Paper ID #41371

Board 428: Work in Progress: An Open Educational Resource to Improve Architectural Engineering Students Conceptual Knowledge When Writing-to-Learn: Investigation 1

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WIP: An Open Educational Resource to Improve Architectural Engineering Students Conceptual Knowledge When Writing-to-Learn: Investigation 1

Abstract

This paper presents the findings of the first of four investigations funded by the NSF to develop and then field test an open educational browser-based writing-to-learn tool called GIKS. The underlying theory is that writing-to-learn with immediate formative feedback presented as concept networks is engaging and effective for learning course lesson concepts. This work was conducted in a second-year architectural engineering course focused on building materials, processes, and modeling. Participants (n=84) completed a lesson (readings, lecture, and labs) followed by writing prompts centered on the following topics: Building with Concrete and also Wood Construction. At the end of each module, students completed the standing end-of-module multiple-choice post-test that included items from those lessons as well as items from other lessons in the module.

Results to date highlight that for both lessons, the group using GIKS scored higher on the concept structure survey (more like the expert network) BUT performed lower on the multiple-choice test, the difference was significant for the Building with Concrete lesson ($p < .05$) but not for the Wood Construction lesson. Descriptive analysis of the group-average networks for Building with Concrete show that the group-averaged network of those using GIKS compared to the control was more like the expert network (54% vs. 36%) and especially more like peers in the other group (67%). For Wood Construction the difference between the groups was less, the group-averaged network of those using GIKS compared to the control was more like the expert (40% vs. 39%) and especially like peers in the other group (72%). These findings show that writing-to-learn with GIKS with immediate network feedback improves conceptual knowledge as expected but at the cost of detail.

Keywords: Writing to learn, conceptual knowledge, group networks, architectural engineering, quantify written work.

Introduction

Conceptual understanding of core engineering fundamentals enables engineers to predict how a system will behave, to determine appropriate solutions for problems, to choose relevant processes for design, and to explain how the world around them works [1]. While conceptual understanding is key, newly entering college students and even recent graduates commonly misperceive significant engineering concepts needed to solve even simple problems in real-world practice [2-4]. In many undergraduate STEM classrooms, instruction of these core topics is often within large lecture based classrooms (100+ students) that are delivered using methods that are predominantly “chalk and talk” [5-6] (U.S. DOE 2001; Young et al., 2012) that cannot optimize student engagement with the topic that often results in only surface learning [7-8]. To counter this, ongoing research and practice in engineering (and more broadly) seek innovative ways to restructure the classroom to focus attention on the learner engagement [9-10]. For example, Roehl et al. [11] found that active learning can be as simple as integrating brief in-class activities within the traditional lecture.

Professional engineering preparation can and must go beyond memorizing facts and "crunching" equations [12-13], it must also include broader conceptual understanding of scientific principles and of phenomena of the domain [13-14] defined here as regularities, patterns, or relationships among objectives, events, and other concepts [15]. Conceptual understanding refers to students' rich cognitive representations of concepts, both concrete and abstract (i.e., a masonry veneer wall composite aligned with heat energy principles) that are necessary to solve problems, make predictions, and generate questions [16]. Increasing students' conceptual understanding is a key to advancing STEM education. One way to do this is by intentionally and explicitly including domain knowledge conceptual representations in our courses.

A key question for this domain of research and for educational advancement is: *How can we improve conceptual understanding?* This NSF funded investigation combines two approaches that have previously shown to support conceptual understanding: 1) writing-to-learn and 2) conceptual structure feedback, that are combined in a browser-based application called Graphical Interface of Knowledge Structure (GIKS). This paper presents a work in progress towards studying how GIKS can be used in larger engineering courses and its impacts.

Writing to Learn

Writing to learn can be an active and engaging STEM disciplinary practice [17-18]. "The importance of incorporating writing in STEM classrooms is heightened by the role it can play in supporting student learning of disciplinary knowledge and thinking." (p. 1548, [19]). More broadly, writing is a learner-centered strategy that intimately aligns with conceptual learning [20-21]. Such writing helps students to improve and refine their thinking about complex scientific phenomena [20, 22], to grasp concepts in a related fashion rather than as discrete sets of ideas [23-25], understand common disciplinary conceptions, and to participate in scientific discursive communities [26]. Additionally, Mason and Boscolo [27] have identified writing as a way to foster conceptual change, especially for the correction of topic misconceptions, by encouraging students to develop more elaborated explanations of scientific phenomena [28-29].

The effectiveness of writing-based interventions to learn domain specific content has been documented across scientific fields including, but not limited to: biology, chemistry, ecology, and physics [29-37]. These and other studies have shown that writing-based STEM interventions can improve students' reasoning and conceptual understanding [33, 38-41] and that writing becomes even more effective when it includes formative feedback and reflection (p. 84, [42]). For example, a meta-analysis by Bangert-Drowns et al. [43] across 47 studies considered the effects of writing-to-learn with feedback compared to writing with no feedback. Feedback was more effective than no feedback for academic achievement, with an effect size of 0.32. For 46 studies that included writing with reflection or not, writing with reflection was more effective for academic achievement with an effect size of 0.44.

Writing to Learn Feedback Tools: Network Graphs and the Existing GIKS Tool

Network graphs as feedback when writing to learn

One way of providing a summary of knowledge is through network graphs. Here, Network Graphs show interconnections between a set of entities (terms, traits, facts etc.) that are each represented by nodes, with node being connected (linked) to corresponding associations. Existing research points to an important mediating role of network graphs as feedback for developing students' conceptual understanding, especially feedback on the correct, incorrect, and missing connections formed by students between concepts [44-46]. Trumpower and Sarwar [47] coined the terms "structural assessment" as measures of students' domain-normative conceptual relationships and "structural feedback" as any form of feedback that aims to improve the quality of students' domain-normative conceptual relationships.

This project is grounded on structural feedback, that when students receive structural feedback, their formed conceptual model becomes more like an expert's model upon review. A meta-analysis by Nesbit and Adescope [48] note, "Structural knowledge establishes a spatial frame that references visual features and verbal knowledge to enable efficient, spatially-indexed memory searches." (p. 418).

The Existing GIKS Tool

A browser-based writing tool called GIKS, that leverages an ALA-Reader algorithm, was developed to promote writing to learn [44]. To use GIKS, an instructor creates a writing task by 1) entering a question or prompt, 2) entering a list of key words (and their synonyms and metonyms), and 3) adding an expert referent network map. These writing prompts can be any combination of text, images, and/or videos. Once created, the instructor provides the URL of the task to students along with a unique ID code. From here students log in to review the writing task, compose a response, and then submit it. Immediately after submission, an interactive network graph of their essay is displayed along with the referent expert network (see Fig. 1).

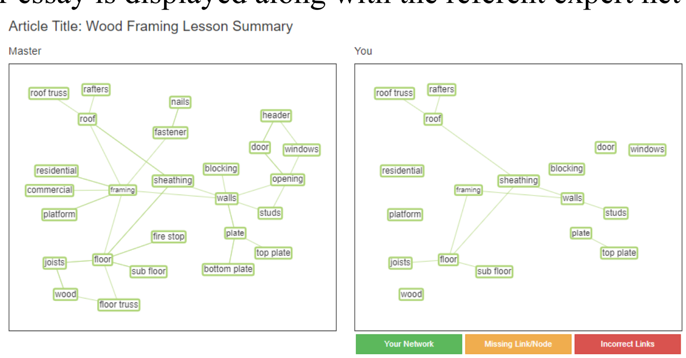

Figure 1: GIKS student network feedback

Rather than seeing a random force-generated network graph each time, the student's term locations align to the "Master" expert network map, thus the student views a network structure of their own essay for the first time laid out in a domain-normative way, where term closeness in 2-dimensional space reflects that of an expert. Clicking on a term in either network highlights that term along with its links and term associates in both networks. Dragging any term in either network moves the same term in the other network. These interactive features allow the students to explore the sometimes complex networks in a term-by-term way. Also, there are control buttons under the student's network. (Fig. 1) If students click the green "Your Network" button, it shows the student's essay network links; clicking the orange "Missing Link/Node" button adds the missing terms and missing links; while clicking the red "Incorrect Links" button shows the incorrect links. You can try GIKS at: *this URL removed for peer review*.

Published research using GIKS

Prior research on GIKS related to this current NSF project includes several studies with the current version of *GIKS,* as well as several studies that are in progress. These include Zimmerman et al. [49], Tawfik et al. [50], Kim, Clariana, and Kim [44], Kim and Tawfik [51], and a dissertation by Wang [52]. Table 1 provide a summary of key area for these studies and highlight their results. These findings directly influenced this current project in terms of the form of the prompt, the extent of content addressed in the prompt (broad rather than narrow), and that *GIKS* has a greater potential as formative feedback while learning, in contrast to its summative value as an essay scoring tool.

Table 1: GIKS studies to Data and their Results

Publication	Focus of Study	Result Highlights
Zimmerman et al. [49]	Estimated the concurrent validity of the *GIKS* scoring approach as an end of course summative evaluation relative to multiple human essay raters.	• Existed a polychoric correlation of GIKS scores with multiple rater scores for writing were between: r = 0.58 to 0.67 for network common links and r = 0.66 to 0.79 for network key words
Tawfik et al. [50]	Used GIKS to analyze argumentation responses of undergraduate business students under scaffolds and faded-scaffolds conditions during ill-structured problem solving. Used three methods to measure students' argumentation including computer-derived association rule mining [53], human-raters using rubrics, and GIKS.	• The raters with rubrics found no statistically significant results. • Both association rule mining and GIKS identified the same latent differences between the groups not noticed by the raters. This sensitivity data provides increasing evidence of the validity of the ALA-Reader approach.
Kim, Clariana, and Kim [44]	Compared three structural feedback approaches designed to support learning through writing and revision. Wrote a summary essay using one of the three structural feedback treatments (GIKS with focused structural feedback network subgraphs, video-delivered information, and targeted multiple-choice questions), and then wrote a summary posttest essay.	• Essay scores significantly improved from lesson-to-post-test for all three forms of feedback, but GIKS obtained the greatest gains, with increase in relevant and decrease in irrelevant relations (these findings exactly align with the findings from Sarwar, 2012, p. 85). • Writing feedback improved most with GIKS, while viewing the multimedia feedback showed the greatest pre-to-post increase in the less important peripheral concepts.
Kim and Tawfik [51]	Examined how high school science students mental models transitioned during problem solving, GIKS essays were used as a posttest measure of knowledge structure, but not as an instructional intervention.	• Results indicate that successful problem-solvers tend to share solution-focused knowledge whereas the less successful problem-solvers tend to share problem-focused knowledge.
Wang [52]	Used GIKS in an undergraduate architectural engineering course (AE 222) to compare the effectiveness of writing with immediate network feedback that is either a "full network" (26 terms) or else a "focused network" (subset of 16 of the 26 terms) that has only the most central terms in order to highlight only the most important relations in the content.	• There was no significant difference observed between full versus focus network feedback on the end-of-module multiple-choice posttest, both were equally effective. • However there was an advantage for the focus network group on the knowledge structure posttest. The focus network group showed 62% overlap with the full expert referent network compared to the full network group that showed only 53% overlap.

Research Design and Methodology

This NSF Level 1 research investigation and software development project will add to the conceptual understanding and the writing-to-learn (WTL) knowledge bases regarding evidence-based practices for STEM teaching and learning in predominantly lecture-based undergraduate STEM courses.

Relevant Research Questions

For this new NSF study, the researchers looked at the prior studies, such as those in Table 1, as well as other literature to formulate a new continued direction for investigation. From the new direction, the following two broad research questions emerged:

- How can we strengthen engineering students' conceptual understanding?
- Does summary writing about lesson content with immediate concept network structure feedback support classroom learning outcomes?

Study Design

This project combines two approaches that support conceptual understanding, writing-to-learn and conceptual structure feedback, in a browser-based application called Graphical Interface of Knowledge Structure (GIKS). To answer the research questions, two separate investigations in an Architectural Engineering (AE) course were conducted. Student learning outcomes include essays, end-of-module subtests, and knowledge structure post-test measures. This WIP presents the findings for Investigation 1.

Participants were assigned to one of two counter-balanced groups (Fig 2). Group A used GIKS software to write a 300-word summary of the first lesson (concrete) but did not write in the second lesson (wood), while group B did not write in the first lesson (concrete) but used GIKS in the second lesson (wood). Doing this, each group served as a control treatment for the other group. All students further completed a concept structure survey [52] after writing that contained 20 key concepts from that lesson. These two concept structure surveys' data were transformed into concept networks and then these networks were compared to an expert network benchmark referent, as well as to networks of the textbook chapter and the PowerPoint slides of the related lesson.

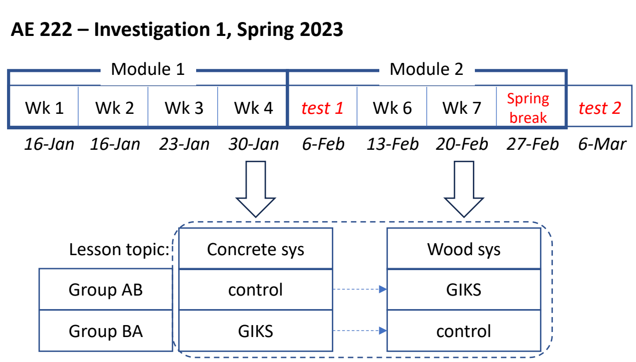

Figure 2: Course timeline and lessons

Investigation 1 Procedures

Investigation 1 conducted in the spring 2023 considers whether writing with GIKS is better than no writing (control group) and the follow up Investigation 2 considers whether writing with GIKS is better than writing without feedback (i.e., by submitting essays as a document using the Canvas LMS drop box).

All students in the course completed two lessons, the first on building with concrete and the second on building with wood; these lessons are presented early in the semester with each lesson lasting for about 3 weeks (Fig.2). Lesson materials and tests for these two lessons have been used regularly for the past several (4) years without modification, and include the textbook readings, PowerPoint lecture/ discussions, and lab session on projects. The only difference from regular course delivery is that participating students near the completion of each lesson were asked to complete one 15-minutes long summary writing task during lab time using the GIKS software. Each group served as a control group for the other group from lesson-to-lesson. After the writing task, all students in both GIKS and the control groups competed a survey of knowledge structure that requited about 15 minutes to complete. At the conclusion of each module, all students completed the end-of-module multiple-choice tests that covered the concrete and then the wood lesson topics, as well as other topics covered in the course. Note that the wood lesson materials, learning outcome measures and approach were previously used in a dissertation by Wang [52].

<u>Participants</u>

Undergraduate students (n = 103) were recruited in an AE course (AE 222 Building Documentation and Modeling) at a large land grant university in the Northeastern U.S. There was an 85% participation rate (n = 87) in this investigation (31 females, 56 males), but there was incomplete data for three students (final sample n = 84). Students in the course were nearly all second year students (sophomores) who had covered basic fundamental engineering theories in previous courses. There were no repeating students in the course that could confound data with excess prior knowledge. The most recent program-wide undergraduate demographics for AE reported by the college are: program total n ≈ 330, 44% reporting as female, and by diversity 75% white, 10% international, and 15% underrepresented (includes American Indian/Alaska Native, Black/African American, Hispanic/Latino, Native Hawaiian/Other Pacific Islander).

<u>Learning Outcomes (Post-test Measures)</u>

Learning outcome measures consists of: 1) knowledge structure networks and 2) declarative-knowledge multiple-choice end-of-module tests of each lesson (i.e., facts, propositional knowledge). Knowledge structure network data were elicited using a multiple-response survey measure described by Wang [52]. The concrete and the wood knowledge structure surveys (KS-survey) were developed in the Canvas LMS system using the quiz feature. Quiz items consisted of the 20 key terms for each lesson that were selected by the course instructor and were used to create expert networks for concrete and for wood. Each of the 20 key terms were presented one-by-one along with the other 19 key terms, and participants were asked to select and enter two terms that are most related to the first key term (Fig. 3).

An excel spreadsheet was used to convert the KS-survey raw data into proximity files (*.prx) for analysis by Pathfinder software [54]. For example, in item 1, if aggregate is associated with cement and materials (i.e., aggregate – cement, aggregate – materials), and in item 2 if admixtures is associated with materials and water (i.e., admixtures – materials, admixtures – water), these linked key terms pairs would be added to a 20 x 20 key term array sing 1 to indicate a linked pair and 0 to indicate no link, and so on until all 20 items have been completed. This 20 x 20 term-term array that consists of ones and zeroes is then analyzed with pathfinder software (with *Minsowski* r = infinity and q = n - 1, i.e., 19) to generate a network structure of the KS-survey data.

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1. The term **aggregate** is most related to what two terms in this list? (type in two terms in the box below separated by a comma):
   List: *admixtures, cement, columns, concrete, curing, finishing, floor, formwork, materials, one way, placing, prestressed, rebar, reinforced, slab, system, two way, wall, water*
2. The term **admixtures** is most related to what two terms in this list? (type in two terms in the box below separated by a comma)
   List: *aggregate, cement, columns, concrete, curing, finishing, floor, formwork, materials, one way, placing, prestressed, rebar, reinforced, slab, system, two way, wall, water*

Figure 3: Two items from the 20-item concrete KS-survey

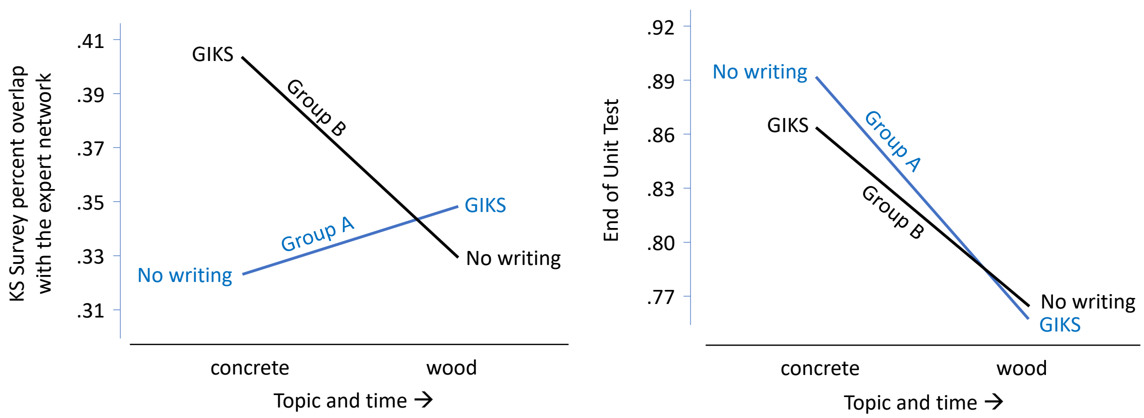
From here, each participants' concrete and wood networks are compared to the expert network referent for concrete and for wood, reported out as percent (%) links in common (number of common links between the two networks divided by the average number of links in the two networks). For this data, the $p < 0.05$ significance threshold is approximately 5 common links (25% overlap), overlap equal to or greater that 25% are significantly similar above chance.

Each of the two end-of-module declarative knowledge multiple-choice tests reside as a test item bank within the AE 222 Canvas LMS. The Canvas quiz system was set to randomly pull items from the test bank consisting of about 150 items to generate a 20-term individualized test for each student at each quiz delivery. Since students did not see exactly the same test items, the test data for each lesson only considered text items for concrete and for wood and these are converted to a percent for each test (correct/total).

Results

The KS network data and the end-of-module multiple-choice test data for the concrete lesson and the wood lesson were analyzed with MANOVA. Homogeneity of covariance matrices cannot be assumed (Box's M test: $p = 0.003$) so the conservative Pillai's trace is reported. There was a statistically significant effect for the GIKS writing intervention versus the no-writing control on the four combined dependent variables, $F(4, 74) = 2.821$, $p = 0.031$; Pillai's trace = 0.132, partial eta squared = 0.132 (Fig. 4).

For the between-subjects follow-up analyses, there is a significant effect of the GIKS intervention for *Concrete network scores*, F(1, 77) = 9.396, p = 0.003, partial eta squared = 0.109 (GIKS > no writing, see Figure 4). But no significant effects were observed for the other three scores: *Concrete multiple-choice test scores*, F(1, 77) = 1.885, p = 0.174, partial eta squared = 0.024; *Wood network scores*, F(1, 77) = 0.749, p = 0.391, partial eta squared = 0.010*; and Wood multiple-choice test scores*, F(1, 77) = 0.223, p = 0.638, partial eta squared = 0.003.



a) KS network similarity to the expert data b) end-of-module multiple-choice test data

Figure 4: KS network similarity and test scores for the concrete lesson and the wood lesson.

Inspection of means shows that the GIKS intervention relative to the no-writing control significantly improves their building with concrete mental model structure similarity to the expert (GIKS > no writing control, see left side of Figure 4) but not multiple-choice test performance (no writing control = GIKS, see right side of Figure 4). This appears to be a disordinal interaction of mental model structure and declarative knowledge that has been reported previously [55-58].

Post hoc descriptive analysis of networks for Building with Concrete show that the group-averaged network of those using GIKS compared to the no-writing control was more like the expert network (GIKS 54% vs. control 36%) and especially like peers in the two group (peer-peer convergence 67%). For Wood Construction, the difference between the group-averaged network similarity to the expert was negligible (GIKS 40% vs. control 39%) but the peer group-averaged networks were quite similar (peer-peer convergence 72%).

Discussion

From this investigation, our deployment of GIKS as a classroom summary writing strategy to show students their conceptual working knowledge of the lesson topics compared to the expert had positive impacts in certain areas. From the Concrete writing activity, writing in GIKS and then seeing the networks immediately had a statistically positive impact over no writing. This was based on the scores from a term-association activity directly after writing. This highlights that when students are exposed to writing with network feedback (showcasing their correct and missing attributes), there is an influence on their ability to associate lesson terms more like the expert. Observations from the classroom suggest that students did compare their networks to that of the expert (through the interface). But on the end-of-module test, there was no statistical improvement for writing with GIKS. In fact there was a decrease in performance (non significant) for those who used GIKS. Why improved mental model knowledge structure sometimes leads to small decreases in declarative memory remains unknown.

Another outcome in this work-in-progress is that student knowledge structures are more closely aligned to that of the lecture PowerPoints over those of the readings. This is no surprise, as the instructors noted that while the assigned readings are given, it has been their observations that many students do not regularly do the reading. But students do seem to rely heavily on what is presented in class, particularly what is written in the lecture slides even more so than that of what is verbally added to the slides.

From a deployment perspective, the utilization of GIKS was fairly smooth and easy to conduct in the lab. Students were in a computer lab and were able to launch the GIKS website and the instructions in the Canvas LMS in order to do the work. No technical issues or clarity problems were observed or voiced to the researchers or lab attendants present.

Conclusions and Future Work

This investigation covered two technical AE topics (concrete and wood) along with writing in GIKS vs. no writing. We observed both positive and some unexpected negative outcomes for short term conceptual knowledge along with longer term technical conceptual assessment (end-of-module tests). As this is a work-in-progress, two more technical topics are being studied next (masonry and sustainability) to see if there are specific content impacts. Additionally, other interventions such as writing in GIKS vs. writing in MS Word or writing in GIKS and getting detailed feedback on why their networks are missing vs their performance against other classmates, are points of future consideration for this funded study that are ongoing. Current results provide early insights into having knowledge representations shown to students can make a difference.

Data Availability

The data presented in this paper, in part, can be requested from the authors in a form that has been aggregated and individual student identifiers have been removed. If you are interested in the data please reach out to the authors via email.

Funding Information

This material is based in part on work supported by a National Science Foundation DUE Grant No 2215807. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the National Science Foundation's views.

References

[1] Litzinger, T., Lattucca, L., Hadgraft, R., & Newstetter, W. (2011). "Engineering education and the development of expertise." *Journal of Engineering Education*, 100(1), 123-150.

[2] Hake, R. R. (1998). “Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses.” *American journal of Physics*, *66*(1), 64-74.
[3] Streveler, R. A., Brown, S., Herman, G. L., & Montfort, D. (2015). Conceptual change and misconceptions in engineering education: Curriculum, measurement, and theory-focused approaches. *Cambridge Handbook*
[4] Trotskovsky, E., Sabag, N., & Waks, S. (2015). “Students' achievements and misunderstandings when solving problems using electronics models—A case study.” *IEEE Transactions on Education*, 58(2), 104-109. doi:10. 1109/te. 2014. 2331918
[5] U. S. Department of Education (2001). “The context of postsecondary education. The condition of education.” *NCES 2001072, National Center for Education Statistics, U. S. Department of Education*, Washington, DC, 74–84.
[6] Young, B., Ellobody, E., & Hu, T. W. C. (2012). “3D visualization of structures using finite-element analysis in teaching.” *Journal of Professional Issues in Engineering Education & Practice*, 138(2), 131-138.
[7] Moon, S. K. (2010). “Design-oriented structural engineering education.” *Presented at the 19th Analysis and Computation Specialty Conference*, 387-395.
[8] Walther, J., Kellam, N., Sochacka, N., & Radcliffe, D. (2011). “Engineering competence? An interpretive investigation of engineering students’ professional formation.” *Journal of Engineering Education*, 100(4), 703-740.
[9] Bergmann, J., & Sams, A. (2012). “Flip your classroom: Reach every student in every class every day.” Eugene, OR: International Society for Technology in Education.
[10] Strayer, J. F. (2012). “How learning in an inverted classroom influences cooperation, innovation and task orientation.” *Learning Environments Research*, 15, 171-193.
[11] Roehl, A., Reddy, S. L., & Shannon, G. J. (2013). “The flipped classroom: An opportunity to engage millennial students through active learning strategies.” *Journal of Family & Consumer Sciences*, 105(2), 44-49.
[12] Driver, R., & Erickson, G. (1983). “Theories-in-action: some theoretical and empirical issues in the study of students' conceptual frameworks in science.” *Studies in Science Education*, 10(1), 37-60.
[13] Gabel, D. (2003). “Enhancing the conceptual understanding of science.” *Educational Horizons*, 81(2), 70-76.
[14] McElwee, P. (1991). “Transition from personal to scientific understanding.” *Research in Science & Technological Education*, 9(2), 139-155.
[15] Pines, L. (1985). “Toward a taxonomy of conceptual relations and the implications for the evaluation of cognitive structure.” *In L. West & A. L. Pines (Eds.), Cognitive structure and conceptual change* (pp. 101-115). Orlando: Academic Press.
[16] Roth, K. J. (1990). “Developing meaningful conceptual understanding in science.” *In B. F. Jones and L. Idol (Eds.), Dimensions of thinking and cognitive instruction* (pp. 139-175). Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.
[17] Emig, J. (1977). “Writing as a mode of learning.” *College Composition and Communication*, 28(2), 122-128
[18] Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth. M. P. (2014). “Active learning increases student performance in science, engineering, and mathematics.” *Proceedings of the National Academy of Sciences of the United States of America*, 111(23), 8410-8415. https://www. pnas. org/content/pnas/111/23/8410. full. pdf
[19] Finkenstaedt-Quinn, S. A., Petterson, M., Gere, A., & Shultz, G. (2021). “Praxis of writing-to-learn: A model for the design and propagation of writing-to-learn in STEM.” *Journal of Chemical Education*, 98(5), 1548-1555.
[20] Bereiter, C., & Scardamalia, M. (1987). “An attainable version of high literacy: Approaches to teaching higher-order skills in reading and writing.” *Curriculum Inquiry*, 17(1), 9-30.

[21] Sampson, V., & Walker, J. P. (2012). "Argument-driven inquiry as a way to help undergraduate students write to learn by learning to write in chemistry." *International Journal of Science Education*, 34(10), 1443-1485.
[22] Hidi, S., & Anderson, V. (1986). "Producing written summaries: Task demands, cognitive operations, and implications for instruction." *Review of Educational Research*, 56 (4), 473-493.
[23] Gaskins, I. W., Guthrie, J. T., Satlow, E., Ostertag, J., Six, L., Byrne, J., & Connor, B. (1994). "Integrating instruction of science, reading, and writing: Goals, teacher development, and assessment." *Journal of Research in Science Teaching*, 31(9), 1039-1056.
[24] Glynn, S. M., & Muth, K. D. (1994). "Reading and writing to learn science: achieving scientific literacy." *Journal of Research in Science Teaching*, 31(9), 1057-1073.
[25] Guthrie, J. T., Wigfield, A., Barbosa, P., Perencevich, K. C., Taboada, A., Davis, M. H., & Tonks, S. (2004). "Increasing reading comprehension and engagement through concept-oriented reading instruction." *Journal of Educational Psychology*, 96(3), 403-423.
[26] Wallace, C. S. (2004). "Framing new research in science literacy and language use: Authenticity, multiple discourses, and the "Third Space"." *Science Education*, 88(6), 901-914.
[27] Mason, L., & Boscolo, P. (2004). "Role of epistemological understanding and interest in interpreting a controversy and in topic-specific belief change." *Contemporary Educational Psychology*, 29(2), 103-128.
[28] Halim, A. S., Finkenstaedt-Quinn,S. A., LauOlsen, L. J., Gere, A. R., & Shultz, G. V. (2018). "Identifying and remediating student misconceptions in introductory Biology via Writing-to-Learn assignments and peer review." *Life Sciences Education*, 17 (28), 1-12.
[29] Moon, A., Zotos, E., Finkenstaedt-Quinn, S., Gere, A. R., & Shultz. G. (2018). "Investigation of the role of writing-to-learn in promoting student understanding of light-matter interactions." *Chemistry Education Research and Practice*, 19, 807-818.
[30] Friend, R. (2002). "Summing it up - teaching summary writing to enhance science learning." *The Science Teacher*, 69 (4), 40-43.
[31] Gunel, M., Hand, B., & McDermott, M. A. (2009). "Writing for different audiences: effects on high-school students' conceptual understanding of biology." *Learning and Instruction*, 19(4), 354-367.
[32] Horton, P. B., Fronk, R. H., & Walton, R. W. (1985). "The effect of writing assignments on achievement in college general chemistry." *Journal of Research in Science Teaching*, 22(6), 535-541.
[33] Kirkpatrick, L. D., & Pittendrigh, A. S. (1984). "A writing teacher in the physics classroom." *The Physics Teacher*, 22(3), 159-164.
[34] Koprowski, J. L. (1997). "Sharpening the craft of scientific writing." *Journal of College Science Teaching*, 27(2), 133-35.
[35] Liss, J. M., & Hanson, S. D. (1993). "Writing-to-Learn in science." *Journal of College Science Teaching*, 22(6), 342-345
[36] Wolfer, A. J. (2000). Introductory college chemistry students' understanding of stoichiometry: connections between conceptual and computational understandings and instruction. *New Orleans, LA: EDRS.* Retrieved from: https://ir. library. oregonstate. edu/concern/graduate_thesis_or_dissertations/6395w9923
[37] Yore, L. D., Hand, B., & Prain, V. (1999). 'Writing-to-learn science: breakthroughs, barriers, and promises." *Resources in Education (ERIC Document Reproduction No. ED 431626)*. Retrieved from https://files. eric. Ed.gov/fulltext/ED441688. pdf
[38] Keys, C. W. (1995). "An interpretive study of students' use of scientific reasoning during a collaborative report writing intervention in ninth grade general science." *Science Education*, 79(4), 415-435.
[39] Moore, R. C. (1994). "Making the transition to formal proof." *Educational Studies in Mathematics*, 27(3), 249-266.
[40] Rivard, L. O. P. (1994). "A review of writing to learn in science: Implications for practice and research." *Journal of Research in Science Teaching*, 31(9), 969-983.

[41] Rivard, L. P., & Straw, S. B. (2000). “The effect of talk and writing on learning science: An exploratory study.” *Science Education*, 84(5), 566-593.
[42] National Academies of Sciences, Engineering, and Medicine. (2016). “Barriers and Opportunities for 2-Year and 4-Year STEM Degrees: Systemic Change to Support Diverse Student Pathways.” *Washington, DC: The National Academies Press*. doi: 10. 17226/21739.
[43] Bangert-Drowns, R. L., Hurley, M. M., & Wilkinson, B. (2004). “The effects of school-based writing-to-learn interventions on academic achievement: A meta-analysis.” *Review of Educational Research*, 74, 29-58.
[44] Kim, K., Clariana, R. B., & Kim, Y. (2019). “Automatic representation of knowledge structure: Enhancing learning through knowledge structure reflection in an online course.” *Educational Technology Research and Development*, 67, 105-122. http://link. springer. com/article/10. 1007/s11423-018-9626-6
[45] Sarwar, G. S. (2012). Comparing the effect of reflections, written exercises, and multimedia instruction to address (Unpublished doctoral dissertation). University of Ottawa, Ottawa, Canada. Retrieved from https://ruor. uottawa. ca/bitstream/10393/22865/3/Sarwar_Gul_Shahzad_2012_thesis. pdf
[46] Sarwar, G. S., & Trumpower, D. L. (2015). “Effects of conceptual, procedural, and declarative reflection on students’ structural knowledge in physics.” *Educational Technology Research and Development,* 63, 185-201.
[47] Trumpower, D. L., & Sarwar, G. S. (2010). “Effectiveness of structural feedback provided by pathfinder networks.” *Journal of Educational Computing Research*, 43, 7-24.
[48] Nesbit, J. C., & Adesope, O. O. (2006). “Learning with concept and knowledge maps: A meta-analysis.” *Review of Educational Research*, 76, 413-448.
[49] Zimmerman, W., Kang, H. B., Kim. K., Gao, M., Johnson, G., Clariana, R. B., & Zhang, F. (2017). “Computer-automated approach for scoring short essays in an introductory statistics course.” *Journal of Statistics Education*, 25, 40-47.
[50] Tawfik, A. A., Law, V., Ge, X., Xing, W., & Kim, K. (2018). “The effect of sustained vs. faded scaffolding on students’ argumentation in ill-structured problem solving.” *Computers in Human Behavior*, 87, 436-449.
[51] Kim, K., & Tawfik, A. A. (2021). “Different approaches to collaborative problem solving between successful versus less successful problem solvers: Tracking changes of knowledge structure.” *Journal of Research on Technology in Education*, published online first, DOI: 10.1080/15391523.2021.2014374
[52] Wang, Y. (2021). Comparative Investigation of full and focused network feedback on students’ knowledge structure and learning (Unpublished doctoral dissertation). The Pennsylvania State University, State College, PA. Retrieved from ETD https://etda.libraries.psu.edu/catalog/18696yjw5074
[53] Hipp J., Güntzer U., & Nakhaeizadeh G. (2000). “Mining association rules: Deriving a superior algorithm by analyzing today’s approaches.” *In: Zighed D. A., Komorowski J., Żytkow J. (Eds.) Principles of Data Mining and Knowledge Discovery.* PKDD 2000. Lecture Notes in Computer Science, 1910, 159-168. Springer, Berlin, Heidelberg.
[54] Schvaneveldt, R. W. (Editor) (1990). Pathfinder associative networks: Studies in knowledge organization. Norwood, NJ: Ablex.
[55] Clariana, R.B., & Marker, A. (2007). “Generating topic headings during reading of screen-based text facilitates learning of structural knowledge and impairs learning of lower-level knowledge.” *Journal of Educational Computing Research*, 37 (2), 173-191.
[56] Clariana, R.B., & Prestera, G.E. (2009). “The effects of lesson screen background color on declarative and structural knowledge.” *Journal of Educational Computing Research*, 40 (3), 281 -293.
[57] Mayer, R. E. (1989). “Models for understanding.” *Review of Educational Research*, 59(1), 43–64. https://doi.org/10.3102/00346543059001043

[58] Ntshalintshali, G. N., & Clariana, R. B. (2020). “Paraphrasing refutation text improved higher knowledge forms and hindered lower knowledge forms: examples from repairing relational database design misconceptions.” *Educational Technology Research and Development*, 68, 2165-2183. https://doi.org/10.1007/s11423-020-09758-5