6-23-2021

Interactive features of E-texts' effects on learning: a systematic review and meta-analysis

Virginia Clinton-Lisell

University of North Dakota, virginia.clinton@und.edu

Ben Seipel

Staci Gilpin

Christine Litzinger

Interactive Features of E-Texts' Effects on Learning: A Systematic Review and Meta-analysis

Virginia Clinton-Lisell[1], Ben Seipel[2] , Staci Gilpin[1,3], and Christine Litzinger[1]

[1]University of North Dakota

[2]California State University, Chico

[3]The College of St. Scholastica

Author Note

Correspondence concerning this article should be addressed to Virginia Clinton-Lisell, who is an Assistant Professor in Educational Foundations and Research at the University of North Dakota. She may be contacted at (701) 777-5793, virginia.clinton@und.edu, or 231 Centennial Dr., Grand Forks, ND, 58202, USA. Her ORCID ID is 0000-0002-4705-2217and she can be followed on Twitter @drclintonlisell.

For the final version, please see:

Clinton-Lisell, V., Seipel, B., Gilpin, S., & Litzinger, C. (in-press) Interactive features of e-texts' effects on learning: A systematic review and meta-analysis. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2021.1943453

Abstract

E-texts afford interactive features that are not feasible with paper texts. Several studies have been conducted examining interactive features of e-texts, but it is uncertain what the overall effect is or what features may be most useful. The purpose of this study is to systematically review and meta-analyze the findings comparing reading performance and/or reading times between e-texts with interactive features and control texts (paper or static e-texts). The systematic search of the literature identified 26 independent studies on reading performance. Based on the meta-analyses, interactive features benefited reading performance ($g = .66$, $p < .001$). Individual studies with positive effects involved multiple interactive features; however, potential contributions of three types of features (questions with feedback, digital glossaries, and collaborative tools) are discussed. Future directions for examining interactive features experimentally to better understand what features are most helpful for whom are described.

Keywords: digital glossaries, interactive e-texts, meta-analysis, reading performance, systematic review

Interactive Features of E-Texts' Effects on Learning and Reading Time: A Systematic Review and Meta-analysis

Reading from screens has become commonplace in educational settings. However, there is ample evidence that reading from screens negatively affects performance compared to reading from paper based on three meta-analyses (Clinton, 2019; Delgado et al., 2018; Kong et al., 2018). Moreover, readers tend to be more overconfident of their perceptions of how well they are understanding a text when reading from screens compared to paper (Clinton, 2019), indicating screen inferiority in both performance and metacognition (Sidi, Ophir, & Ackerman, 2016). In the studies reviewed in these meta-analyses, the conditions for reading were similar across medium. There are numerous ways in which screens could enhance or scaffold the reading experience that are not possible with paper. Multiple studies have been conducted examining how interactive features of digital texts may affect reading comprehension (e.g., Jin, 2013; Sommers et al., 2019; Weng et al., 2018). It is possible that these interactive features could overcome issues with screen inferiority. The purpose of this systematic review is to provide a cohesive overview of the research conducted on interactive e-texts, which are electronic reading materials with features intended to assist or engage readers in a manner afforded by screens, but not feasible with paper. By doing so, the effectiveness of various features may be better understood.

Reading inherently involves interaction between the reader and the text, whether that text be viewed on a paper book, tablet, or computer (Mangen & van der Weel, 2016). Furthermore, texts of any medium can be designed to be interactive in that they have features designed to encourage the reader to respond to the text in some manner (Kucirkova, 2017). However, the affordances of screens permit interactions that are not possible with paper medium. When reading from screens as opposed to paper, interactivity involves digital features that can be activated by the reader through touch and click such as visual presentations, prompts to guide reader thinking, or hyperlinks to helpful content (Kucirkova, 2017). The focus of this review is findings relevant to interactive features of e-texts that could not be easily replicated with paper. By focusing on digital interactivity, this review can illuminate how affordances of screen could enhance performance thereby potentially overcoming the screen inferiority noted in previous findings (Clinton, 2019; Delgado et al., 2018; Kong et al., 2018).

Theoretical frameworks

According to the construction-integration model of text comprehension, readers are thought to construct three different levels of representations of a text: the surface structure, the textbase and the situation model (Kintsch, 1998). In the surface structure are the words and syntax that create ideas in a text, known as propositions. These propositions within the text are connected to each other in the textbase level of representation. The situation model is constructed when readers incorporate relevant background knowledge and personal experiences with the textbase to create a mental representation of the text. Interactive features could potentially support the development of each of these levels of representation.

Digital glossaries (also known as “digital dictionaries” or “embedded glossaries” utilized through “enhanced text” or “hypertext”) are one interactive feature of e-books that can assist a reader with the surface structure level of representations of the words in the text. Glossaries that are either digital or on paper allow readers to comprehend text that may otherwise be too difficult to understand (Nation, 2001). Digital glossaries are electronic databases of key terms or vocabulary used in electronic text (Dimitrova & Koseka-Toszewa, 2009). Digital glossaries can provide definitions of the word (through text, audio, illustration, or video), highlight context clues, translation, provide a pronunciation guide, sound out a word, or provide background knowledge. Digital glossaries generally can function in one of two ways: existing/embedded hyperlinks in the electronic text or by digital highlights of word or phrase generated by the reader. Digital glossaries may support textbase development because readers who better understand the words expressing ideas in the text would logically be better able to appropriate connect ideas within the text. Furthermore, digital glossaries can provide background knowledge that may assist in situation model construction.

Prompts and questions posed by interactive e-books could also facilitate successful construction of the textbase and situation model. Prompts and questions that guide the reader to effectively connect different ideas in the text (for textbase development) and between ideas in the text and background knowledge (for situation model development; Bos et al., 2016). Moreover, interactive features can help students by providing background knowledge to construct a situation model. For examples, interactive features can provide links to additional relevant material, videos with explanations, and interactive simulations that could give students background knowledge to help them develop in-depth situation models.

Interactive features that provide feedback to readers can improve comprehension accuracy at different levels of representation, depending on the design of the question or prompt (Bos et al., 2016). Feedback while learning from text has been found to improve comprehension performance, especially if provided through a computerized system (Swart et al., 2019). Computerized systems afford immediate and automatic feedback, which is not feasible with paper (Swart et al., 2019). This may be particularly beneficial for reading from screens because readers tend to be overconfident in their perception of learning (i.e., they think they understand the text better than they actually understand it; Clinton, 2019; Lauterman & Ackerman, 2014).

Getting feedback may help readers have more accurate awareness of their understand of the text, which could potentially overcome the issue of overconfidence (Dunlosky & Lipko, 2007).

Cognitive load theory provides a useful framework for evaluating interactive features of e-texts and interpreting the findings. Cognitive load theory is based on the understanding that human cognitive resources are limited. For this reason, the amount of information (i.e., load) that readers need to process affects learning new knowledge (Sweller et al., 2019). Cognitive load can be intrinsic or extraneous. Intrinsic cognitive load is inherent to the knowledge being learned (Sweller, 2020). It can only be reduced by changing the content or the knowledge base of the reader. In contrast, extraneous cognitive load is unnecessary to the knowledge being learned and can be reduced or increased based on instructional procedure and information presentation (Sweller et al., 2019).

Both intrinsic and extraneous cognitive load could be affected by interactive features of e-texts. Depending on the readers' needs and the design, interactive features that provide students with background knowledge (e.g., links to additional material, videos, interactive simulation, digital glossaries) could affect cognitive load in manner beneficial or deleterious to learning. If the background knowledge provided by the features is helpful, the knowledge base of the reader would increase, logically reducing intrinsic cognitive load and supporting learning from the text. Conversely, if the background knowledge provided by the features is not helpful, these features would add to extraneous load and likely interfere with learning from the text. Similarly, questions with feedback could help readers have more accurate understanding of the new knowledge. Or answering questions and reviewing feedback could be extraneous cognitive load if it is unneeded information that is not helpful for learning. It should be noted that computer-provided feedback that is automatic and immediate is thought to involve less extraneous cognitive load that paper modes of feedback (e.g., looking up answers in a key, scratching off correct responses, Swart et al., 2019). Because interactive features could relate to cognitive load in potentially helpful or unhelpful manners, a systematic review and meta-analysis of interactive features is needed.

The Current Study

The purpose of this review is to synthesize and conduct a meta-analysis on the research findings on interactive features of e-texts. Specifically, the effects of interactive features of e-texts compared to static e-texts and/or paper texts on learning is compared. A meta-analysis was conducted to determine the overall effect of interactive feature. The findings were further examined to consider the effects of various kinds of features.

Method

The authors confirm that the data supporting the findings of this study are available within its supplementary materials.

The inclusion criteria included the following: 1) there were comparisons of interactive e-text condition(s) to control conditions with either static e-text or paper text, 2) there was a measure of learning from text, 3) the statistics necessary for conducting the meta-analysis were either reported or the author(s) of the report provided these statistics upon request, and 4) texts were not designed for second language acquisition (to avoid confounds related to second language reading, Melby-Lervåg & Lervåg, 2014), 5) the same basic text was read for interactive and control conditions (i.e., comparisons of different text topics in which one was interactive and the other was not were ineligible), 6) the e-text was not designed to develop decoding (i.e., the focus of the interactive features were to support reading to learn, not learning to read; Harri-Augstein, Smith, & Thomas, 2017). For the e-text to be considered interactive, it had to have at least one interactive feature that required a screen to be functional (i.e., would not be possible using paper). For example, an embedded video link would be considered interactive, but a notetaking function (that could be easily replicated with paper) would not be considered interactive for this meta-analysis. Questions with immediate and automatic feedback on responses were considered interactive because this type of feedback is not feasible with paper (readers could look up answers to questions in a paper text, but this would not be immediate and automatic feedback), but questions or other types of prompts that did not provide feedback that the reader could easily ignore on paper were not considered interactive features. This is to focus on the systematic review and meta-analysis on interactive features afforded by screens rather than all possible interactive features of text independent of medium.

There were multiple steps in the systematic search for relevant studies comparing learning from interactive e-texts to non-interactive versions (static e-texts, paper texts, or both) was conducted (see Figure 1). The first step was searching for relevant literature with combinations of the search terms “interactive,” “read*, “vocabulary,” “comprehension,” “screen,” “ebook,” “electronic textbook,” “digital scaffold,” “app,” and “digital read*” (with * as a joker) in the databases SCOPUS, PsychInfo, ERIC, and Proquest Dissertations and Theses in June of 2019. This yielded 5,128 citations. There were 1,491 duplicate citations that were deleted. Abstracts of the remaining 3,637 citations were screened based on inclusion criteria using Rayyan (Ouzzani et al., 2016). The fulltexts of 119 were examined for more in-depth examination of relevance, which lead to 13 relevant reports being identified. A forwards search of work that had cited each of these relevant reports was conducted using Google Scholar (this search engine was chosen to avoid possible publisher bias, Wohlin, 2014), which yielded 7 more reports. A backwards search reviewing the citations of each relevant report for more possible reports was also conducted. This resulted in one additional report. The first author of this meta-analysis emailed the corresponding authors of the relevant reports asking if they were aware of any additional reports they could share. This results in 2 additional reports. The references of a scoping review (Spencer et al., 2020) were searched, which lead to 3 more reports identified. Therefore, a total of 26 relevant reports with 26 independent studies were found.

Coding

The relevant reports were coded to provide descriptive information (see Table 1). To describe the studies, basic bibliographic and methodological information (number of participants, design and context) is provided. This coding was conducted by the first three authors with 25% overlap to assess reliability ($\kappa = .89$). The first author resolved any disagreements.

Statistical Procedures

To assess the effects of interactive e-text, we calculated Hedges' *g* to aggregate effects across studies. Hedges' *g* corrects for bias due to sample size, which is appropriate for this meta-analysis given the small samples of some of the studies (Hedges, 1981). Based on the recommendations of Harrer et al. (2019a), the Hedges' *g* for each effect size was calculated using the "esc" package in R (Lüdecke, 2018) using the means, standard deviations, and number of participants for each condition for the metrics of interest. If these descriptive statistics were not reported nor provided by the author upon request, then Hedges' *g* was estimated based on *t*-test, *p* values, and/or *F* statistics using Comprehensive Meta-Analysis (version 3; Biostat). A positive Hedges' *g* indicates a greater value in the dependent variable for the interactive e-text.

Some studies reported more than one learning measure; therefore, there was more than one effect size for those studies calculated. These effect sizes within the same study were dependent because they were from the same sample. To account for these dependent effect sizes, robust variance estimation (RVE) was used, which is more accurate than aggregating multiple effect sizes within a study (Tanner-Smith et al., 2016). A correlation among dependent effects of .8 was assumed. The package “robumeta” in R was used to calculate the aggregate effect size statistics using RVE (Fisher & Tipton, 2014). In addition, a small sample size correction for RVE was included in the analyses (Tipton, 2015; see Tipton & Pustejovsky, 2015).

Based on the RVE analyses of 26 studies with 42 effect sizes and a total of 2,114 participants, learning performance was better for interactive texts than control texts, Hedges’ g = .66, SE = .14, 95% CI [.38, .95], $p < .001$. See Figure 2 for a forest plot of each effect size. To assess the heterogeneity of the findings by study, I^2, which is an estimate of variability across studies that is assumed to not be from chance, was used (Higgins & Green, 2011). As a percentage, I^2 has a range of 0-100 and higher numbers indicate higher heterogeneity. The I^2 was 85.57 which indicates substantial heterogeneity.

One concern with any meta-analysis is that statistically significant findings are more likely to be reported, a phenomenon known as publication bias. To assess publication bias, two techniques were used. The first was a visual inspection of a funnel plot and the second was using the statistic of Eggers’ test of the intercept (Cooper, 2015; see Follmer, 2018, for a similar approach). In funnel plots, the effect sizes of studies are plotted based on their size on the y axis with smaller studies being towards the bottom and the effect size is on the x-axis with the mean effect size indicated with a vertical line through the plot. If the distribution of effect sizes is asymmetrical on the two sides of the mean effect and larger studies are closer to the mean than smaller studies, then publication bias is suspected (Egger et al., 1997). Based on the funnel plot in Figure 3, the distribution is fairly symmetrical and there does not appear to be differences in proximity to the mean based on the size of the study. Egger’s test of the intercept was calculated using the “demetar” package in R (Harrer et al., 2019b; note that aggregate effect sizes were used for these tests as there is not a function that accounts for dependent effect sizes in assessing publication bias). The Egger’s test of the intercept did not significantly differ from zero, β = 2.08, *p* = .09, 95% CI [-.25, 4.41]. Given these findings, publication bias is unlikely.

An outlier analysis was conducted to determine how the removal of extreme effect sizes would affect the findings. A study’s effect size was considered an outlier if its confidence interval was outside the confidence interval of the overall effect. The finding outlier function through the “dematar” package in R was used (Harrer et al., 2019b). Based on this function, there were 8 outliers identified (Alekhalfi et al., [2020], Arowsi et al., [2019], Ebied [2015], Freund et al., [2016], Hsiao et al., [2016], Lustria [2007], Weng et al. [2018], and Zarzour & Sellami [2017]). Based on an RVE analysis of the remaining 18 studies (with 34 effect sizes), there was a positive effect of interactive e-text, Hedges’ *g* = .60, SE = .09, 95% CI [.41, .79], $p < .001$. In other words, the findings were similar although the effect size slightly lower with the outliers excluded than with the outliers included. The I^2 with the outliers removed was 51.65 indicating a reduction in heterogeneity with the removal of outliers, although there was still moderate heterogeneity.

Discussion

The purpose of this review was to aggregate the findings on interactive e-texts in terms of learning. Based on the results of a meta-analysis of 26 studies, there was a moderately-sized, positive effect of interactive e-texts over control texts (static e-texts and/or paper texts). This positive effect remained significant, although somewhat smaller, after the removal of eight potential outliers in analyses.

In the studies meta-analyzed, there were many different types of interactive features involved. This likely contributed to the heterogeneity in the findings noted in the results. A review of the findings to consider which features were beneficial and which were not helpful would help in understanding these findings. There were 17 studies in which statistically significant positive effects on at least one learning measure were noted (Asrowi et al., 2019; Chang et al., 2019; Chaudhri et al., 2013; Chen et al., 2014; Chen et al., 2018; Dennis et al., 2016, Ebied 2015; Jin, 2013; Hsiao et al., 2016; Jin, 2013; Li et al., 2013; Lustria, 2007; Mochizuki et al., 2019; Sommers et al., 2019; Zarzour & Sellami, 2017; Zarzour & Sellami, 2018a; Zarzour & Sellami, 2018b). Most of these studies with positive effects had multiple interactive features making it challenging to discern the features or combination of features most effective. It should be noted that there are some commonalities about the specific features, namely questions with feedback, collaborative annotations, and digital glossaries, which are discussed further.

Questions or other assessments with feedback were considered to be particularly helpful as they could guide the reader to make accurate connections thereby promoting better textbase and situation model development. Five of the studies with positive effects involved some form of questions or prompts with feedback (Asrowi et al., 2019; Chaudhri et al., 2013; Chen et al., 2018; Hsiao et al. 2016; Sommers et al., 2019). However, there were some exceptions. There were two studies that used questioning with feedback and had null results because they likely lacked sufficient power to detect a benefit (Blake, 2016; Koć-Januchta et al., 2020). Another study with questions and feedback had null results likely due to a ceiling effect (Almekhalfi et al., 2020). Liu and colleagues (2020) did not have a significant benefit of the interactive e-text for learning, but the students in the interactive e-text condition spent less time studying than those in the static e-text condition. This indicates that learning from the interactive e-text was more efficient in this study (Liu et al., 2020). Taken together, these findings support the notion that answering questions and receiving feedback does not interfere with learning through increased extraneous load. In addition, these findings converge with a meta-analysis finding that providing feedback to readers benefits comprehension (Swart et al., 2019).

Four studies in which digital glossaries were an interactive feature indicated benefits of interactivity (Asrowi et al., 2019; Chaudhri et al., 2013; Chen et al., 2018; Jin, 2013). With digital glossaries, readers could access word information in an immediate manner rather than finding and using a paper dictionary. Knowing the words likely helped readers appropriately make connections within the text for textbase development, and between the text and their background knowledge, for situation model development (Perfetti & Stafura, 2014). In addition to overall text comprehension support, it is possible that digital glossaries benefited vocabulary learning from the text which has been noted in previous studies on second language acquisition (Yun, 2011). However, readers also learn vocabulary incidentally (i.e., without explicit instruction or definitions provided) in first and second languages (Nagy, Herman, & Anderson, 1985; Pellicer-Sanchez, 2017); therefore, it is possible that providing readers with definitions could interfere with incidental vocabulary acquisition. Future research would be helpful to examine this specific issue of digital glossaries on first language vocabulary acquisition while reading.

Collaborative digital tools in which students could share their annotations on the readings, ask questions, and discuss the text while reading were an interactive features in six studies (Chen et al., 2014; Dennis et al., 2016; Weng et al., 2018; Zarzour & Sellami, 2017; Zarzour & Sellami, 2018a; Zarzour & Sellami, 2018b). In five of these studies (Chen et al., 2014; Dennis et al., 2016; Zarzour & Sellami, 2017; Zarzour & Sellami, 2018a; Zarzour & Sellami, 2018b), these collaborative tools appeared to benefit learning from the text (a negative effect was found in Weng et al., 2018, which is discussed in the following paragraph). One benefit of these collaboration tools is that students can share their knowledge (Chen et al., 2014), which would likely help with building a situation model as well as decreasing intrinsic load through the improvement of the knowledge base. Through discussions, students are able to use the tools to engage with their peers about the reading in a manner that could potentially assist in making connections for the development of the textbase and situation model.

There was one study in which interactive features had a statistically significant negative effect on learning (Weng et al., 2018). Perceived intrinsic and extraneous cognitive load did not reliably differ between the interactive e-text and the static e-text; therefore, increased cognitive load from the additional information involved with the interactive features is an unlikely reason for these results. One potential reason, based on teacher reports, is that the students with interactive e-text had fewer interactions among their peers and their teacher than did students with the static e-text. This converges with findings regarding storybooks for young children in which there are more adult-child interactions with paper books than interactive e-books (Strouse & Ganea, 2017). In addition, students reporting higher levels of perceived learning for the interactive e-text compared to the static e-text indicating that students reading the interactive e-text were overconfident about their learning (Weng et al., 2018). Weng and colleagues suggest that students may have had the illusion that they understood the material better than they actually did because the simulations made the material too easy to understand whereas students with static e-texts had to put more effort into understand the text. That is, the interactive e-text may have lacked desirable difficulties to promote learning because the simulations promoted learning fluency (e.g., Sungkhasettee et al., 2011; see Bjork, 1994, for more on desirable difficulties). The interactive e-text included questions with feedback, which may support more accurate comprehension monitoring (Swart et al., 2019). However, students reported that there were not enough questions with feedback and Weng and colleagues noted that the content of the questions in the interactive e-text did not align well with the content of the learning measure items.

An e-text may have optimal interactive features to promote learning; however, these features can only be effective if readers know how to use them and actually use the features. For example, with digital glossaries, readers need to be cognizant of the signal that a word has digital glossary information (e.g., notice the different font or color), know how to interact with that word to access the glossary information (e.g., click or press on it), and actually press on that word in order to have the digital glossary affect learning. This is also true for other interactive features such as prompts and questions. In one study, readers could interact with the e-text to be provided with hints and prompts designed to help their reading (ter Beek et al., 2019). There were no overall effects of the interactive e-text compared to the static e-text used as a control. However, approximately half of the readers with interactive e-texts never used the hints. A follow-up examination noted that although pretest scores were comparable, hint users scored higher on the posttest than did non-hint users. These findings indicate that it is possible the interactive e-text would have been more effective had the features been used by all the readers. A system in which readers are required to respond to hints and prompts before continuing reading, such as the one used in Li et al. (2013) with positive results for interactive e-texts, could potentially be more effective. It is possible that the null results for interactive e-texts in Freund et al. (2016) could also be due to readers not accessing the interactive features. In Freund et al. (2016) readers could click on links to obtain additional information that could assist in comprehension. There were not data reported on whether readers actually accessed this information; however, time on task was similar for interactive and static e-text conditions. If readers were actually clicking on the links with additional content and reading it, they would logically have more time on task in the interactive e-text condition. For this reason, it is likely readers were not actually using the interactive feature.

Limitations and Future Directions

There are limitations both within this review and the studies reviewed that need to be addressed. The number of studies was modest and some of the studies had very small sample sizes. Both of these factors limit the generalizability of the findings. Moreover, the research designs and contexts across studies were variable. Some were randomized experiments with pretest comparisons indicating baseline comparisons that allow for causal inferences (What Works Clearinghouse, 2020). Others were quasi-experimental comparisons in which random assignment was not used, which makes confounding factors that affect results more likely. In addition, some studies were incorporated in the context of a class whereas others involved studies unrelated to coursework. Logically, student motivation to learn from the text would be different if actual grades are involved.

Conclusion

Previous meta-analyses have indicated that reading from screens is less efficient than reading from paper (Clinton, 2019; Kong et al., 2018), but these comparisons did not involve potential affordances of screens in terms of interactive features. In this systematic review and meta-analysis, comparisons of interactive e-texts with control texts on learning were made. Interactive e-texts were found to benefit learning compared to control texts. These findings may be useful for teachers to select types of reading material as well for curriculum developers in terms of which features may be helpful for learning from e-texts.

References

Almekhlafi, A.G. (2020). The effect of E-books on Preservice student teachers' achievement and perceptions in the United Arab Emirates. *Education and Information Technologies.* https://doi.org/10.1007/s10639-020-10298-x

*Asrowi., Hadaya, A., & Hanif, M. (2019). The impact of using the interactive e-Book on students' learning outcomes. *International Journal of Instruction, 12*(2) 709-722. https://doi.org/10.29333/iji.2019.12245a

Bjork, R. A. (1994). Memory and metamemory considerations in the training of human beings. In J. Metcalfe & A. P. Shimamura (Eds.), *Metacognition: Knowing about knowing* (pp. 185–205). Cambridge, MA: MIT Press.

*Blake, J. S. (2016). *Use of an Interactivat iTextbook in a College Nutrition Course: Effects on Student Comprehension, Knowledge, Application, and Engagement*. Unpublished dissertation. Boston University https://hdl.handle.net/2144/19510

*Brown, Kayla, (2016). *Designing for Comprehension: A Comparison of Interactive and Non-Interactive Textbooks*. Unpublished dissertation. Iowa State University. https://lib.dr.iastate.edu/etd/15669

Bos, L. T., De Koning, B. B., Wassenburg, S. I., & van der Schoot, M. (2016). Training inference making skills using a situation model approach improves reading comprehension. *Frontiers in Psychology*, *7*, 116. https://doi.org/10.3389/fpsyg.2016.00116

*Chang, L., Wu, T. T., & Su, C. Y. (2019, December). The influence of interactive and non-interactive e-book on the learning effectiveness of high and low achievement nursing students. In Inønningsbakk L., Wu TT., Sandnes F., Huang YM. (Eds.) *International*

Conference on Innovative Technologies and Learning (pp. 14-23). Springer. https://doi.org/10.1007/978-3-030-35343-8_2

Chaudhri, V. K., Cheng, B., Overtholtzer, A., Roschelle, J., Spaulding, A., Clark, P., M. Greaves, & Gunning, D. (2013). Inquire Biology: A textbook that answers questions. *AI Magazine*, *34*(3), 55-72. https://doi.org/10.1609/aimag.v34i3.2486

*Chen, G. D., Chang, C. K., Wang, C. Y., & Jian, X. L. (2018). Development and evaluation of a novel e-book interface for scaffolding thinking context to learn from writing examples. *Interactive Learning Environments*, *26*(7), 970-988. https://doi.org/10.1080/10494820.2018.1427113

Clinton, V. (2015). Examining associations between reading motivation and inference generation beyond reading comprehension skill. *Reading Psychology,36*(6), 473-498. https://doi.org/10.1080/02702711.2014.892040

Cooper, H.M. (2015). *Research synthesis and meta-analysis: A step-by-step approach, 5th Edition*. Sage Publications: Thousand Oaks, CA.

Delgado P., Vargas C., Ackerman R., Salmerón L. (2018). Don't throw away your printed books: a meta-analysis on the effects of reading media on reading comprehension. *Educational Research in Review*, *25*, 23-38. https://doi.org/10.1016/j.edurev.2018.09.003

*Dennis, A. R., Abaci, S., Morrone, A. S., Plaskoff, J., & McNamara, K. O. (2016). Effects of e-textbook instructor annotations on learner performance. *Journal of Computing in Higher Education*, *28*(2), 221-235. https://doi.org/10.1007/s12528-016-9109-x

Dimitrova, L., & Koseska, V. (2009). Classifiers and digital dictionaries. *Cognitive Studies| Études cognitives*, *9*, 117-131.

Dunlosky, J., & Lipko, A. R. (2007). Metacomprehension: A Brief History and How to Improve Its Accuracy. *Current Directions in Psychological Science, 16*(4), 228–232. https://doi.org/10.1111/j.1467-8721.2007.00509.x

*Ebied, M. M. A., & Rahman, S. A. A. (2015). The effect of interactive e-book on students' achievement at Najran University in computer in education course. *Journal of Education and Practice, 6*(19). Retrieved from https://files.eric.ed.gov/fulltext/EJ1079544.pdf

Egger, M., Smith, G., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *BMJ*, 315(7109), 629-634. https://doi.org/10.1136/bmj.315.7109.629

Fisher Z., & Tipton E. (2014). robumeta: An R-package for robust variance estimation in meta-analysis. Retrieved from arXiv preprint arXiv:1503.02220

Follmer, D. J. (2018). Executive function and reading comprehension: A meta-analytic review. *Educational Psychologist*, *53*(1), 42-60. https://doi.org/10.1080/00461520.2017.1309295

*Freund, L., Kopak, R., O'Brien, H. (2016). The effects of textual environment on reading comprehension: Implications for searching as learning. *Journal of Information Science 42*(1), 79-93. https://doi.org/10.1177/0165551515614472

Harrer, M., Cuijpers, P., Furukawa, T.A, & Ebert, D. D. (2019). Doing Meta-Analysis in R: A Hands-on Guide. https://bookdown.org/MathiasHarrer/Doing_Meta_Analysis_in_R/

Harrer M, Cuijpers P, Furukawa T, Ebert DD (2019). *dmetar: Companion R Package For The Guide 'Doing Meta-Analysis in R'*. R package version 0.0.9000, http://dmetar.protectlab.org

Harrer, M. & Ebert, D. D. (2018). *Doing Meta-Analysis in R: A practical Guide*. PROTECT Lab Friedrich-Alexander University Erlangen-Nuremberg. https://bookdown.org/MathiasHarrer/Doing_Meta_Analysis_in_R/

Harri-Augstein, S., Smith, M., & Thomas, L. (2017). *Reading to learn*. Routledge.

Higgins, J. P. T., & Green, S. (Eds.). (2011). *Cochrane handbook for systematic reviews of interventions version 5.1.0*. London, UK: The Cochrane Collaboration. Retrieved from www.handbook.cochrane.org.

*Hsiao, CC., Tiao, MM. & Chen, CC. (2016). Using interactive multimedia e-Books for learning blood cell morphology in pediatric hematology. *BMC Medical Educucation (16)*, Article number 290. https://doi.org/10.1186/s12909-016-0816-9

*Jin, S. H. (2013). Visual design guidelines for improving learning from dynamic and interactive digital text. *Computers & Education*, *63*, 248-258. https://doi.org/10.1016/j.compedu.2012.12.010

Kintsch, W. (1998). *Comprehension: A paradigm for cognition*. Cambridge University Press.

*Koć-Januchta, M. M., Schönborn, K. J., Tibell, L. A., Chaudhri, V. K., & Heller, H. C. (2020). Engaging with biology by asking questions: Investigating students' interaction and learning with an artificial intelligence-enriched textbook. *Journal of Educational Computing Research 58*(6), 1190-1224. https://doi.org/10.1177/0735633120921581.

Kong, Y., Seo, Y. S., & Zhai, L. (2018). Comparison of reading performance on screen and on paper: A meta-analysis. *Computers & Education, 123*, 138-149. https://doi.org/10.1016/j.compedu.2018.05.005

Kucirkova, N. (2017). An integrative framework for studying, designing and conceptualizing interactivity in children's digital books. *British Educational Research Journal, 43(6),* 1168-1185. https://doi.org/10.1002/berj.3317

Lauterman, T., & Ackerman, R. (2014). Overcoming screen inferiority in learning and calibration. *Computers in Human Behavior*, *35*, 455-463. https://doi.org/10.1016/j.chb.2014.02.046

*Li, L-Y., Chen, G-D., Yang, S-J. (2012). Construction of cognitive maps to improve e-book reading and navigation. *Computers & Education, 60*,(1), 32-39. https://doi.org/10.1016/j.compedu.2012.07.010

*Liu Y, Chou PL, & Lee BO. (2020). Effect of an interactive e-book on nursing students' electrocardiogram-related learning achievement: A quasi-experimental design. *Nurse Education Today, 90*, Article Number 104427. doi: 10.1016/j.nedt.2020.104427.

Lüdecke, D. (2018). *Effect Size Computation for Meta Analysis*. https://CRAN.R-project.org/package=esc

*Lustria, M.L.A. (2006). Can Interactivity Make a Difference? Effects of Interactivity on the Comprehension of and Attitudes Toward Online Content. *Journal of the American Society for Information Science and Technology, 58*(6), 766-776. 10.1002/asi/20557

Mangen, A., van der Weel, A. (2016). The evolution of reading in the age of digitization: an integrative framework for reading research. *Literacy,50*(3), 116-124. https://doi.org/10.1111/lit.12086

Mathes, T., Kuss, O. (2018). A comparison of methods for meta-analysis of a small number of studies with binary outcomes. *Research Synthesis Methods, 9*(3), 366-381. https://doi.org/10.1002/jrsm.1296

*Mochizuki, T., Nishimori, T., Tsubakimoto, M., Oura, H., Sato, T., Johansson, H., Nakahara, J. & Yamauchi, Y. (2019). Development of software to support argumentative reading and writing by means of creating a graphic organizer from an electronic text. *Educational Technology Research and Development*, *67*(5), 1197-1230. https://doi.org/10.1007/s11423-019-09676-1

*Morris, N. P., & Lambe, J. (2017). Multimedia interactive ebooks in laboratory bioscience education. *Higher Education Pedagogies*, *2*(1), 28-42. https://doi.org/10.1080/23752696.2017.1338531

Nation, I. S. P. (2001). *Learning vocabulary in another language*. Cambridge: Cambridge University Press.

Ouzzani, M., Hammady, H., Fedorowicz, Z., & Elmagarmid, A. (2016). Rayyan—a web and mobile app for systematic reviews. *Systematic reviews*, *5*(1), 210. https://doi.org/10.1186/s13643-016-0384-4

Pellicer-Sánchez, A. (2017). Learning L2 collocations incidentally from reading. *Language Teaching Research*, *21*(3), 381-402. https://doi.org/10.1177/1362168815618428

Perfetti, C., & Stafura, J. (2014). Word knowledge in a theory of reading comprehension. *Scientific studies of Reading, 18*(1), 22-37. https://doi.org/10.1080/10888438.2013.827687

Schwarzer, G. (2007). Meta: An R package for meta-analysis, *R News, 7*(3), 40–45.

Sidi, Y., Ophir, Y. & Ackerman, R. Generalizing screen inferiority - does the medium, screen versus paper, affect performance even with brief tasks?. *Metacognition Learning* **11,** 15–33 (2016). https://doi.org/10.1007/s11409-015-9150-6

*Sommers, S. R., Shin, L. M., Greenebaum, S. L., Merker, J., & Sanders, A. S. (2019). Quasi-experimental and experimental assessment of electronic textbook experiences: Student perceptions and test performance. *Scholarship of Teaching and Learning in Psychology*, *5*(1), 11. https://doi.org/10.1037/stl0000129

*Stirling, A., & Birt, J. (2014). An enriched multimedia eBook application to facilitate learning of anatomy. *Anatomical Sciences Education*, *7*(1), 19-27. https://doi.org/10.1002/ase.1373

Strouse, G. A., & Ganea, P. A. (2017). A print book preference: Caregivers report higher child enjoyment and more adult–child interactions when reading print than electronic books. *International Journal of Child-Computer Interaction*, *12*, 8-15. https://doi.org/10.1016/j.ijcci.2017.02.001

Sungkhasettee, V.W., Friedman, M.C. & Castel, A.D. (2011). Memory and metamemory for inverted words: Illusions of competency and desirable difficulties. *Psychonomic Buletnl Review* 18, 973-978. https://doi.org/10.3758/s13423-011-0114-9

Swart, E. K., Nielen, T. M., & de Jong, M. T. S. (2019). Supporting learning from text: A meta-analysis on the timing and content of effective feedback. *Educational Research Review*, 100296. https://doi.org/10.1016/j.edurev.2019.100296

Sweller, J. (2020). Cognitive load theory and educational technology. *Educational Technology Research and Development*, *68*(1), 1-16. https://doi.org/10.1007/s11423-019-09701-3

Tanner-Smith, E. E., Tipton, E., & Polanin, J. R. (2016). Handling complex meta-analytic data structures using robust variance estimates: A tutorial in R. *Journal of Developmental and Life-Course Criminology*, 2(1), 85-112. https://doi.org/10.1007/s40865-016-0026-5

*ter Beek, M., Opdenakker, M. C., Spijkerboer, A. W., Brummer, L., Ozinga, H. W., & Strijbos, J. W. (2019). Scaffolding expository history text reading: Effects on adolescents' comprehension, self-regulation, and motivation. *Learning and Individual Differences*, *74*, 101749. https://doi.org/10.1016/j.lindif.2019.06.003

Tipton, E. (2015). Small sample adjustments for robust variance estimation with meta-regression. *Psychological Methods, 20*(3), 375–393. https://doi.org/10.1037/met0000011

Tipton, E., & Pustejovsky, J. E. (2015). Small-Sample Adjustments for Tests of Moderators and Model Fit Using Robust Variance Estimation in Meta-Regression. *Journal of Educational and Behavioral Statistics*, *40*(6), 604–634. https://doi.org/10.3102/1076998615606099

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of statistical software*, *36*(3), 1-48. https://doi.org/10.18637/jss.v036.i03

*Weng, C., Otanga, S., Weng, A., & Cox, J. (2018). Effects of interactivity in E-textbooks on 7th graders science learning and cognitive load. *Computers & Education*, *120*, 172-184.

What Works Clearinghouse. (2020). What Works Clearinghouse: Standards Handbook Version 4.1. Institute of Education Sciences. https://ies.ed.gov/ncee/wwc/Handbooks

Wohlin, C. (2014) Guidelines for snowballing in systematic literature studies and a replication in software engineering. In *8th International Conference on Evaluation and Assessment in Software Engineering* (EASE 2014), pp. 321–330. https:/doi:10.1145/2601248.2601268

Yun, J. (2011). The effects of hypertext glosses on L2 vocabulary acquisition: A meta-analysis. *Computer Assisted Language Learning*, *24*(1), 39-58. https://doi.org/10.1080/09588221.2010.523285

*Zarzour, H., & Sellami, M. (2017). A linked data-based collaborative annotation system for increasing learning achievements. *Educational Technology Research and Development*, *65*(2), 381-397.

*Zarzour, H., & Sellami, M. (2018a). An investigation into whether learning performance can be improved by CAALDT. *Innovations in Education and Teaching International*, *55*(6), 625-632. https://doi.org/10.1080/14703297.2017.1286997

*Zarzour, H., & Sellami, M. (2018b). Effects of a linked data-based annotation approach on students' learning achievement and cognitive load. *Interactive Learning Environments*, *26*(8), 1090-1099. https://doi.org/10.1080/10494820.2018.1446989