Support for Reading Comprehension in Digital Course Texts

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Abstract: Both reading textbooks and answering quizzes lead to better recall of learning content and better learning outcomes, especially when both forms are combined interactively. Nevertheless, existing solutions in learning management systems usually offer reading and quizzes separately. This work aims to improve this by measuring and visualizing students' reading comprehension based on their answers to automatically displayed questions about the text sections they have just read. First, a comprehensive overview of the state of research on reading comprehension is given. Then, a prototypical realization of a partially adaptive system for supporting reading comprehension is presented. Finally, possible extensions to improve adaptivity, interventions, automation, and measurement of reading comprehension are discussed.

Keywords: reading comprehension; reading analytics; learning analytics

1 Introduction

Textbook reading has been shown to be an important factor in student test scores, both print and electronic [DW13]. While [LGS12] confirm that quiz score and final grade are significantly positively correlated with self-reported percentage of completed reading of textbooks, [Ya21] suggest that repeated testing could improve reading skills, reading engagement, and reading comprehension, leading to an improved recall of learning content and key concepts. Studies from educational science have shown that adjunct questions are a form of active learning that increase attention to important parts of the text, and active processing of the topic leads to better learning outcomes [Sy20]. Reading comprehension is a complex process with as many interpretations as there are of reading because it is often viewed as the essence of reading, essential for academic and lifelong learning, getting scientific attention as a cognitive process despite this fundamental importance only since the 1970s. Furthermore, comprehension monitoring is an important strategy to improve text understanding and is unlikely to develop spontaneously [NRP00].

Both reading textbooks and answering quizzes lead to better recall of learning content and better learning outcomes, especially when both forms are combined interactively (e.g. [NRP00; CM07; PW01; Ya21]). Nevertheless, existing solutions in learning management systems (LMS), e.g. Moodle, usually offer reading and quizzes separately.

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Moreover, previous research has focused on enriching of digital texts or visualizing concept maps or summary learner metrics in dashboards, but rarely on real-time visualization of personal reading comprehension in the text itself.
The goal of this work is to address this gap by investigating how to measure the reading comprehension of individual students in LMS and how it can be visualized there adaptively to the reading and learning progress and the individual comprehension level. Thus, this study examines and answers the following research question (RQ1): How can reading comprehension be modeled and represented in digital texts?
Concretely, reading comprehension is modeled based on answering multiple-choice (MC) questions (MCQ) that cover text sections just read and that are automatically displayed depending on reading activity.

After an overview of the state of research on reading comprehension and its measurement and visualization (section 2), the considered design variants of a partially adaptive system for supporting reading comprehension are discussed and a prototypical realization in Moodle is presented (section 3). In the summary (section 4), possible extensions to improve adaptivity, interventions, automation, and measurement of reading comprehension are highlighted.

2 Related Work about Reading Comprehension

There are numerous studies on reading comprehension and its measurement, also with question types other than MC, through objective, linguistic text features such as readability, or behavioral data such as scrolling activity, or gaze data from eye-tracking. Their presentation is followed by a brief overview of similar solutions in LMS and a differentiation from other learning and reading analytics tasks. Finally, related work about the visualization of reading progress and comprehension is discussed.

In a 1944 survey, [Da44] explored the question of how reading comprehension is defined in the literature. By clustering a list of several hundred skills, he identified a ranking of nine mental skills that are deemed most important for reading comprehension. Even then, the still typical tool to measure reading comprehension was deployed: a MC test to measure these nine skills. The skills build upon each other and range from the most basic skill, "knowledge of word meanings", to the ability to draw inferences about the writer's purpose, intent, and point of view – the why, not the what of what is being said. The analysis of the inter-correlations between the skills suggested that reading comprehension is not a unitary ability, but composed of several mental abilities. Because of this, [Da44, p. 193] suggested that learning exercises composed of reading passages followed by factual questions to be answered will not train all the aforementioned skills.

For [AP84], comprehension meant the interpretation of new information in the interaction with old knowledge. Reading with the intention of learning ideas and information means to find a mental "home" in the knowledge store of the memory. Poor reading

comprehension leads to 1. gaps in knowledge, 2. to a poor understanding of the relationships of facts, and 3. to less making inferences about the interconnections among ideas.
According to the so-called *simple model* of [GT86], reading comprehension is the product of decoding and listening comprehension, thus combining a bottom-up process of word identification with a top-down process of deriving syntactic and semantic relationships of the words. Both skills are necessary for understanding the meaning of the text, but neither is sufficient [CS06, p. 278].

The findings were confirmed by the National Reading Panel (US) review of the research literature of the last 20 years in 2000: the role of vocabulary learning, together with reasoning, is critical for reading comprehension [NRP00, p. 4-5], even if they noted that the skills perspective of [Da44] has been questioned since. They stressed the constructivist aspect of reading as intentional, meaning-constructing thinking through the reciprocal interchange between the prior knowledge and experience of the reader and the message in the text. Reading is a purposeful and active process, requiring knowledge of the world, like language and print, to understand, learn and memorize the meaning of the text, and to put it to use by communicating the read information with others.
The Panel named eight comprehension instruction methods with a firm scientific basis: making readers aware of their understanding during reading (comprehension monitoring) and thus breaking through student's passivity and engaging them in their own learning, visualizations of the meanings and relationships of underlying ideas in the text and the story structure, question answering (having the strongest scientific evidence for its effectiveness) and feedback on the correctness, and question generation and summarization by the reader. Explicit instruction on comprehension strategies ("cognitive strategy training") is believed to improve text understanding, information use, and motivation for reading, and it is unlikely that these strategies are developed spontaneously [NRP00, p. 4-40ff.].

[PLO05] argued for reading comprehension skill as understanding writing, i.e. printed word identification, as well as spoken language, i.e. listening comprehension, in congruence to the simple model of [GT86]. Deeper comprehension is building a mental model (situational model) of the message of the text, by processes at multiple levels, like word, sentence, and text level. In most research, they said, comprehension is assessed by readers answering questions of short texts following their reading. In order to achieve coherence in the mental model of a text, it is important to monitor its comprehension, to verify the understanding, and correct it if inconsistencies are detected, by reading the text again.

In comparing different reading comprehension assessments, [Fl06] argued that readability, i.e. the difficulty of the text and its semantic and syntactic characteristics, is a major determinant of the inferences that a reader can make about the text and the inferences the researcher then makes about the reader's comprehension. What is measured depends on the concept of what is being measured as well on the characteristics of the diagnostic test.
This problem was illustrated by [CS06] in a comparison of scores from three commonly

used reading comprehension tests. They stated that tests also differ in whether readers are allowed to see the text while answering questions. In an experiment with first to tenth graders (N=97), they tried to predict these scores by measures of cognitive skills that research suggests should contribute to comprehension. Their results were inclusive: measures of rapid serial naming, verbal memory, IQ, or attention did hardly improve predictions, while word recognition/decoding and oral language proficiency together accounted for 50-70% of the variance. Reading speed explained additional 1-6%. They concluded that other skills that account for the unexplained variance have to be found and that the differences among reading comprehension measures need to be examined. In their study, only 25% of children that were identified as weak comprehenders by one test were so by all three tests.

[Al09] defined three different levels of comprehension measurable with MCQs, similar to [Da44]: 1. literal comprehension: a surface-level understanding of the text, whereby questions can be answered by explicit information directly stated in a single location in the text; 2. inferential comprehension: the ability to infer and draw conclusions about the intended meaning of the author; 3. evaluative comprehension: a critical, applied understanding to one's practical or theoretical expertise and previous knowledge, connecting the written word to other texts and the understanding of the world.

Using Bloom's taxonomy, [Sy20] classified two types of questions: factoid/low-level and synthesis/high-level, assigning the former to the "remember" level and the latter to the "analyze" level of cognitive complexity, and used short, free-response questions in order to avoid participants guessing the right answer that had to be corrected manually.
[Br11] extended the requirements for answers even further than [Sy20]: participants received a set of so-called stimulus documents as sources which they had to read to answer multiple questions in their own document. The authors used machine learning to create a model to classify individual text comprehension using features of source and student documents and Latent Semantic Analysis. This approach has an even higher effort of manual grading.

In their study, [Cr17] compared the accuracy of machine learning models using linguistic features (lexical sophistication, text cohesion, syntactic complexity) to different classic readability formulas which take human judgments derived from text comprehension scores of MCQs as the gold standard. Since these formulas only rely on lexical and syntactic features, not on semantic and discourse features, nor on the reader's world knowledge, they can give nonsense texts a high readability score. Readability formulas are often used for predicting text level and are more related to how fast a text can be read and not just comprehended.

[Go21] used scrolling interactions to predict text readability for adult learners of English. They also used reading comprehension scores measured by MCQs to just read text, to compare self-reported language proficiency with what they called subjective readability or leveling, which combines objective readability with the reader's background. Predictions from scrolling behavior were even compared to baseline predictions with traditional readability, but also linguistic measures like lexical richness (type-token ratio). Interaction measures used for prediction were the total reading time, scroll speed of each scroll interaction, the scrolling acceleration by dividing the difference between final and initial scroll speed by time, and the number of text regressions, i.e. upward scrolling actions to recover areas of text. Even though the prediction from scrolling interactions was worse than from traditional and linguistic measures, their study showed that scrolling behavior is correlated to the objective as well as subjective readability.

[Sy20] combined the analysis of attention signals, obtained from gaze tracking, with the research of how adjunct questions displayed during reading, i.e. questions inserted into the text, affect the learning outcome. Since the use of gaze tracking is not practical in university courses, the research they cited that cursor and mouse movements can be used as a proxy for gaze in certain reading scenarios is noteworthy.

The integrated Moodle Quiz activity[2] offers the management and visualization of questions and answers, while the Lesson activity[3] offers the possibility to provide study material in a structured and adaptive way (manually predefined, not automated), e.g. by alternately displaying course texts and questions. Also, other LMS like Coursera and Ilias[4] provide either a separation of reading and quiz activities or strictly defined learning paths which are unrelated to individual reading progress and comprehension levels.

Related topics in reading analytics are reading styles, engagement and motivation. As an intermediate step toward predicting student academic success, [BO19] identified reading styles from learning log data on reading and navigation within e-books of one university semester. The two high-level reading styles investigated were receptive reading – sequentially and steady from start to end – and response reading – active engagements with the arguments of the text through changes of pace, using bookmarks, memos, and markers. In their study, students used linear, forward-oriented, receptive reading most of the time and showed low interaction with other features. Reading styles did not correlate with final course grades, total reading and grades did, however.

In an experiment with a similar design as [Sy20] (pretest, posttest, automatic question generation), [Ya21] measured reading engagement similarly to [BO19] via reading time, number of highlights made, memos posted, and bookmarks added, in an e-book reading system. In addition, they measured reading skills as text-marking skills: by calculating the similarity between the sentences used by the artificial intelligence (BERT) to generate questions and the content marked by the students. Their results from a four-week experiment in two university courses were promising: although the control group was encouraged to restudy the key concepts of the text as often as possible, the experimental group, which could use machine-generated cloze item practice, had significantly higher reading skills, reading engagement and scores on the reading comprehension MC posttest in the final week. Thus, repeated tests could improve reading skills and engage-

[2] https://docs.moodle.org/311/en/Quiz_activity, retrieved August 10, 2022
[3] https://docs.moodle.org/311/en/Lesson_activity, retrieved August 10, 2022
[4] https://www.coursera.org and https://www.ilias.de, retrieved August 10, 2022

ment as an indirect, and comprehension as a direct testing effect, leading to enhanced retention of learning content.

[Su18] showed that online reading duration is a strong indicator of reading motivation in students, which itself is important to enhance intensive reading behaviors. In their study, they collected log data of 160 students during a two-month online course with reading material, quizzes, and a post-test questionnaire measuring the motivation of the students. After clustering the students according to their motivation and reading duration, they did a sequential analysis of behavior records transformed into six codes (e.g. intensive reading, skim reading, passing a test). Groups of high reading duration had also higher motivations and more phases of intensive reading, and they more interactively combined reading and tests during their online activities.

In a 2004 paper, [SHW04] presented an e-book user interface that displays the organizational and narrative thread structure of a book to support reading comprehension. [GPB13] developed a reading system for social visualization of reading progress at the chapter, section, and page levels to allow comparison of one's progress with that of others.
[MC15] study student engagement of an LMS which is specialized to extensive reading. For one year, students had access to a library of 500 books, including post-reading quizzes. A dashboard allowed students and teachers to monitor quiz results, total reading time, and reading progress, measured as words-per-minute counts, books read and total words read. Despite students' high satisfaction with the system, they read on average only one-fifth of the expected reading.
[Th20] model domain concepts by generating students' knowledge states to automatically identify recommended personalized sections of textbook materials. These sections are tailored to address knowledge gaps revealed by failed assessments.
In the study of [Ki20], students and experts created summaries of a text. A concept map was automatically created from each summary, and both concept maps were compared. Based on this comparison, students were presented with several types of feedback: similarity indices, an exemplary summary of an expert with highlighted concepts, and a graphical representation of the student's and expert's concept map.
[WW21] implemented a digital textbook that allows students to draw concept maps to the text they are reading, which are then scored using an expert map, similar to [Ki20]. Their novel approach is to provide adaptive feedback during concept mapping in the form of process-based diagnostic instructions that respond to defined patterns.

In summary, there is a solid scientific basis for measuring and reinforcing reading comprehension, motivation and duration with embedded MCQs about the text just read. However, LMS development seems to lag behind this evidence. Previous research has mainly addressed feedback by comparing concept maps, learner dashboards, or visual enhancements of digital texts to represent and improve reading comprehension, but not a real-time estimation of reading comprehension per section directly in the respective text.

3 Design and Realization

The prototype of a partially adaptive system for supporting reading comprehension is implemented as part of *Longpage*, which extends the Moodle page with functionalities that simplify reading on screen or provide advantages that are not available when reading printed works or PDF files: students can annotate texts, mark and comment sections, and share this information with others. A reading progress indicator marks how often certain sections of text have already been read by fellow students.
Reading comprehension is calculated as the ratio of correct answers to questions after a section or to all questions on the current page. The distinction between comprehension levels is left to the teacher as a recommendation when creating and assigning questions.

The integration of a reading comprehension estimation into Longpage breaks down into three main parts: an option for the teacher to create and edit questions and assign them to parts of text, the display of the embedded questions for the student with the option to answer them, and the display of the estimated reading comprehension for each text section. A screenshot of the implemented prototype is shown in fig. 1.

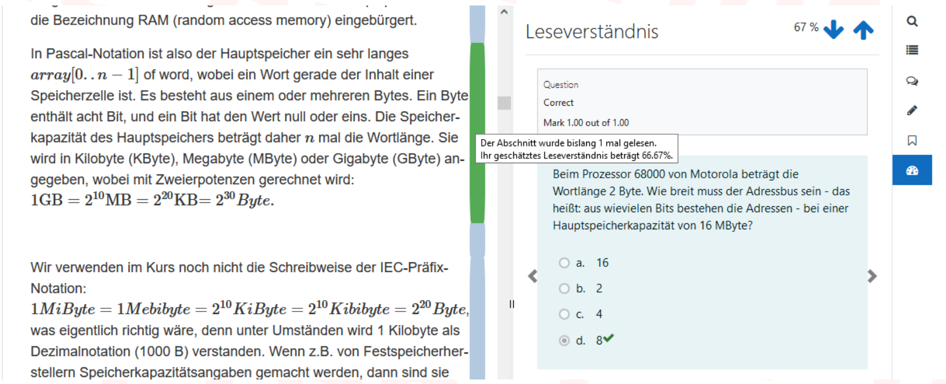

Fig. 1: Screenshot of prototype: text (left), reading progress bar (middle), questions (right)

Moodle already provides the functionality to create, preview and edit questions and their answer options with the so-called question bank.[5] For the assignment of these questions to text sections, there is no default functionality available. Two solutions were considered and evaluated: assignment via tags referring to section IDs, and assignment directly in the text via HTML attributes. For this prototype, the second solution was chosen, as placing questions in the text where they later appear is more intuitive for less technically adept users, and the assignment cannot be changed incidentally by reordering sections as when using tags. As reuse of existing open-source code is recommended, a collection of third-party plugins was installed: *Embed question atto button*[6] makes it possible to assign questions to sections. After putting the cursor at a certain position in the text, the teacher

[5] https://docs.moodle.org/311/en/Question_bank, retrieved August 10, 2022
[6] https://moodle.org/plugins/atto_embedquestion, retrieved August 10, 2022

can select a question from the question bank. Then, a cryptic code will be inserted inside the text identifying the question. *Embed question filter*[7] is a Moodle text filter plugin that converts this cryptic code into HTML for rendering the question inside of Longpage like in a quiz. Multiple questions have to be added sequentially without line breaks so that the script can associate sections and questions correctly. The questions are hidden per default.

Displaying questions, answers and resulting scores in the student view is already possible in Moodle with the quiz activity. What remains to be discussed is where to show the questions, when to show them, and the selection of questions to show for the individual student. As questions should be rendered inside a Longpage and not on a separate page, there are at least three possible ways how to embed them: directly in the text under a section, in the side panel of Longpage, or in an overlay on the side, similar to chatbots.
In this work, questions are displayed in the side panel, similar to [Sy20] where the question area is at the bottom of the page, because with direct embedding, the reading flow will be interrupted – detrimental to reading comprehension [Fo15] –, and the impression of a static text will be broken in favor of a more interactive text, which could be distracting. An overlay could be associated negatively by students, as they are often used for marketing purposes, even though it could be the basis of an assistance function or virtual agent to build upon (e.g. like in [AlSnMc15]).
The reading intention has to be distinguished by reading activity: there could be several reasons for a student to open up a text page and scroll through it, e.g. reading it for building up reading comprehension, just skimming through it to get an overview, or scrolling through it to find an answer to a question, maybe using the search functionality of the browser [PM12]. Only the first reason seems like a reasonable time to show questions.
But in this prototype, scrolling intention is not distinguished: when skimming over the section, the questions are faded in and out so fast that they are actually never visible to the human eye, which makes further optimization unnecessary. Also, as the questions are displayed on the side panel, the students can actively express their reading intention by opening or closing the sidebar.
Question selection according to comprehension levels and answer history is deferred, too, because this feature makes only sense if there is a vast catalog of questions, which makes this a good feature for optimizations later on.

Using the Intersection Observer API[8] available in a modern web browser, a custom script clones the HTML code of a hidden question when the student scrolls over it, pastes it to the side panel and sets it to visible. When the original hidden question inside of the text is scrolled outside of the view, the cloned question in the side panel will be removed. This way, for the student, the question appears in the side panel as long as the corresponding text section is visible. If there are multiple questions per section, they can be clicked through in a carousel by clicking on the left and right arrows. Thus, students can answer as many questions as they like, until the contingent on questions is ex-

[7] https://moodle.org/plugins/filter_embedquestion, retrieved August 10, 2022
[8] https://www.w3.org/TR/intersection-observer, retrieved August 10, 2022

hausted. With two arrows, up and down, it is possible to jump to the next section with questions available.

The reading progress indicator already present in Longpage is shown immediately on the right side of the text as a bar. Its width signifies the frequency, its color is always grey-blue. The indication for reading comprehension could either be built upon it because of the related concepts, or shown separately in another bar right or left, or shown by font or text background color. The text could be harder to read with colors, and the highlighting and commenting functions of Longpage could interfere. Although another bar could have different widths depending on the comprehension level of the section, it could be too much distraction from the text, and make reading confusing.
Thus, in this prototype, reading comprehension is displayed by coloring the existing reading progress bar according to the estimated comprehension level. Hovering the mouse cursor over the bar displays the value for the estimate. In further versions, the values for multiple comprehension levels could be shown, too.

Moodle follows a client-server model, whereas the client part runs in the web browser and is written in HTML, CSS, and JavaScript, and the server part is written in PHP. The client part of Longpage is written as a single-page application using Vue.js, a JavaScript framework[9]. This means that content, e.g. reading comprehension data, can be reloaded dynamically without reloading the whole web page via Asynchronous JavaScript and XML (AJAX). This is important, as this data can change while the student is reading and answering section-related questions. Thus, questions, answer options, and reading comprehension information are rendered in the browser, while the latter is calculated as follows:
When the student submits an answer, an AJAX call is triggered so that the PHP function on the server is executed that calculates the comprehension values for the whole page. This is necessary because a question can be referenced several times on the same page, so a new answer could potentially change the estimated reading comprehension in multiple sections. This function iterates over all questions on the page, fetches the student's last five attempts no older than three months for each question, and calculates the average scores. Finally, a JSON array with all scores is sent back to the client, which iterates through it and changes the color and tooltip text of all reading progress bars accordingly. An overall reading comprehension estimate for the page is added to the sidebar.

4 Conclusion and Outlook

In this work, we showed how reading comprehension can be modeled and visualized in digital texts (RQ1). Questions are displayed adaptive to reading progress, and reading comprehension per section is calculated and displayed from the answers. Ideally, when a text is filled by the instructor with many questions for each section, it results in a kind of

[9] https://vuejs.org, retrieved August 10, 2022

text coverage for the students to monitor their learning progress. Following this study, usability, user, and field studies are planned to evaluate the prototype.

Of course, many more improvements are conceivable: adaptivity could be improved by preselecting questions according to comprehension levels [Al09], question difficulty, scrolling intention [Sy20], learning profile including further learning activities [Ya21], or time since last answer. The first two should be fairly easy to implement: an input field for the difficulty level needs to be added to each question, and the questions could be displayed according to the student's current comprehension estimate. Reducing questions when comprehension is high or displaying e.g. a help button when there are many wrong answers (fading) is another form of adaptivity, as well as hints which text should be reread in case of wrong answers [Th20], reinserting not understood text parts in the text, collapsing understood sections, or simplifying not understood sections by replacing difficult words [NRP00, p. 4-4]. Allowing students to manually adjust objective to subjective comprehension or including self-evaluation as another variable when calculating reading comprehension or selecting questions would make the solution more adaptive, too.

To make interventions based on reading comprehension of individual students possible, a dashboard for the instructors is needed. They could further be supported by as much automation as possible: manually generated questions as well as other contents like assignments and self-assessments could be automatically matched to text sections with semantic matching, with the possibility to correct matches manually. Topic modeling would make it possible to map text segments and questions to underlying concepts to calculate reading comprehension more flexibly. Automatic question generation would support both instructors and students, as many detailed questions increase frequency and accuracy of reading [Sy20]. The measurement of reading comprehension could be improved by additional factors, e.g., comprehension levels, text-marking [Ya21], reading frequency, or course activities. Thus, there are still many opportunities to improve adaptive support for reading comprehension in digital course texts to enhance the reading experience and learner success.

Acknowledgements This research was supported by *CATALPA - Center of Advanced Technology for Assisted Learning and Predictive Analytics* of the FernUniversität in Hagen, Germany.

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