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Animation Analytics in an Interactive Textbook for Material and Energy Balances

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Abstract

Interactive textbooks generate big data through student reading participation, including animations, question sets, and auto-graded homework. Animations are multi-step, dynamic visuals with text captions. By dividing new content into smaller chunks of information, student engagement is expected to be high, which aligns with tenets of cognitive load theory. Specifically, students' clicks are recorded and measure usage, completion, and view time per step and for entire animations. Animation usage data from an interactive textbook for a chemical engineering course in Material and Energy Balances accounts for 60,000 animation views across 140+ unique animations. Data collected across five cohorts between 2016 and 2020 used various metrics to capture animation usage including watch and re-watch rates as well as the length of animation views. Variations in view rate and time were examined across content, parsed by book chapter, and five animation characterizations (Concept, Derivation, Figures and Plots, Physical World, and Spreadsheets). Important findings include: 1) Animation views were at or above 100% for all chapters and cohorts, 2) Median view time varies from 22 s (2-step) to 59 s (6-step) - a reasonable attention span for students and cognitive load, 3) Median view time for animations characterized as Derivation was the longest (40 s) compared to Physical World animations, which resulted in the shortest time (20 s).

Introduction and Background

Internet access makes viewing information on virtually any topic available to billions of people across the globe. Advancements in affordable screens and devices enabled high quality images, animations, and high-definition video on topics from entertainment to household repair demonstrations. Specifically in higher education, these technological advancements are changing the traditional 20th century textbook and lecture courses into active student instruction [1]. Undergraduate students entering engineering programs in the 21st century may also be exposed to interactive instruction and are inclined to prefer digital technology for instruction [2]. These students categorized as the "Net Generation", "Millennial students", or "digital natives" have an inclination for learning through visual means [2, 3]. Educational animations provide one such platform to explain, present, and scaffold learning as "chunks" of new material to learn [4, 5].

Animations have been recognized as a promising tool to bring visual and textual information together to present instructional material [6]. On one hand, computer-generated animations used for online gaming, films, cartoons, and broadcast media have emerged primarily for entertainment. On the other hand, educational animation create projections of phenomena for learning [7]. While some early research in animation instruction failed to provide positive evidence for their use [8, 9], further research applying cognitive load theory to educational animations resulted in positive learning gains with educational animations [6, 10-16].

Interactive textbooks enable students to see and use animations as a form of active learning [17-19]. Animations provide a self-regulated learning environment where the students manipulate and control the animation progression. Research has shown that control of content presentation improves student learning and retention to match cognitive load, specifically germane cognitive load, and improves student learning and retention [1, 4, 8, 10, 14, 18, 20-22]. An animation is a sequence of visual steps that introduce and move images, figures, and text to explain or convey a concept. Educational animations are designed to provide information in a multi-sensory format [8, 10, 14, 23]. Multi-step animations divide content into small chunks of information that engage the student and require attentiveness. Animation re-watch may be initiated at any time, which may be analogous to online videos that are re-viewed thousands or millions of times [8]. Overall, animations provide a promising pedagogical tool that will be examined using cognitive load as the primary educational framework.

Features of Educational Animations

Static images in the form of tables, figures, and graphs presented in engineering textbooks rely on text that supports explanations and derivations of the technical content. Flipping pages between the text and these images can be distractive for the learning process because the information is dispersed. While the information may be presented in the text along with the associated images, the information is not guided and may require significant cognitive load to connect visuals with concepts conveyed in text.

Educational animations research on learning and instruction applies the cognitive load theory framework to design animations for learning by reducing the cognitive load on working memory. Multimodal learning, or multimedia learning, is defined as learning through the use of pictures and words that construct mental representations for learning [12]. Principles of reflection, feedback, and pacing apply the cognitive load theory of multimodal learning environments for educational animation design [17, 24]. Text (words) and visual (pictures) appearing together create instructional media for integrating, organizing, and retrieving long term memory [17].

Research in cognitive load theory presents three categories of cognitive load on the working memory [24]. Intrinsic cognitive load is defined by learning task complexity and interactivity; Extraneous cognitive load involves the tasks that cause unnecessary interaction of the senses and may inhibit learning; Germain cognitive load is the remaining working memory available for learning. Thus, for educational purposes, animations must consider modality that use senses and processing abilities of the memory to support learning. Multimodal principles are applied to animations design in an interactive textbook explored here.

The Material and Energy Balance (MEB) zyBook interactive textbook contains animations that were designed for educational purposes [18, 25]. MEB animations apply cognitive load theory with small chunks of material to build new ideas, concepts, or equations. Multiple student-initiated steps using clicks advance through the animation sequence. User interactivity and the ability of the digital tool to capture user device activity generates big data [4]. Specifically, the data generated from an interactive textbook identifies student participation through "learning by doing". Analysis of big data generated from animation usage in an engineering interactive textbook provides a method of understanding learning by doing methods.

Few research papers investigate animation duration and its relationship with usage. Thus, the research questions will quantify animation views and view time as a function of cohort, content, and animation type. This paper expands upon the work in progress contribution in 2021 [26]. One goal for studying student usage and engagement is the opportunity to design better digital tools for students in the future.

Research questions

By examining 5 cohorts of interactive textbook data including 60,000 animation views, five research questions will be addressed.

1) Does animation watch rate vary by course content?
2) How does animation view time vary by cohort?
3) How does animation view time vary by step count?
4) How does animation view time vary by animation view attempt?
5) If animations are characterized by type, does animation view time vary by animation type?

Materials and Methods

The research is based on data from 2016 through 2020 cohorts gathered from the interactive textbook used for a Material and Energy Balance (MEB) chemical engineering course. Student participation data are generated by clicks while progressing through different assignments, including reading participation, animation views, and challenge activities (a form of auto-graded homework). The animations are spread across almost every section and chapter (Table 1), and over 130 animations were available for the last three cohorts. In general, the duration of an animation is between 20 and 60 s depending on the number of steps.

Table 1. Animation count in Material and Energy Balances zyBook by chapter and cohort.

Chapter	Chapter title	2016	2017	2018	2019	2020
1	Quantities, units, calculations	9	9	9	9	9
2	Material balances	19	19	19	19	19
3	Reacting systems	11	13	13	13	13
4	Solids, liquids, and gases	9	10	11	11	14
5	Multiphase systems	8	13	13	13	15
6	Energy balances	8	8	15	15	15
7	Reaction and energy balances	5	5	7	7	7
8	Transient systems	3	3	4	4	4
9	Spreadsheets	0	0	41	41	47
	Total animations=	**72**	**80**	**132**	**132**	**143**

The MEB course was taught at a public university, and the size of the five cohorts varied from 93 to 104 students. Students were primarily in their first year of college majoring in chemical engineering or environmental engineering with approximately 60% male and 40% female [4]. Reading participation includes clicks for animation views, the focus here, as well as learning questions. Reading participation has been discussed previously with median reading participation over 90% [25, 27, 28]. Auto-graded online homework in the zyBook is outside the scope of this paper [4, 25].

While the course applies active learning in different ways, the focus here is on analytics related to animation usage. Specific to animations, each click was uniquely recorded. Thus, each step of an animation is watched, and the length of time watching is the difference between time stamps. One animation titled Finding bubble and dew points on a P-xy diagram (see Appendix) is an example of an animation frequently re-watched by students and includes a screenshot of the sequence of steps. Over 60,000 completed animation views are analyzed (Table 2). Two limitations are noted. First, the analysis does not investigate partial views – many animations have 4 to 6 steps and re-watching some steps may occur. Secondly, animation views do not account the length of time watching an animation or how long students may reflect after individual steps.

Table 2. Animation views in Material and Energy Balances zyBook by chapter and cohort. View rounded to nearest 100 views for easier readability.

Chapter	Chapter title	2016	2017	2018	2019	2020	Sum
1	Quantities, units, calculations	1700	900	1000	1000	1000	5600
2	Material balances	2500	1800	2000	2100	2000	10400
3	Reacting systems	1300	1500	1400	1500	1500	7200
4	Solids, liquids, and gases	1000	1000	1200	1200	1500	5900
5	Multiphase systems	1000	1300	1400	1500	1500	6700
6	Energy balances	800	800	1600	1700	1600	6500
7	Reaction and energy balances	500	500	700	700	700	3100
8	Transient systems	300	300	400	400	400	1800
9	Spreadsheets	0	0	4200	4200	4600	13000
	Total animation views=	9100	8100	13900	14300	14800	60200

Evaluating the time spent by students to complete watching or re-watching animations from 2017 through 2020 cohorts was compiled and used for answering the research questions. 2016 was removed from watch time analysis because a 2X speed feature was added in 2017. Thus, watch times in 2016 were different than the other four cohorts. Maximum view time limitation for analysis is 180 s for all animations. This time limit was applied to remove cases where a student may be interrupted by another task during an animation and then resume the animation at a later time. Also, the time that a student spends viewing an animation on the last step after the actions complete is unknown.

An example 4-step animation sequence shows all the steps with the text and figure progress (Appendix A-1). Other examples are shown as completed animations of different animation types (Appendix A-2). In brief, an animation starts as a static image with a "Start" button. Once started, the animation performs the actions of Step 1, usually the final static image is removed in Step 1 and parts of the content reappear. An arrow to the right of the step numbers appears when each step is complete. Clicking the arrow continues the animation and builds on the previous steps to completion. The final step completes construction of the initial static image, and a completed view is recorded. A subsequent watching is called re-watch and may be initiated at any time, and student can re-watch animations as often as they like during the semester.

Animation usage data analysis was done using spreadsheet functions, pivot tables, or statistical analysis using Python. Python and several Python libraries were used for analysis of the timestamp data. The Pandas library was used to calculate step times as the difference between the logged events for each student on each animation [29]. View time was calculated as the sum of a student's step times from the "start clicked" event to the "animation completely watched" event. The animation view time will be analyzed by aggregate (all cohorts), year, chapter, and total steps in an animation.

Metric Definitions

Definitions of key terms include:

Animation Views (Usage): Animation view accounts for the animation view data and does not consider the time spent watching or re-watching the animations. Completed animation views are logged when a student has completed all the animation steps. Animation views when reported as a percentage account for student withdrawal, so View (%) = Completed views (#)/students currently enrolled (#)× 100.

Animation View Time: Animation view time accounts for the time students spend watching, reflecting upon, or re-watching each animation step and animations as a whole. Each step has a minimum duration for actions to occur. After actions cease, students may reflect or immediately click to initiate the next step. First animation view time quantifies the first completed view for each student.

Animation Characterization: Defines distinct animation content. The characterization descriptions (Table 3) were defined by two of the authors. This limitation is noted and assigning characteristics by other subject matter experts is a plan for future work.

Table 3. Animation characterizations and abbreviations.

Abbreviation	Description of Animation Characterization Content
C	Conceptual: present conceptual thought or ideas dynamically.
D	Derivation: present equations or calculations based on first principles in a constructive sequence
FP	Figures/Plots: construct information previously presented as a static table or chart
PW	Physical World: animate how a system or process works
SS	Spreadsheet: demonstrate cell formatting, keystrokes, functions, and formulas common across spreadsheet applications and platforms

Results and Discussion

Interactive textbook usage data from five cohorts includes 60,000 animation views and will be used to answer the five research questions pertaining to animation watch rate and view time across several cohorts.

RQ1. Does animation watch rate vary by course content?

Animation views across the five cohorts were aggregated as the variations were not significant. Aggregated animation views by chapter were generally over 100% (Figure 1). Average animation views were 110% across five cohorts. Thus, about 10% of animation views were students re-watching the course content. While Chapters 1 to 8 were covered in order, Chapter 9 covering spreadsheets is dispersed throughout the semester. While views declined across the semester from 130% (Chapter 1) to 107% (Chapter 6) to 100% (Chapter 8), the engagement was still much higher than static textbooks. Static textbook reading rates are normally reported between 20% and 50% [28, 30]. Chapter 8 covers transient systems, which was only assessed with a single quiz and not covered on the final exam. Thus, a lower animation usage of 100% for Chapter 8 aligns with the emphasis within the course.

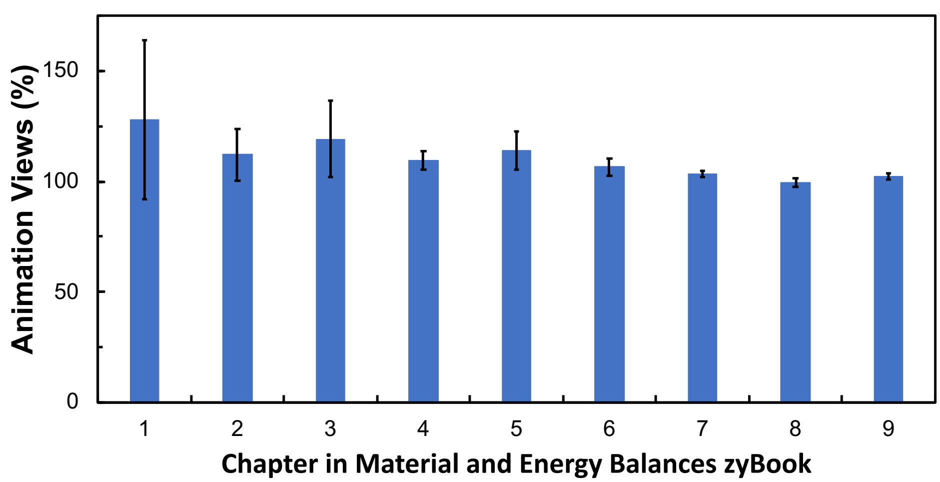

Figure 1. Animation views by chapter of the Material and Energy Balances zyBook. Average and standard deviation aggregated across five cohorts.

Animation re-watch views by chapter (Figure 1) are generally 0% to 15%. However, re-watch of 28% in Chapter 1 and 19% Chapter 3 were observed. Early semester reading and homework assignments are generally not heavy, so students may have more time and interest in re-watching the material due to the new format and novelty of the zyBook. Re-watching animations in Chapter 3 is likely related to the content, i.e., reacting systems. While reacting system material balances are introduced in Chapter 3, reacting systems with energy balances are added later in the semester with Chapter 7. Thus, details related to yield, selectivity, conversion, etc. are needed for solving reacting systems at two distinct points in the semester. Chapter 9's content related to spreadsheets was introduced in 2018 and re-watch views range between 1 and 4%; many students are digital natives who have used spreadsheets for years before entering the university. Other analytics related to auto-graded problems on the topic of spreadsheets was recently published elsewhere [31].

Two limitations are noted. First, the analysis does not investigate partial views – many animations have 4 to 6 steps and re-watching some steps is likely. Secondly, animation views do not account the length of time watching an animation or how long students may reflect after individual steps. Animation view time is further investigated by the next four research questions.

RQ2. How does animation view time vary by cohort?

First animation view times changed little from cohort to cohort (Figure 2). The 1st quartile represented the fastest quarter of the cohort took ~20 s to watch an animation, while the 3rd quartile or the slowest quarter of animation watchers took between 45 and 47 s. The median was ~30 s for all cohorts when aggregating all of the animations across the entire book. The view time between cohorts shows statistical similarity using ANOVA analysis. Here, the aggregated MEB animation view times by cohort provide a benchmark for animation duration. Animation speed is not addressed in this contribution and may be an area for further research. The literature identifies slow animation speeds having negative student feedback and wastes time [32]. Overall, the length of animation viewing is similar to observations of instructional videos, which ranged from 5 s to 12 min [33-35].

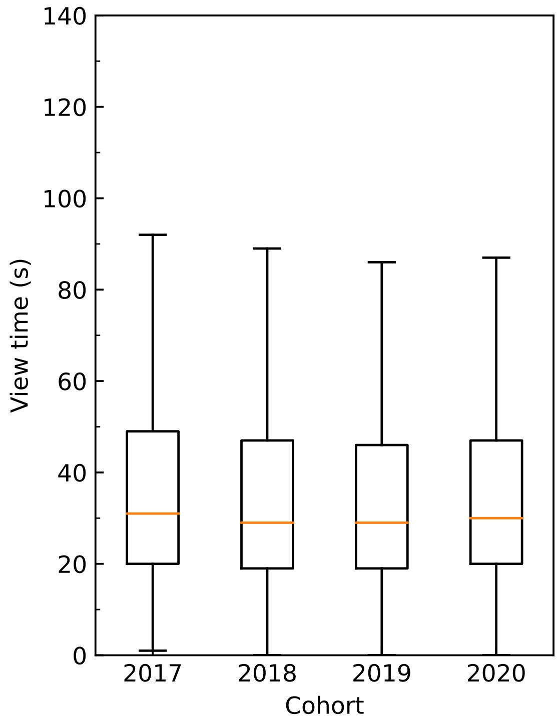

Figure 2. First animation view time for all animations as a function of cohort.

RQ3. How does animation view time vary by step count?

Animations have various step counts (Table 4); steps are generally based on the number of chunks that an expert author believes a learner needs to build new knowledge and alignment with cognitive load theory. Step counts of 2, 3, and 4 animation steps are the most common accounting for 83% of the animations. While the author creating the animations believes that each step is appropriate, animation view time may provide a learning analytic to quantify readers' attention span. For example, if too many actions occur in one step, do learners re-watch immediately before moving on could be a future research question?

Table 4. Number of animations by step count for 2020 cohort.

Steps	Animations
2	37
3	37
4	42
5	16
6	7

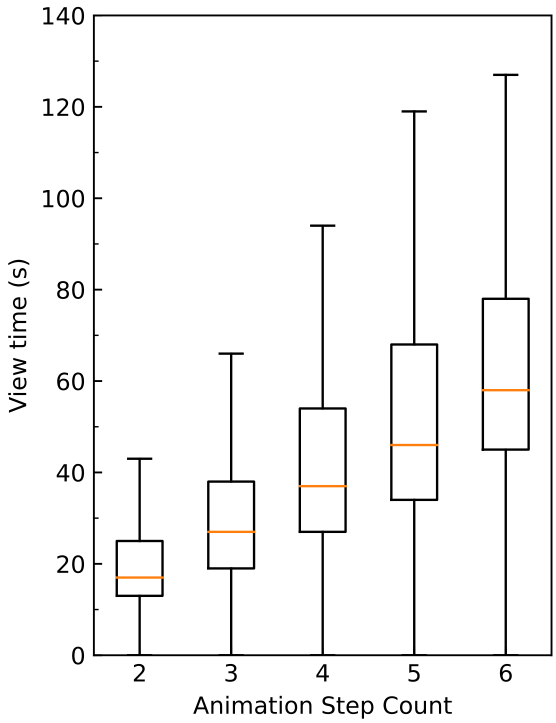

Figure 3. First animation view time for all animations as a function of animation step count.

The median view time increased with the number of steps: 2 step (17 s); 3-step (27 s); 4-step (37 s); 5-step (46 s); 6-step (58 s) (Figure 3). View time quantified only first completed view. Thus, a linear trend of the median view time with a slope of 10 s/step was measured across the animations in aggregate. Taking one minute or less to completely watch an animation generally aligns with trends in web analytics, i.e., shorter videos normally have more completed views. In addition, the linear trend through the 3rd and 1st quartiles are 13 s/step and 7 s/step, respectively, indicating a divergence in student reflection time on longer animations. The larger slope for the 3rd quartile view time indicates that some students reflect more on higher step count animations, which may be worth further investigation related to chunking and cognitive load.

RQ4. How does animation view time vary by animation view attempt?

Animation view time decreases with each subsequent completed view (Figure 4). The median animation view time declines from 29 to 18 to 8 s between first, second, and third views. The 1st quartile view time decreased from 20 s for the first view to 3 s for both second and third views. Therefore, a fraction of the students re-watch the entire animation in the minimum possible time and do not reflect on any specific step. The 3rd quartile view time declines a small amount between the first and second views (45 to 40 s) and a much larger decrease of 20 s between the second and third views. Thus, some students may be earnestly re-watching most of the steps during a second view but focusing on fewer concepts during a third view.

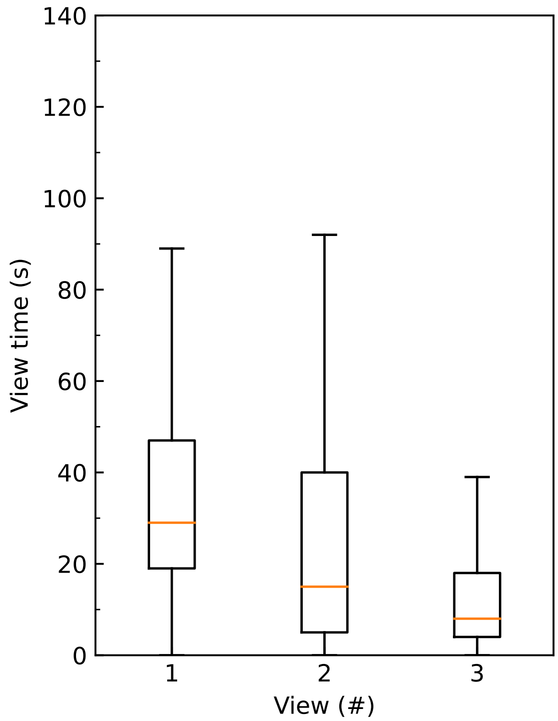

Figure 4. Animation view time for all animations as a function of attempt.

One limitation of view time analytics is that reflection time beyond the minimum time for each step to complete is not quantified. Also, examining view times for the entire animation does not identify specific steps that students spend the most time reflecting upon. Finally, the amount of time that a student reflects after the final step is completed is unknown and only recorded when the next learning activity is initiated.

RQ5. If animations are characterized by type, does animation view time vary by animation type?

Distinguishing animations by type instead of content provides another perspective on the view analytics. Five characterizations show a distribution of animation type in the MEB zyBook (Table 5). Noting that not all animations were available for all cohorts (Table 1), Figures and Plots is the most common characterization. All five categories accounted for at least 16 different animations.

Table 5. Number of animations for the 2020 cohort by characterization.

Characterization	Animations
C - Conceptual	28
D - Derivation	27
FP - Figures & Plots	28
PW - Physical World	30
SS - Spread Sheet	30

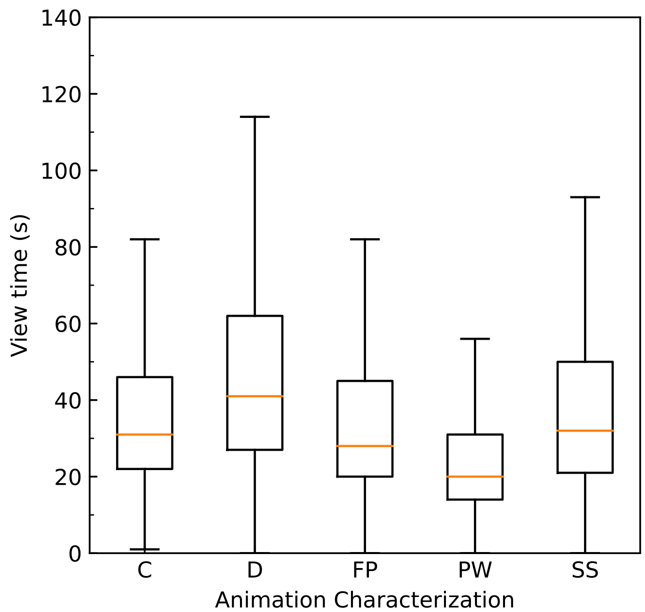

Figure 5. First animation view time for all animations as a function of animation characterization.

First animation view times by characterization (Figure 5) shows that Derivations (D) animations have a median watch time of 41 s, which is twice as long as the shortest median view time for Physical World (PW) animations (20 s). Concept (C), Figures and Plots (FP), and Spreadsheet (SS) animations have median view time around 30 s. The shorter view times for the Physical World animations may be related to the learners being comfortable with explanation of equipment and physical process. The 3rd quartile for Derivation animations is 60 s, which is twice the median view time for all animations. The 1st quartile view time of 29 s for Derivation animations matches the median of the other animations, which is an interesting finding that may be related to the number of animations steps as well as characterization. Thus, further work into animation characterization should normalize view time by the number of animation steps.

Conclusions

Animation watch rate in an interactive textbook for a material and energy balances course revealed high student usage. Reading assignments introduce new information to students, and interactive textbooks allow reading assignments with animations to be an active and graded activity. Educational animations apply cognitive load theory that divide engineering concepts into chunks that can help learners. Using an interactive textbook containing over 140 animations across five cohorts generated over 60,000 animation views. Animation views of 100% or higher were observed across content, animation type, and cohort. This high engagement is a positive finding since textbook reading in higher education is significantly lower and has declined over many years [30]. Additional animation views do not help a students' grade, so a re-watch rate of 10% indicated student self-motivation and interest in learning. Since animations considered cognitive load theory when authoring, these interactive tools appear to provide a viable educational tool for presenting engineering topics.

Median view time across four cohorts and all animations was 30 s, which is a reasonable time for the average human's attention span. Animation re-watch may be more likely when students know that watching an animation will take one minute or less in most cases. The median first animation view time by chapter ranges from 22 to 42 s, which shows that content is not a significant factor in increasing view times. Median view time increased linearly with step count increasing 10 s per step. Median animation view time declined from 29 s (1st view) to 18 s (2nd view) to 8 s (3rd view). Since repetition is a best practice of learning, even shorter view times may be beneficial for learning. Finally, view time by characterization showed that Derivation animations has the longest median time of 41 s, which is twice as long as view time for Physical World animations at 20 s; Figures and Plots, Conceptual, and Spreadsheet animations' watch times were in between these values.

While some limitations of this work were noted, such as not measuring time-on-task. The median animation view times between 20 and 60 s seemed reasonable to retain student attention, however, a thorough evaluation of the duration and attention span could be an area of further study. Cognitive load design was considered by partitioning animations into logical chunks of information, but no assessment has been conducted about chunking to promote germane cognitive load.

Overall, examining learning analytics related to animations merits further investigations to overcome limitations of the results presented here. Normalizing animation views and view time by step count may provide new insights across content and animation characterization, which should be the subject of future research.

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References

[1] A. Edgcomb, F. Vahid, R. Lysecky, A. Knoesen, R. Amirtharajah, and M. L. Dorf, "Student performance improvement using interactive textbooks: A three-university cross-semester analysis," in *ASEE Annual Meeting*, Seattle, WA, 2015, doi: https://doi.org/10.18260/p.24760.

[2] G. E. Kennedy, T. S. Judd, A. Churchward, K. Gray, and K.-L. Krause, "First year students' experiences with technology: Are they really digital natives?," *Australasian journal of educational technology,* vol. 24, no. 1, 2008, doi: https://doi.org/10.14742/ajet.1233.

[3] A. R. Bonamici, "The Net Generation: Implications for Libraries and Higher Education," 2007.

[4] K. E. Chapman, M. E. Davidson, and M. W. Liberatore, "Student success and attempts on auto-graded homework across multiple cohorts in material and energy balances," *Chemical Engineering Education,* vol. 55, no. 1, pp. 43-50, 2021, doi: https://doi.org/10.18260/2-1-370.660-123169.

[5] M. W. Liberatore, K. Chapman, and M. Davidson, "Quantifying success and attempts on auto-graded homework when using an interactive textbook," in *ASEE Annual Conference*, 2020, pp. 1-12, doi: https://peer.asee.org/35116.

[6] R. E. Mayer and R. Moreno, "Aids to computer-based multimedia learning," *Learning and instruction,* vol. 12, no. 1, pp. 107-119, 2002, doi: https://doi.org/10.1016/S0959-4752(01)00018-4.

[7] T. Silvio, "Animation: The new performance?," *Journal of Linguistic Anthropology,* vol. 20, no. 2, pp. 422-438, 2010, doi: https://doi.org/10.1111/j.1548-1395.2010.01078.x.

[8] P. Ayres and F. Paas, "Making instructional animations more effective: A cognitive load approach," *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition,* vol. 21, no. 6, pp. 695-700, 2007, doi: https://doi.org/10.1002/acp.1343.

[9] R. Ploetzner, S. Berney, and M. Bétrancourt, "A review of learning demands in instructional animations: The educational effectiveness of animations unfolds if the features of change need to be learned," *Journal of Computer Assisted Learning,* vol. 36, no. 6, pp. 838-860, 2020, doi: https://doi.org/10.1111/jcal.12476.

[10] P. Ayres and F. Paas, "Can the cognitive load approach make instructional animations more effective?," *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition,* vol. 21, no. 6, pp. 811-820, 2007, doi: https://doi.org/10.1002/acp.1351.

[11] R. Moreno, "Optimising learning from animations by minimising cognitive load: Cognitive and affective consequences of signalling and segmentation methods," *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition,* vol. 21, no. 6, pp. 765-781, 2007, doi: https://doi.org/10.1002/acp.1348.

[12] R. E. Mayer and R. Moreno, "Animation as an aid to multimedia learning," *Educational psychology review,* vol. 14, no. 1, pp. 87-99, 2002, doi: https://doi.org/10.1023/A:1013184611077.

[13] A. Kohnle, M. Douglass, T. J. Edwards, A. D. Gillies, C. A. Hooley, and B. D. Sinclair, "Developing and evaluating animations for teaching quantum mechanics concepts,"

European Journal of Physics, vol. 31, no. 6, p. 1441, 2010, doi: https://doi.org/10.1088/0143-0807/31/6/010.
[14] P. S. Steif and A. Dollar, "Study of usage patterns and learning gains in a web-based interactive static course," (in English), *Journal of Engineering Education,* vol. 98, no. 4, pp. 321-333, Oct 2009, doi: https://doi.org/10.1002/j.2168-9830.2009.tb01030.x.
[15] N. Hubing, D. B. Oglesby, T. A. Philpot, V. Yellamraju, R. H. Hall, and R. E. Flori, "Interactive learning tools: Animating statics," 2002, pp. 1-10, doi: https://doi.org/10.18260/1-2--10367.
[16] T. A. Philpot, D. B. Oglesby, R. E. Flori, V. Yellamraju, N. Hubing, and R. H. Hall, "Interactive learning Tools: Animating mechanics of materials," 2002, doi: https://doi.org/10.18260/1-2--10366.
[17] R. Moreno and R. Mayer, "Interactive multimodal learning environments," *Educational psychology review,* vol. 19, no. 3, pp. 309-326, 2007, doi: https://doi.org/10.1007/s10648-007-9047-2.
[18] M. W. Liberatore, "Reading analytics and student performance when using an interactive textbook for a material and energy balances course," in *ASEE Annual Conference & Exposition*, Columbus, OH, 2017, pp. 1-13, doi: https://peer.asee.org/28780.
[19] A. M. Lesgold, "The nature and methods of learning by doing," *American Psychologist,* vol. 56, no. 11, p. 964, 2001, doi: https://doi.org/10.1037/0003-066X.56.11.964.
[20] S. K. Donohue and L. G. Richards, "Factors affecting student attitudes toward active learning activities in a graduate engineering statistics course," 2009: IEEE, pp. 1-6, doi: https://doi.org/10.1109/FIE.2009.5350587.
[21] J. Hackathorn, E. D. Solomon, K. L. Blankmeyer, R. E. Tennial, and A. M. Garczynski, "Learning by Doing: An Empirical Study of Active Teaching Techniques," *Journal of Effective Teaching,* vol. 11, no. 2, pp. 40-54, 2011.
[22] S. Freeman *et al.*, "Active learning increases student performance in science, engineering, and mathematics," *Proceedings of the National Academy of Sciences,* vol. 111, no. 23, pp. 8410-8415, 2014, doi: https://doi.org/10.1073/pnas.1319030111.
[23] M. T. Chi, "Active-constructive-interactive: a conceptual framework for differentiating learning activities," *Topics in Cognitive Science,* vol. 1, no. 1, pp. 73-105, Jan 2009, doi: https://doi.org/10.1111/j.1756-8765.2008.01005.x.
[24] F. Paas, A. Renkl, and J. Sweller, "Cognitive load theory: Instructional implications of the interaction between information structures and cognitive architecture," *Instructional science,* vol. 32, no. 1, pp. 1-8, 2004, doi: https://doi.org/10.1023/B:TRUC.0000021806.17516.d0.
[25] M. W. Liberatore, "High textbook reading rates when using an interactive textbook for a Material and Energy Balances course," *Chemical Engineering Education,* vol. 51, no. 3, pp. 109-118, 2017, doi: https://journals.flvc.org/cee/article/view/104416.
[26] S. J. Stone and M. W. Liberatore, "Attitudes Toward and Usage of Animations in an Interactive Textbook for Material and Energy Balances," in *ASEE Virtual Annual Conference*, 2021, doi: https://doi.org/10.18260/1-2--36728.
[27] M. W. Liberatore and K. Chapman, "Reading anytime: Do students complete missed readings after the due date when using an interactive textbook for material and energy balances?," in *ASEE Annual Conference*, Tampa, FL, 2019, pp. 1-10, doi: https://peer.asee.org/33224.

[28] M. W. Liberatore, K. E. Chapman, and K. M. Roach, "Significant reading participation across multiple cohorts before and after the due date when using an interactive textbook," *Computer Applications in Engineering Education,* vol. 28, no. 2, pp. 444-453, 2020, doi: https://doi.org/10.1002/cae.22210.
[29] W. McKinney, "Data structures for statistical computing in python," in *Proceedings of the 9th Python in Science Conference*, 2010, vol. 445, no. 1: Austin, TX, pp. 51-56.
[30] C. M. Burchfield and T. Sappington, "Compliance with required reading assignments," (in English), *Teaching of Psychology,* vol. 27, no. 1, pp. 58-60, Win 2000, doi: https://psycnet.apa.org/record/2000-07173-017.
[31] L. J. Gorbett, K. E. Chapman, and M. W. Liberatore, "Deliberate practice of spreadsheet skills when using copiable, randomized, and auto-graded questions within an interactive textbook," *Advances in Engineering Education,* vol. accepted., 2022.
[32] S. Kriglstein, M. Pohl, and C. Stachl, "Animation for time-oriented data: An overview of empirical research," 2012: IEEE, pp. 30-35, doi: https://doi.org/10.1109/IV.2012.16.
[33] A. L. Griffin, A. M. MacEachren, F. Hardisty, E. Steiner, and B. Li, "A comparison of animated maps with static small-multiple maps for visually identifying space-time clusters," *Annals of the Association of American Geographers,* vol. 96, no. 4, pp. 740-753, 2006, doi: https://doi.org/10.1111/j.1467-8306.2006.00514.x.
[34] M. Chan and J. Black, "When can animation improve learning? Some implications on human computer interaction and learning," 2005: Association for the Advancement of Computing in Education (AACE), pp. 933-938.
[35] D. H. O'Day, "The value of animations in biology teaching: a study of long-term memory retention," *CBE—Life Sciences Education,* vol. 6, no. 3, pp. 217-223, 2007, doi: https://doi.org/10.1187/cbe.07-01-0002.

Appendix

Screenshots of animations statically capture a sequence of steps for an animation characterized as FP (Figure A-1) as well as one screenshot from an animation representing the other four characterizations (C, D, PW, SS) (Figure A-2). The step counts can be determined from the number of captions in Figure A-2.

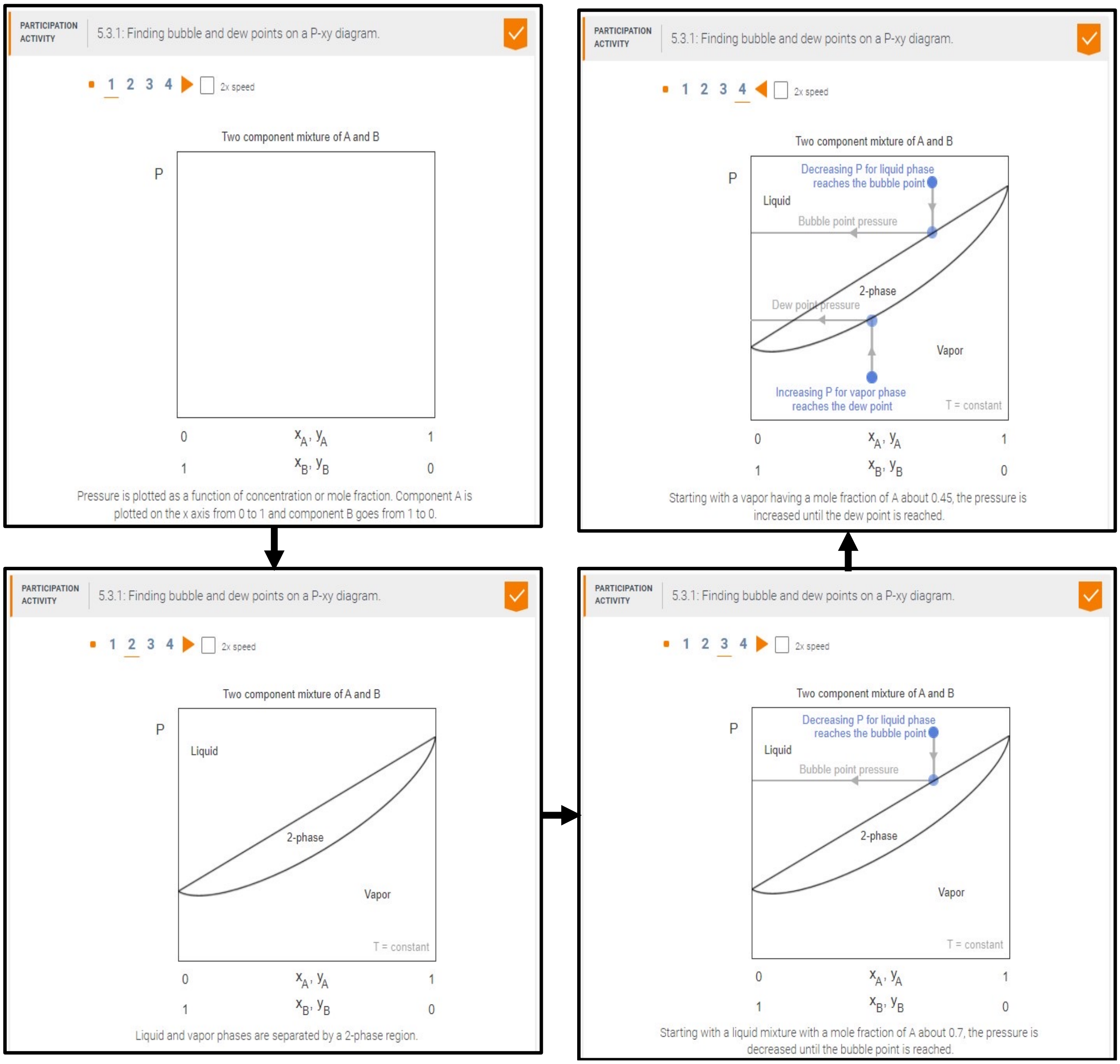

Figure A-1. Animation titled Finding Bubble and Dew Points on a P-xy Diagram. The animation includes four sequential steps and is characterized as Figures & Plots (FP).

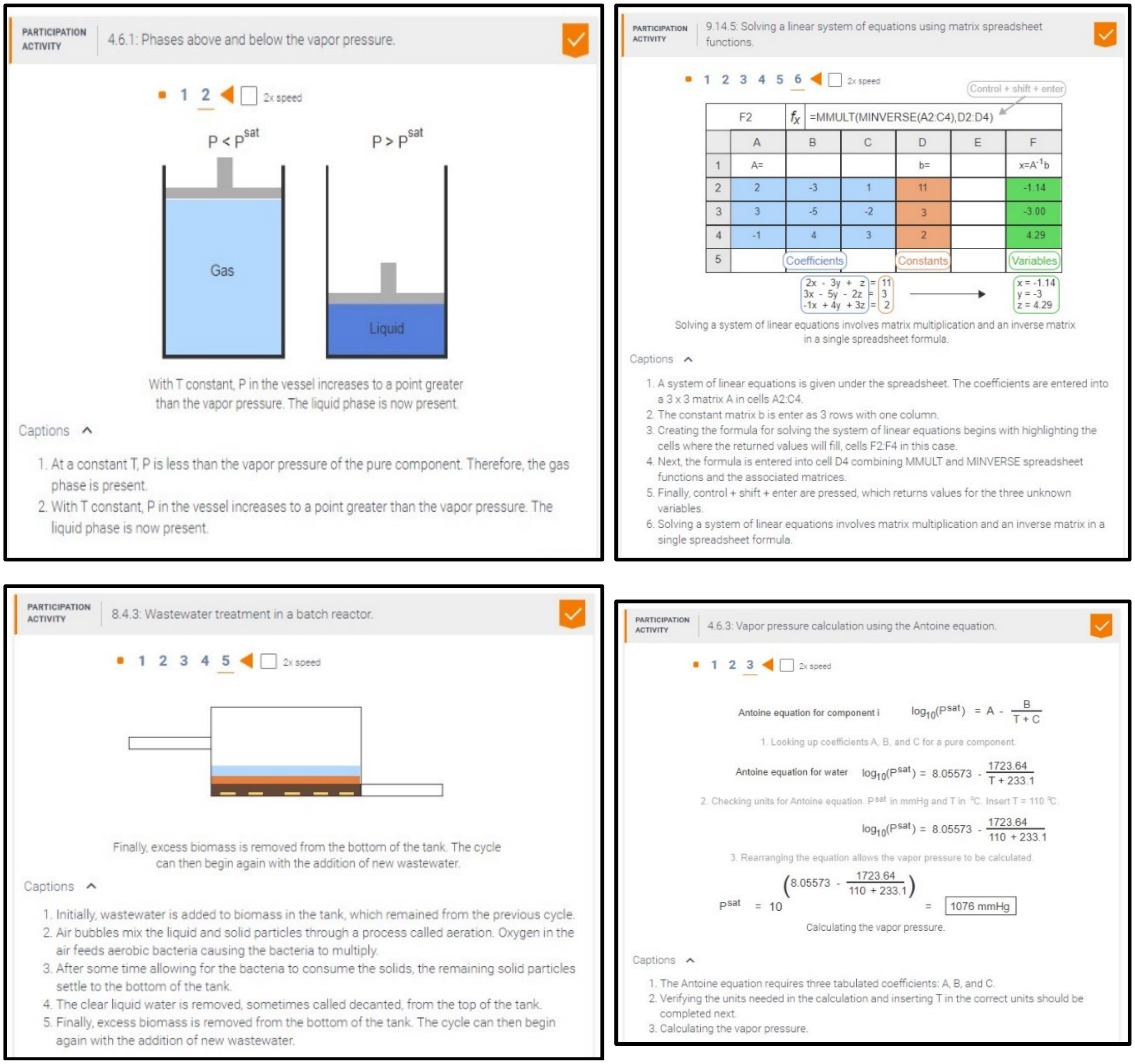

Figure A-2. Four animations representing characterizations; Conceptual C (top left), Spreadsheet SS (top right), Physical World PW (bottom left), and Derivations D (bottom right).