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Clustering of Animation View Times in an Interactive Textbook for Material and Energy Balances

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Abstract

Data science tools can help elucidate trends from clickstreams and other interactions generated by students actively using interactive textbooks. Specifically, data generated when using animations, which are multi-step visuals with text captions, will be presented in this work. Each animation step divides content into appropriate chunks, and so aligns with tenets of cognitive load theory. Both the quantity and timing of students' clicks record provide large data sets when examining students across hundreds of animations and multiple cohorts. Specifically, an interactive textbook for a chemical engineering course in Material and Energy Balances will be examined and build upon data presented previously. While most of the previous data focused on very high reading completion rates (>99% median) compared to traditional textbooks (20-50%), a deeper examination of how long students take when watching animations will be explored. With over 140 unique animations and tens of thousands of completed views over five cohorts, a spectral clustering algorithm applied to students' animation view times distinguished several types of animation watching behavior as well as monitor changes in this animation watching behavior over the course of a semester. After examining different numbers of clusters, two or three clusters in each chapter captured the animation usage. These clusters usually correspond to a group of students who watched animations at 1x speed (longer), another group who watched at 2x speed (shorter), and a third group, when present, who watched irregularly, including skipping animations. Overall, more students belonged to the belonged to the cluster with longer view times, with 63% of students aggregated over all cohorts and chapters compared to 35% of students in the cluster with shorter view times. The remaining 2% of students belonged to the irregular cluster, which was present in less than one quarter of the chapters. Many students stayed in the same cluster between chapters, while a smaller fraction switched between the longer and shorter clusters.

Introduction and Background

Big data has exploded with the introduction of affordable, touch-screen devices from phones to tablets to laptops. The high-quality visual experiences have led to a transition in some technologies in higher education, including textbooks. After about 100 years of static, paper textbooks being the primary resource for many engineering courses, online homework and interactive textbooks have become more common and may be preferred with students who are digital natives [1, 2]. Many interactive textbooks contain educational animations, which are multi-step interactive visuals that present and explain new course concepts in small steps, or chunks, which aligns with cognitive load theory [3, 4].

Computer-generated animations have become ubiquitous in online games, films, and web-based video sites, like YouTube. However, educational animations focus more on teaching and learning and less on entertainment [5]. Some research applied cognitive load theory related to educational animations usage and found positive learning gains [4, 6-9]. The field of educational animations has dramatically expanded from single or small numbers of stand-alone items to dozens of animations delivered inline within a digital textbook. Animations provide a mechanism for students to actively engage with new concepts outside of class, which may be considered a form of active learning [10]. By using clicks to proceed through animations, the activity also involves self-regulation [4, 9, 11]. Additionally, the incorporation of touch (via clicking) and sight to read/watch actions in an animation also aligns with the tenets of multimedia learning [12].

Educational animations combine words and images together. The animation author, usually the expert engineer in this case, organizes, parses, and times the actions to match perceived cognitive load [10, 13-15]. Animations can replace different components of a traditional print text. Examples include constructing a figure from defining the axis to the data and trends within or revealing individual steps of a derivation. Related to the animations discussed here, five types of animations were characterized for a chemical engineering course: conceptual, derivation, figures/plots, physical world, and spreadsheets [15].

The specific chemical engineering content is important. The material and energy balances course is usually the first fundamental engineering course that many chemical engineering students take. The content centers on developing engineering problem solving skills and provides an overview for many subsequent chemical engineering courses. Many contributions of the literature related to this course are available, e.g., [16-18].

Overall, learning analytics research related to animations is a nascent field. Specifically, our recent papers [15, 19] quantified animation view rates and view times globally over the entire course and multiple cohorts as well as students' attitudes toward educational animations. Now, new research questions examine students' animation watching behavior at different time points during a semester as well as characterizing different ways students use animations. Thus, a machine learning technique, called clustering, will group similar data into clusters or segments. The goal of clustering is to identify patterns and relationships within the data that may not be apparent through simple visual inspection. Clustering is particularly useful when dealing with large datasets without any predefined classifications. By clustering the data, we can identify natural groupings and patterns, which can then be used to summarize the data and guide further analysis. We employ clustering analysis in this work, which aims to explore patterns in students' animation watching behavior.

Research questions

The clustering of thousands of animation views across multiple cohorts were examined. The research questions are:

1) How many clusters capture animation watching behavior?
2) What fraction of a cohort is present in each animation watch cluster?
3) How do clusters change over the course of a semester and between cohorts?

Materials and Methods

Over 140 multi-step animations are currently available in the Material and Energy Balances (MEB) zyBook (Table 1), which has been in use since 2016 [20]. Animation views are monitored by clicks completed by each student. With at least one animation present in most sections across the book, animation view rates have been documented in the context of reading participation [21, 22]. Analytics related to auto-graded online homework in the MEB zyBook have been discussed elsewhere [23] and is outside the scope of this paper. Screenshots from an example animation (Figure 1) show the combination of process flow diagram, equations, and captions. Students generally watch an animation for between 20 and 60 s (1^{st} to 3^{rd} quartiles), which varies based on the number of steps.

Table 1. Animation count in MEB zyBook (2020 version).

Chapter	**Chapter title**	**Animations**
1	Quantities, units, calculations	9
2	Material balances	19
3	Reacting systems	13
4	Solids, liquids, and gases	14
5	Multiphase systems	15
6	Energy balances	15
7	Reaction and energy balances	7
8	Transient systems	4
9	Spreadsheets	47
	Total =	**143**

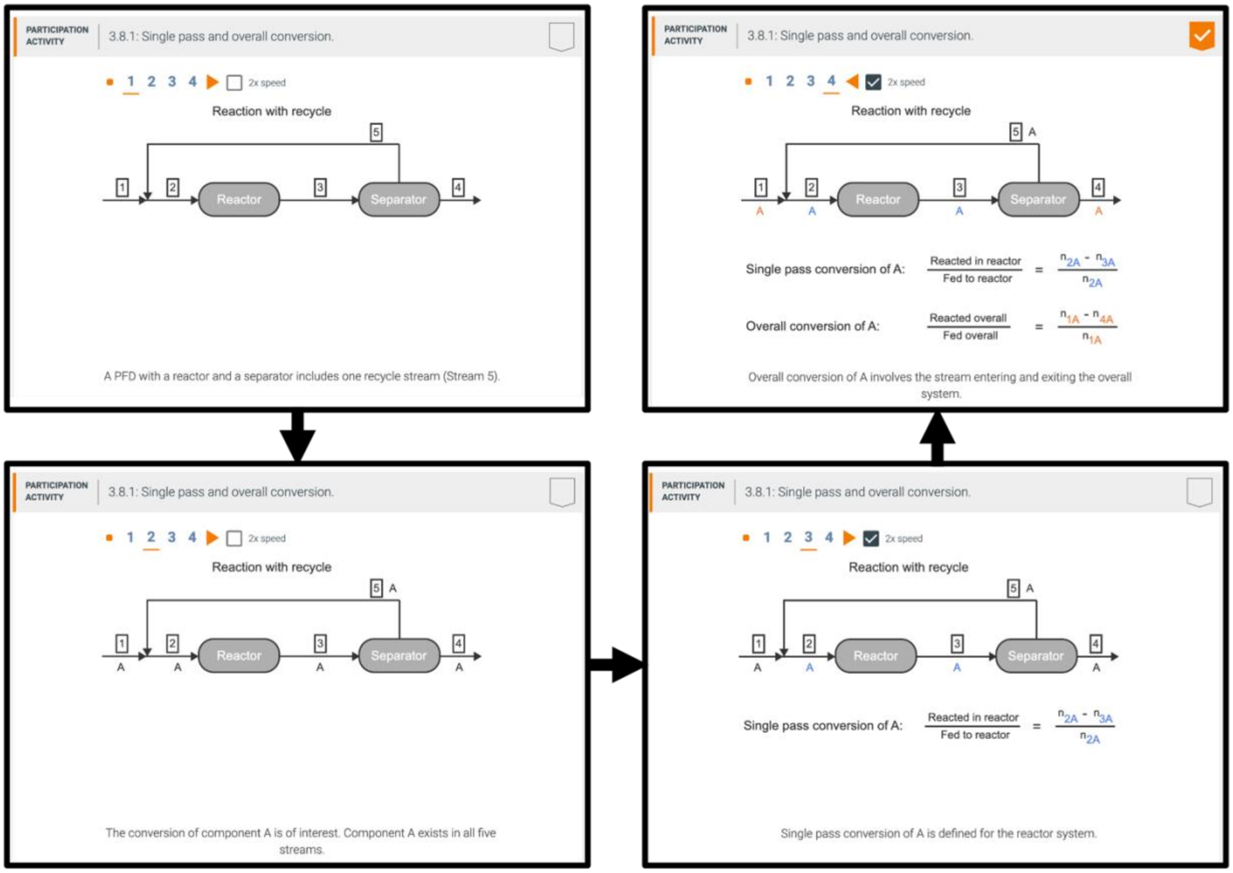

Figure 1. MEB zyBook animation titled Single pass and overall conversion. The final screenshot of each of the four steps are shown with captions.

Five cohorts of animation click data were examined for the clustering analysis; individual cohorts varied between 93 and 104 students at a public university. Most students were in their first year of college (freshman) majoring in chemical engineering or environmental engineering. The cohorts nominally contained 60% male and 40% female students. These percentages are indicative of gender at birth; other gender-related terms [24] and discussion may be relevant but are outside of the scope here.

In total, 60,000 completed animation views were analyzed. Animation view time accounts for the time that a student watches all steps in an animation, e.g., four steps in Figure 1. After the actions of an individual animation step are complete, a student may pause and reflect or immediately click to start the next step. We investigate the animation view times for the first time a student watches each animation. Re-watching an animation or intermediate steps in an animation before completing an animation view can occur but are not investigated further. A limitation of the click analytics is that the time reflecting on the final step of the animation is unknown. While students in the 2016 cohort could only watch animations at one speed, subsequent cohorts had access to a 2x speed feature, which speeds up the actions of each animation step. View times greater than 180 s were removed as outliers that were not relevant for further analysis, as these likely indicate that a student switched to another task and then came back later to complete the animation.

Animation usage data analysis was done using Python and several Python libraries, including Pandas [25] and Scikit-learn [26]. Animation view times were computed as part of a previous analysis, which found that they depend roughly linearly on the number of steps in the animation [15]. We first preprocessed the view times t_i using the log transform $\log(1 + t_i)$ to symmetrize their distribution and then standardize the data by subtracting the mean and dividing by the standard deviation for each animation to remove the dependency on the number of steps in the animation. Students who did not start viewing an animation are assigned a view time of 0, which results in a highly negative value once log transformed and standardized.

For each chapter, we performed normalized cut spectral clustering [27] on the standardized view times to identify the clusters of students. Normalized cut spectral clustering works by first constructing a similarity graph between students, where each student is connected to its k most similar students, i.e., the ones with most similar standardized view times. The algorithm then tries to identify clusters in the similarity graph by minimizing the cut (surface area) to volume ratio for each cluster. We choose $k = 6$, which is the minimum value that guarantees that the similarity graph is connected. We varied the number of clusters between 2 and 7 for each chapter and then choose the number of clusters by visually examining each set of clustering results from plots of the view times of the individual students in each cluster. We exclude Chapter 9 on spreadsheets from our analysis because different portions of it were assigned to students at different times. Chapters 1-8, which we consider in this study, were assigned to students in sequential order.

Results and Discussion

Cluster analysis of animation click data will address the three research questions.

RQ1. How many clusters capture animation watching behavior?

In a previous study [15], we found that students were highly engaged with the animations, with an average of 110% views across five cohorts. Thus, some students re-watch already completed animations. Although views show some decline over the semester, student engagement for animation textbooks remained significantly higher than for static textbooks. Also, re-watch views of animations by chapter ranged from 0% to 15%. Since early semester reading and homework assignments may not be as long, students may have more time and interest in re-watching animations. Specifically, rewatch views of 28% in Chapter 1 and 19% in Chapter 3 were observed, likely due to the novelty of the zyBook format and the unfamiliar content on reacting systems, respectively. The varying rates of animation views for different chapters indicate different animation-watching behavior, thus, the number of clusters and size of the clusters for each chapter were examined for this study.

The chosen number of clusters for each chapter and cohort (Table 2) was either 2 or 3. In 2016, two clusters were appropriate for all chapters, which is likely due to the lack of the 2x speed option for this cohort. For the 2017 to 2020 cohorts, two clusters were selected 22 times (69%), and three clusters were chosen 10 times (31%). Across five cohorts, nine instances of three clusters of animations viewers occurred; six of the nine instances occurred in the first three chapters. Thus, the disappearance of the third cluster may correspond with some of these students withdrawing from the course during the middle of the semester.

Table 2. The number of clusters selected for each cohort and chapter of the MEB zyBook.

	Year				
Chapter	**2016**	**2017**	**2018**	**2019**	**2020**
1	2	2	2	3	3
2	2	3	3	2	3
3	2	2	2	3	2
4	2	2	2	2	2
5	2	2	3	2	3
6	2	2	2	3	2
7	2	2	2	2	2
8	2	2	2	2	2

RQ2. What fraction of a cohort is present in each animation watch cluster?

Previously, animation view time varied little between cohorts with a median of 30 s. However, the subtleties of different groups of students watching behaviors cannot be captured when examining view times in aggregate, e.g., box plots capture the middle 50% of students. So now, the purpose was to investigate how students can be categorized based on their animation viewing speeds. Students have two main options when viewing animations: watching at 1x speed or selecting the 2x speed option and watching more quickly. Other unique animation watching behaviors could include prolonged viewing or not viewing at all.

The fraction of each cohort represented in two or three clusters was averaged across all chapters and shows some variation (Table 3). In aggregate for the five cohorts, the majority of students (63%) choose to view animations at the slower, 1x speed, resulting in longer view times. The longer view time cluster varies significantly across cohorts and chapters ranging between 48% and 85%. The shorter view time cluster, which corresponds with using the 2x speed option, represents 35% of students when taking the five cohorts in aggregate. The range for the shorter view time cluster is 15% to 49% across all cohorts, which is a smaller variation than the longer view time cluster. Finally, the remaining 2% of students are categorized under a third, irregular view time cluster. The unique view time behaviors include prolonged watching and non-viewing. This cluster's proportion ranges from 0% to 15% across chapters and cohorts. These proportions can be seen in the alluvial plots in Figures 3 to 7.

Table 3. Fraction of cohort (rounded to nearest percent) in each cluster averaged over 8 chapters of the MEB zyBook.

	Year					
Cluster type	**2016**	**2017**	**2018**	**2019**	**2020**	**Aggregated**
Longer	69	64	65	54	63	63
Shorter	31	34	34	42	34	35
Irregular	---	2	1	4	3	2

Chapter 5 (Vapor-liquid equilibrium) of cohort 2020 provides a way to demonstrate the grouping of individual student data into three clusters (Figure 2). Animation view times for 96 students were separated into three clusters. Fifteen animations were assigned within seven sections over two different reading assignments for this cohort. In this case, 68% of the students had longer view times (green), 21% has shorter view times (blue), and 11% showed a step change in behavior between the two reading assignments (red), i.e., between reading the first five sections and the last three sections.

The first four sections of Chapter 5 covers vapor-liquid equilibrium concepts and includes 9 animations that average 4.3 steps per animation. Section 5.5 was included in the first reading assignment, but this section does not include any animations. The final three sections of Chapter 5 provide details on equipment, which included absorbers, stripping columns, and flash tanks. Six animations in the final 3 sections average 3 steps per animation. Some noteworthy trends include the similar view times for the shorter and longer clusters for the last three sections, with the students in the shorter cluster having increased view times. The significant decrease in view time for the third cluster for the second reading assignment shows that this group of students generally did not view the animations before the reading assignments due date. The loss of engagement for this cluster of students correspond to the campus closure and shift to remote instruction due to COVID-19. Thus, cluster analysis clearly captures disruptions in student behaviors that may be lost when examining only average or aggregated reading participation when using the interactive textbook.

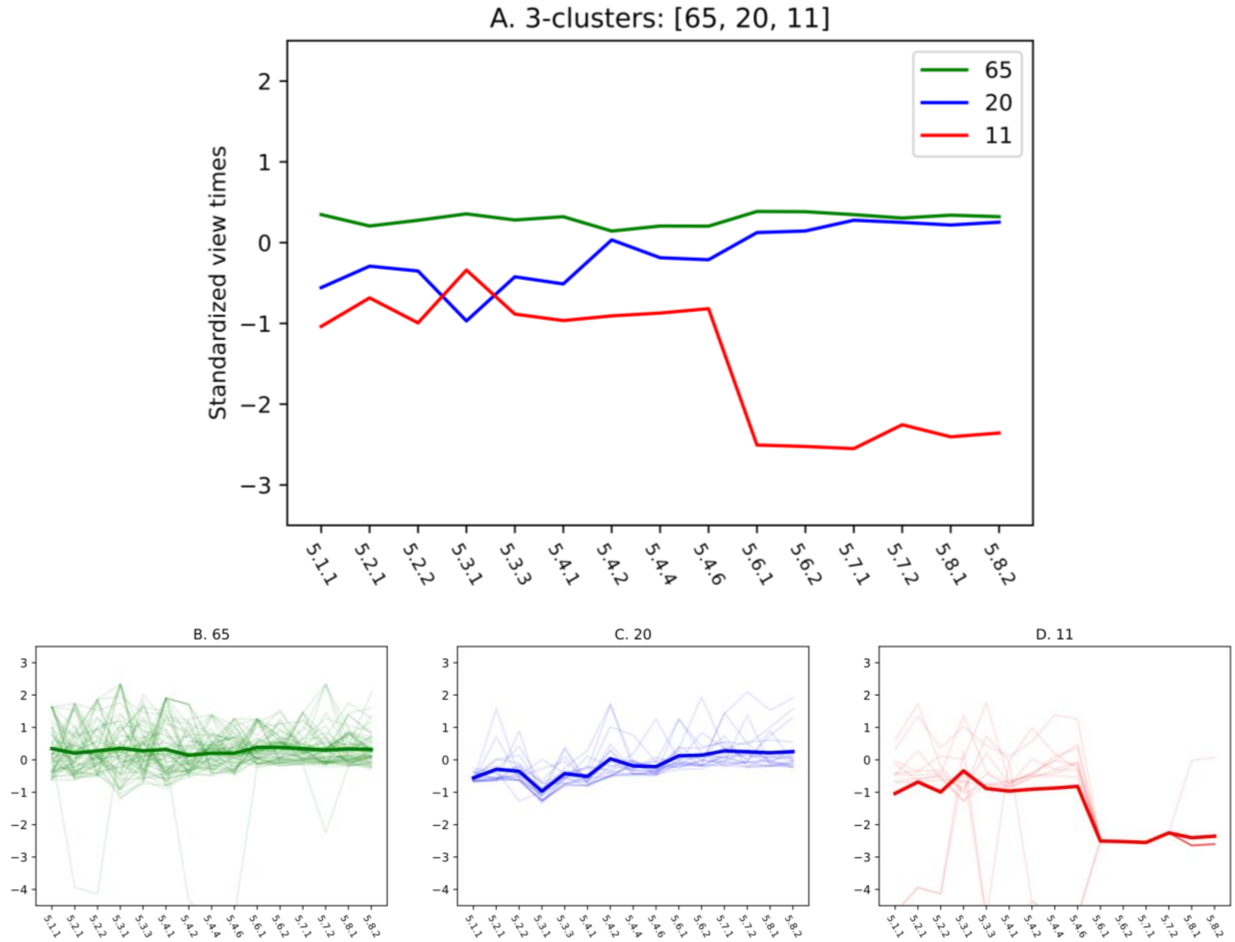

Figure 2. Clustering results for Chapter 5 of the MEB zyBook for the 2020 cohort. A: Cluster centroids for the three clusters of students: longer view times (green), shorter (blue), and irregular (red). The title shows the number of students in each of the three clusters. B-D: Each pane shows the standardized view times for all students in a cluster along with the number of students in the cluster. The darker line denotes the cluster centroid. Numbers above panels indicate numbers of students in each cluster.

RQ3. How do clusters change over the course of a semester and between cohorts?

To visualize this categorization for each cohort and chapter, we created an alluvial plot where each cluster is color-coded. Green represents longer viewing times, blue represents shorter view times, and red indicates students who either did not view the animations for an extended period, did not view at all, or move between longer and shorter view times within a chapter. Each cohort is represented by its own figure below (Figures 3 to 7), which includes the fraction of the cohort in each cluster across all chapters.

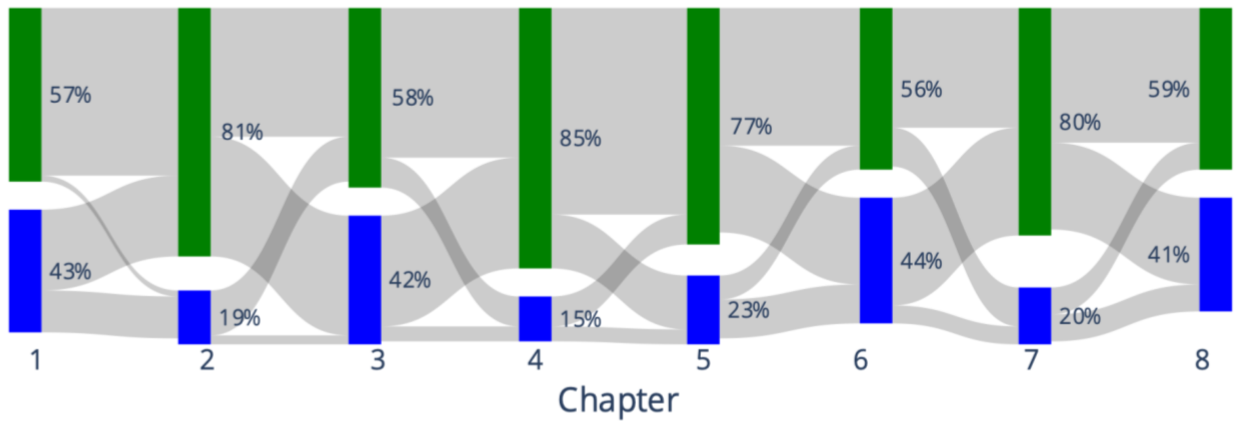

Figure 3. Alluvial plot clustering animation viewing behavior for the 2016 cohort using the MEB zyBook.

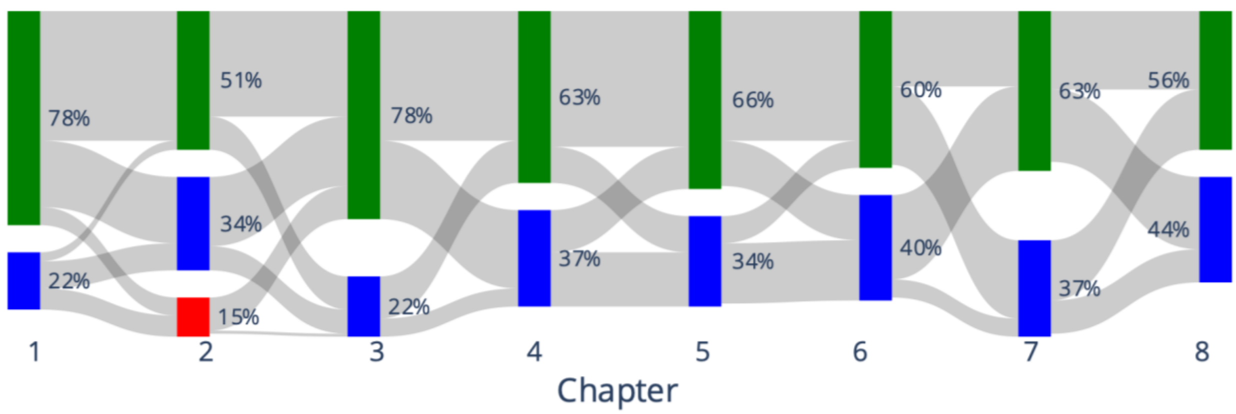

Figure 4. Alluvial plot clustering animation viewing behavior for the 2017 cohort using the MEB zyBook.

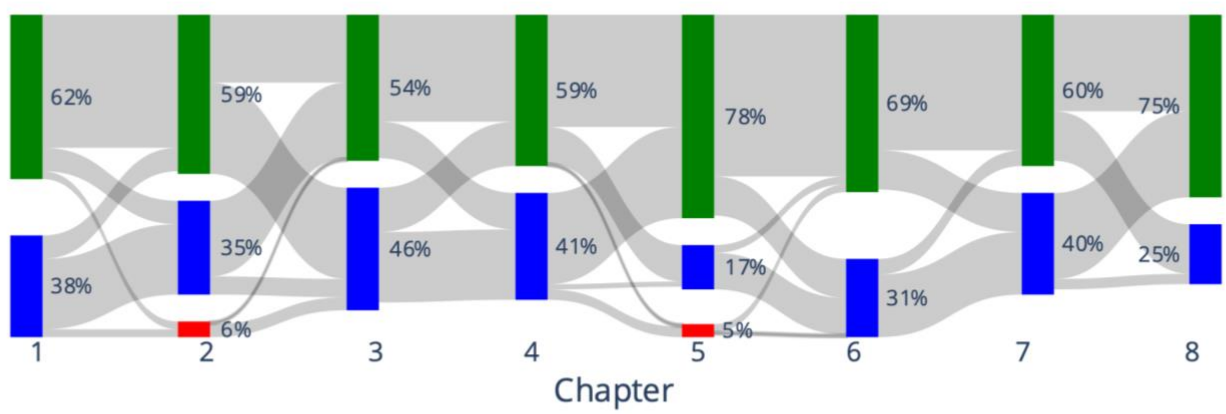

Figure 5. Alluvial plot clustering animation viewing behavior for the 2018 cohort using the MEB zyBook.

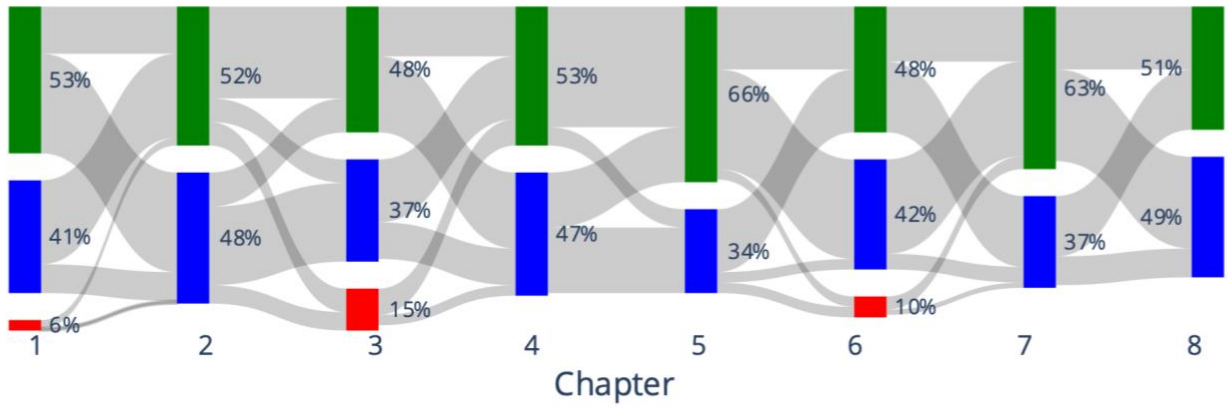

Figure 6. Alluvial plot clustering animation viewing behavior for the 2019 cohort using the MEB zyBook.

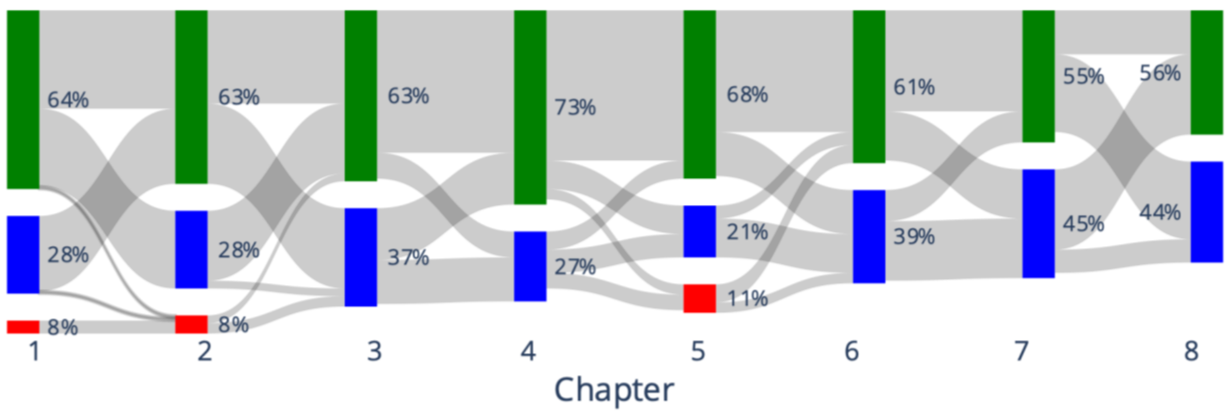

Figure 7. Alluvial plot clustering animation viewing behavior for the 2020 cohort using the MEB zyBook.

In our previous study, we noted several factors that influenced animation view times, including course content, step counts, animation category, and the number of attempts or replays of the animation [15]. Now, observing changes in cluster sizes adds a new lens to understanding students' animation watching methods. First, most of the students in each cohort stay in the same cluster from chapter to chapter, e.g., green to green, while a smaller fraction shifts between clusters. Similarly, the number of students in both the longer and shorter clusters does change almost every chapter and cohort.

Some trends emerge across the different cohorts. First, the fraction of students in the longer cluster (green) tends to decrease slightly from the beginning to end of the semester. This suggests that some students may initially be watching animations more frequently at 1x speed and then switch over to 2x speed as the semester progresses. Second, the irregular cluster (red) tends to appear only for a single chapter and then disappears, suggesting that there is no clear loss of engagement in groups of students who stop watching animations during any particular chapter. Such students tend to continue watching animations in future chapters, rejoining the longer or shorter cluster.

Finally, correlating the size of clusters with course content by chapter would be a logical next step in this research. Cluster size may be related to the quantity of animations within a reading assignment, content of the chapter, design of the animations (analogous to animation characterization [15]), or the timing during the semester. Elucidating what factors lead more students to view animations more slowly could be beneficial for learning.

Conclusions

Clustering analysis of animation watch times in an interactive textbook for a material and energy balances course quantified student engagement in a new way. Animations serve as one of the interactive reading participation activities within the interactive textbook. While reading participation, animation watch and re-watch rates, and animation watch times have been discussed more globally in previous publications, clustering analysis provides new insights on how students use animations and what fraction of a cohort uses animations in certain ways. Focusing on over 90 unique animations across eight chapters and thousands of views over five cohorts examined student engagement from this new perspective.

For clustering analysis to be effective, high student participation is needed. As reported previously, animation view rates were 100% or higher for the eight chapters examined [15], which is dramatically higher than traditional textbook reading rates [28]. In addition, these educational animations divide new concepts and content into chunks, which align with cognitive load theory. The first research question found two or three clusters of animation viewing, which were designated longer, shorter, and irregular. Over the five cohorts, about 70% of the chapters clustered into two clusters and 30% into three clusters. Aggregating across five cohorts found 53% of views in the longer cluster, 45% in the shorter cluster, and 2% in the irregular cluster. Therefore, more students watch animations at the default speed than opt for clicking and using the 2x speed feature. Finally, alluvial plots visualize the flow of students in each cluster across the eight chapters of interest. Some students switch between longer and shorter clusters for each chapter with no distinguishable pattern at the individual cohort level.

Overall, clustering expands the field of learning analytics, which specifically involved view times of animations in this case. Following individual students' movement between clusters or parsing out students by major, gender, or other demographics summarize a couple of many potential research directions that could be investigated in the future.

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