collecting data about the effectiveness of the courses with the purpose of improving and refining is referred to as formative assessment (Tempelaar et al. 2013). Such an assessment can be conducted using analytical methods that exploit data recorded on learning platforms. However, due to the lack of appropriate technical skills, instructors need assistance to be able to adopt these methods (Spector et al. 2016). In this perspective, we described in this paper a log-based approach to help course authors revise their contents. Different indicators are computed from learners' reading logs, and used for detecting learners' reading issues and generating corrective revision suggestions. The results are reported to the authors using a learning dashboard.

The evaluation study showed that the authors' opinions on the relevance of the indicators were mixed (as shown in Table 11), suggesting the need to refine and extend this set. This involves identifying aspects of course reading that best reflect learners' level of comprehension and then defining indicators that address these aspects. The comprehension issues identified using the indicators seemed to provide authors with valuable knowledge for course revision. Although this knowledge does not always correspond to their expectations (58% of the expected issues were detected), it often leads them to acquire new insights (78% of the detected issues were not expected, among which 80% were found relevant). The revision suggestions also proved to be useful in helping authors improve their courses (63% of the revision suggestions were deemed appropriate to address the associated issues). The task-based study showed that the authors managed to properly use CoReaDa with no major difficulties. This is supported by the acceptance questionnaire results. According to TAM, the opinion of the authors on both the *perceived usefulness* and *ease of use* of the dashboard (resp. 77% and 72% of the responses were positive) reflect their good attitude towards using the dashboard for their revision tasks.

This study, despite its encouraging results, had several limitations. It only involved online courses delivered in informal settings. In addition, the second and third sub-studies involved only a limited number of participants (8 authors). Nielsen (2000) argues that five users are enough for reliable usability testing. However, to be able to generalize our

findings, a broader study that involves more course authors from different learning settings is mandatory. A large-scale longitudinal study is also required to assess the impact of using CoReaDa from an instructional design perspective. More broadly, the long-term impact of using reading analytics for enhancing learning outcomes needs to be demonstrated. This is one of our future perspectives that also include the integration of logs of other learning activities, learner profiles and assessment results into the analytical process.

The three sub-studies, taken together, demonstrate the potential of the Course Reading Dashboard to improve authors' responsiveness to learner reading issues in informal, online classes. The results show that, as argued by many authors (e.g., Hayes 2004; MacArthur 2012), helping course authors to identify barriers to learners' understanding and to implement appropriate corrective measures would encourage them to revise their courses more thoroughly, on a more regular basis. Although participant responses, as well as limitations of the study, indicate the need for further research, our findings strongly suggest that proposed indicators are relevant, that the CoReaDa analytics tool effectively identifies potential issues and recommends solutions, and that the dashboard itself is easy to navigate and use. This study may serve as a springboard to further exploration of learning analytics and user-friendly dashboard tools for real-time improvement of informal, online courses.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent Informed consent was obtained from all individual participants included in the study.

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