Extent of Pre-class Video Viewing in Multiple Flipped Engineering Courses

Benjamin Keith Morris, University of Georgia

Benjamin Morris is a senior at The University of Georgia with a major in Mechanical Engineering.

Dr. Siddharth Savadatti, University of Georgia

Dr. Siddharth Savadatti received his PhD in Computational Mechanics from North Carolina State University in 2011 and has since been on the faculty of the College of Engineering at the University of Georgia. He teaches mechanics and numerical methods courses such as Statics, Fluid Mechanics, Programming, Numerical Methods for Engineers and Finite Element Analysis. In addition to traditional face-to-face classes, he has designed and taught courses in fully online and completely flipped formats.

©American Society for Engineering Education, 2019

Extent of pre-class video viewing in multiple flipped engineering courses

Abstract

This paper presents data on the extent to which pre-class videos were viewed by students in three different undergraduate flipped engineering courses (numerical methods for engineers, fluid mechanics and engineering statics).

Flipped classes are typically characterized by pre-class preparatory activities that are followed by more active/collaborative in-class activities. Engagement with pre-class activities is essential for the flipped model to work, and knowing the current extent of student engagement with pre-class resources is a necessary first step towards improving them. Towards this end, this paper presents and compares data on the extent of video viewing (coverage) of pre-class videos in three flipped undergraduate engineering courses.

The dataset consisting of a total of 280 students watching 318 pre-class videos across the three courses shows that, roughly speaking, when a video was watched before class, it was watched to three quarters of its duration; courses with students of higher academic levels (e.g. juniors vs. sophomores) had greater coverages; for some courses, coverage was significantly affected by the day of the week the video was due to be watched by; coverage did not always drop as the semester progressed, but it did drop with increasing average duration of videos; and coverage was significantly and inversely correlated to video duration for all courses.

Introduction

The flipped (or inverted) form of teaching has been gaining increased attention in the engineering education community over the last decade. A flipped class, in its most general sense, is characterized by swapping of activities that were traditionally performed in the classroom with those that were traditionally performed outside of it. Thus, lectures or instructor-led problem-solving sessions (traditional in-class activities in many engineering courses), are presented to students outside of class and prior to it (in the form of readings and/or online screencasts/videos) with in-class time being dedicated to more student-led problem solving or group activities. The idea behind this swap is that students would now come to class prepared by having already engaged with the readings/videos outside of class, and so would be in a better position to actively engage with the material to a deeper level during class. Broadly speaking, pre-class materials in a flipped class aid basic knowledge acquisition, while in-class activities promote more active application of this knowledge.

Engagement with pre-class readings/videos is essential for the truly flipped model to work – without engagement with pre-class materials students are unlikely to benefit from in-class activities (which should ideally be designed for applying/deepening the basic knowledge already acquired). Moreover, lack of engagement with pre-class resources might force instructors to revert to traditional in-class activities (like lectures and instructor-led problem-solving sessions) that reduce the opportunities for students to actively engage with the material in the classroom. Hence, to extract the full benefit of the flipped model, it is important that pre-class resources are designed to promote as much engagement with them as possible.

Knowing the current extent of student engagement with pre-class resources is a necessary first step towards improving them. Since pre-class videos are a very common pre-class resource in flipped engineering classes, this paper presents and compares data on the extent of video viewing (coverage) of pre-class videos in three flipped undergraduate engineering courses (numerical methods for engineers, fluid mechanics and engineering statics) as an initial step towards improving engagement with pre-class resources.

Literature Review

While the literature on flipped classes is extensive [1]-[3], studies on student engagement with pre-class materials are fewer, especially those related to viewing of pre-class videos designed to primarily substitute (not supplement or review) traditional in-class lectures and instructor-led problem-solving sessions. Initial studies on engagement with pre-class videos were based on student self-reports that suffer from usual self-reporting biases and only recently have studies started using data captured by video management systems to report objective and reliable viewing trends [4]. Among the studies using data captured by video management systems, only a handful ([4]-[8]) report video coverage (instead of just the number of videos accessed/clicked), and all except the last of these are on courses related to engineering.

In an undergraduate introductory computer science course with 59 students (spread over 3 semesters) and 25 pre-class videos, Dazo et al. [4] showed that mean video coverage calculated at the end of the semester rose dramatically (from 36.7% to 85.3%) when a participation grade was introduced along with automatic reminders and feedback on which segments of the videos had (and had not) been viewed. However, performance was only significantly correlated with video coverage when the coverage was low (and not when it was high). In an undergraduate introductory mechanics course with 46 students and 49 pre-class videos, Gross and Dinehart [5] reported mean video coverage of 56% before class (61% by end of semester). Coverage decreased steadily and significantly over the semester reducing from 75% at the beginning of the semester to 40% by its end. Students' individual evaluation of the value and importance of the pre-class videos, perception of increased workload in the later parts of the semester, and easier topics towards the end of the semester were given as likely reasons for the low coverage. There was no correlation between the duration of videos (4-30 min) and their coverage, or between the day of week they were assigned and their coverage. No correlation was found between coverage and pre-course GPA or class performance, and females had a significantly and substantially higher video coverage than their male counterparts. In an undergraduate mechanics of materials course with 165 students and 89 pre-class videos, Ahn and Bir [6] reported mean video coverage of 78% calculated at the end of the semester (a short quiz on content covered in the videos was administered at the beginning of each class). There was no significant correlation between the duration of videos (1-22 min) and their coverage.

In our previous work [7] concerning an undergraduate statics course with 69 students and 89 pre-class videos, we reported mean coverage of 77% calculated before class (77% by end of semester). Coverage decreased over the semester, but not substantially (from 83% to 72%). The requirement of solving auto-graded pre-class problems based on the video content and the absence of any in-class lecture/review was stated as the likely cause for greater viewership compared to [5]. There existed a weak negative correlation between coverage and video duration

(3-57 min), and no correlation was found between coverage and pre-course GPA or class performance or gender.

The above studies [4]-[7] also reported additional viewing metrics (e.g. punctuality, participation, full viewing) but the current paper focusses on coverage and only results related to coverage are mentioned above for relevance.

Need/Purpose

Coverage of pre-class videos is expected to depend on a variety of factors (number/duration of videos, course content/structure, student composition/academic level, instructional strategies etc. to name just a few). Systematic studies of the effects of individual factors would need to keep all except a few factors constant. The studies on the coverage of pre-class videos in flipped engineering classes [4]-[7] give us valuable insights on video viewing trends, but no factor is constant between them (they are based on different course structures and are taught by different instructors); this makes it difficult to extract effects of individual factors on video viewing behavior. As a small step towards overcoming this difficulty, we present data on coverage of pre-class videos in three different engineering courses with almost identical course structures that were taught by the same instructor.

The purpose of this study is to present data on coverage of pre-class videos for three flipped undergraduate engineering courses (numerical methods for engineers, fluid mechanics and engineering statics) with the eventual aim of improving engagement with pre-class videos by studying current pre-class video viewing trends that hold over multiple engineering courses.

Course Structure

This paper contains video viewing data from all sections of three flipped courses taught by the same instructor over two semesters at the College of Engineering at the University of Georgia (UGA); CVLE2710:Numerical Methods for Engineers and ENGR3160:Fluid Mechanics taught during Spring 2016, and ENGR2120:Engineering Statics taught during Fall 2016. These courses are referred to as *Numerical*, *Fluids* and *Statics* respectively throughout this paper. Class days/duration, enrollment and grading weights of these courses are listed in Table 1.

All three courses were taught in an identical flipped format that required pre-class, in-class, and post-class work as shown in Figure 1 for almost every class (exceptions were the first class of the semester and some classes following the tests). Students (a) watched pre-class videos and solved pre-class problems before attending a class (these were their pre-class activities), (b) started solving in-class problems while attending their scheduled class sessions (this was their in-class activity), and (c) completed solving the in-class problems after leaving their scheduled class sessions (this was their post-class activity). All pre-/in-/post-class activities required individual work, but students were free to discuss with their peers and request help from the instructor or undergraduate teaching assistant.

Table 1. Details of the three flipped engineering courses that provided the data for this paper.

Course (*short name*)	CVLE2710: Numerical Methods for Engineers (*Numerical*)	ENGR3160: Fluid Mechanics (*Fluids*)	ENGR2120: Engineering Statics (*Statics*)
Credit hours	2	3	3
Semester	Spring 2016	Spring 2016	Fall 2016
Class days	Tue, Thu	Mon, Wed, Fri	Mon, Wed, Fri
Class duration	75 min/class period 150 min/week	50 min/class period 150 min/week	50 min/class period 150 min/week
Sections	4 sections	1 section on Mon/Wed that is split into 2 smaller sections on Friday	3 sections on Mon/Wed that are split into 5 smaller sections on Friday
Total enrollment	163	49	70
Grading weights	Pre-class problems:7.5% In-class problems: 7.5% Tests (3): 50% Final Exam: 35%	Pre-class problems: 5% In-class problems: 5 % Tests (3): 60% Final Exam: 30%	Pre-class problems: 10% In-class problems: 5 % Tests (3): 55% Final Exam: 30%

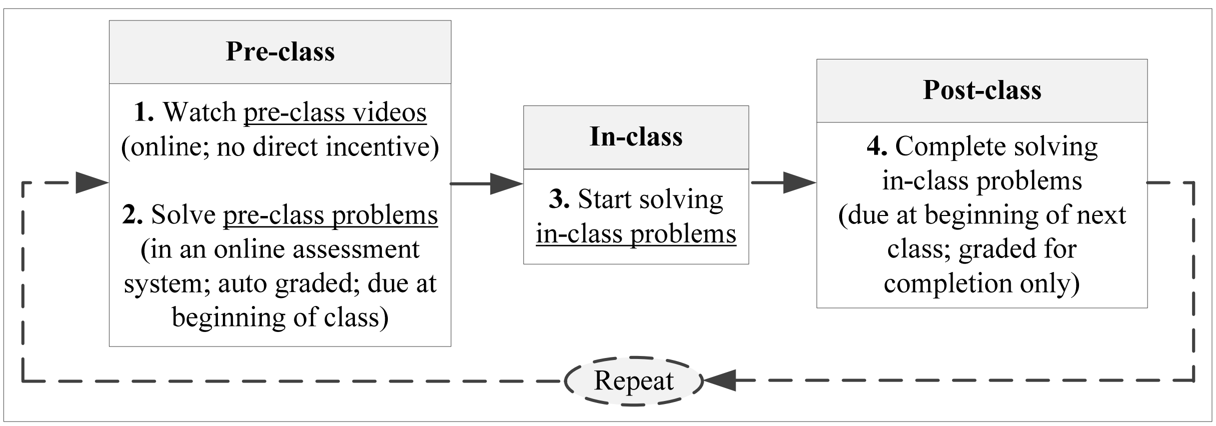

Figure 1. Pre-, in-, and post-class activities in the three flipped courses.

The following are worth noting:

a) Pre-class problems (Figure 1) were based on the concepts covered in the pre-class videos. Since these were auto-graded (worth 5-10% of the course grade as shown in Table 1) and due at the beginning of the scheduled class session, they served as an indirect check/incentive to watch the videos. Moreover, the in-class problem-solving activity was not instructor-led and there were no in-class lectures. Hence, students who did not watch the pre-class videos were typically unable to start solving in-class problems. Being unable to solve in-class problems in the presence of the instructor was a deterrent to not watching pre-class videos.

b) Even though there were no in-class lectures and the instructor did not lead in-class problem-solving, attendance (measured indirectly through submission of in-class problems) was robust for all three courses (87–94%).

c) Sections of *Fluids* and *Statics* were split into smaller sections on Friday (Table 1). This split into larger and smaller sections was primarily to maximize student-faculty interaction under the constraint of limited faculty availability, and there was generally no difference in course activities between the larger Monday/Wednesday sections, and the smaller Friday sections.

d) We were unable to record data from one student in *Numerical* and one student in *Statics* – thus our analysis was informed by data collected from 162 students from *Numerical* and 69 students from *Statics* (as against the 163 and 70 students listed in Table 1). All 49 students' data was recorded for *Fluids*.

e) Data for *Statics* was already presented in [7], but is reproduced here to facilitate comparison.

Pre-class videos were hosted on UGA's media storage and streaming system (Kaltura) that required students to log in with their UGA MyID to access them. Pre-class problems were assigned on online assessment systems that accompanied the respective textbooks ([9]-[11]). In-class problems were usually chosen from the respective textbooks, and an online discussion forum (Piazza) and daily instructor office hours were available for all three courses.

Data and Analysis Methodology

Viewing information for the pre-class videos assigned in the three flipped courses forms the primary data of this paper. All pre-class videos were created by the common instructor of the three courses and their number, duration and distribution are shown in Table 2 with the summary statistics in Table 3.

Table 2. Number, duration and distribution of pre-class videos in the three flipped courses.

Course	*Numerical*	*Fluids*	*Statics*
Total number of pre-class videos	138	92†	89
Total duration of pre-class videos (hrs.)	28.8	36.0	30.8
Total number of class periods which required viewing of pre-class videos	24	40	38
† Viewing data from 1 video not recorded – Fluids data is based on 91 videos			

Table 3. Summary statistics of pre-class videos in the three flipped courses.

	Mean	Median	S.D.	Max.	Min.
Numerical					
Number of videos assigned per class period	5.75	6	1.27	9	3
Duration of videos per class period (min)	72.1	73.7	8.68	86.0	49.4
Duration of videos (min)	12.5	11.6	5.25	28.5	2.28
Fluids					
Number of videos assigned per class period	2.3	2	0.75	4	1
Duration of videos per class period (min)	54.0	56.3	14.7	81.9	26.0
Duration of videos (min)	23.5	23.5	10.5	53.0	4.95
Statics					
Number of videos assigned per class period	2.3	2	1.13	6	1
Duration of videos per class period (min)	48.6	48.2	9.57	67.8	29.3
Duration of videos (min)	20.7	17	13.1	56.9	2.98

The video streaming system (Kaltura) recorded the number of views and total viewing time for each student and each video at the end of each day, and this data was used in combination with the known video durations to calculate the main video metric used in this paper, *Coverage*. *Coverage* is defined as the total amount of a video or set of videos viewed (in terms of time) out of the possible amount of time that could be spent viewing those videos, expressed as a percentage. *Coverage* may be defined per student or per video using the formula

$$Coverage = \left(\frac{\sum \text{Viewing time}}{\sum \left(\text{Number of views} \times \text{Video length} \right)} \right) \times 100$$

where the sums are taken over the number of students if *Coverage* is to be calculated per video and the sums are taken over the number of videos if *Coverage* is to be calculated per student. *Coverage* presented in this paper is per video.

Before Class Coverage is calculated with the viewing time and number of views occurring before (and including) the video's due date. *End of Semester Coverage* is calculated with the viewing time and number of views occurring before (and including) the last day of the semester. Examples of *Coverage* calculation, Katura's discrete recording of viewing time, and comments on effects of repeat viewing can be found in [7]. Other video metrics like *Participation* and *Full Viewing* that were introduced in [7] are not presented in this paper for brevity.

Mere viewing of videos does not guarantee engagement with the material presented in the videos. However, requiring the submission of pre-class problems after watching the videos, and requiring solving of in-class problems without the aid of any in-class lecture (Figure 1 and the notes following it) helped encourage engagement with the videos. Robust average scores for pre-class and in-class problems for all three courses (82–94%) corroborate this.

Results and Discussion

A first glance at Table 3 shows that the videos in *Numerical* are substantially shorter than those in *Fluids* and *Statics*. A one-way ANOVA confirmed that the video durations between the three courses are significantly different ($p < 0.001$) with a post-hoc Tukey HSD test showing a statistically significant difference in video durations between *Numerical* and *Fluids* ($p = 0.001$), and between *Numerical* and *Statics* ($p = 0.001$), but not between *Fluids* and *Statics*. Note however that the mean duration of videos per class period in *Numerical* is substantially greater than that in *Fluids* and *Statics* (72.1 min. vs. 54.0, 48.6 min.) – this means that even though *Numerical* had shorter videos, it actually had greater video content to be watched per class period.

Overall distribution of Coverage

Summary statistics for *Coverage* for all three courses are presented in Table 4. Mean *Before Class Coverage* was 83/81/77% implying that on an average, a video was watched to 83/81/77% of its duration by every student who watched it before class in *Numerical/ Fluids/Statics* respectively. Similar means hold for *End of Semester Coverages.* The summary statistics do not change much from *Before Class* to *End of Semester*, indicating that any additional coverage that occurred after class was minor (additional coverage here refers to coverage that went beyond that which occurred before class and it is not related to repeat viewing of portions already viewed before class). *Before Class Coverage* is plotted in Figure 2. *End of Semester Coverage* does not vary much from *Before Class Coverage* (Table 4) and their plots are not shown.

Table 4. Summary statistics for *Coverage* of pre-class videos for the three flipped courses.

		Before Class (*End of Semester*)				
Viewing metric	Course	Mean	Median	S.D.	Max.	Min.
Coverage	*Numerical*	83% (83%)	84% (84%)	7% (7%)	97% (97%)	63% (64%)
	Fluids	81% (82%)	82% (82%)	8% (8%)	96% (96%)	60% (63%)
	Statics	77% (77%)	77% (77%)	7% (6%)	92% (92%)	61% (61%)

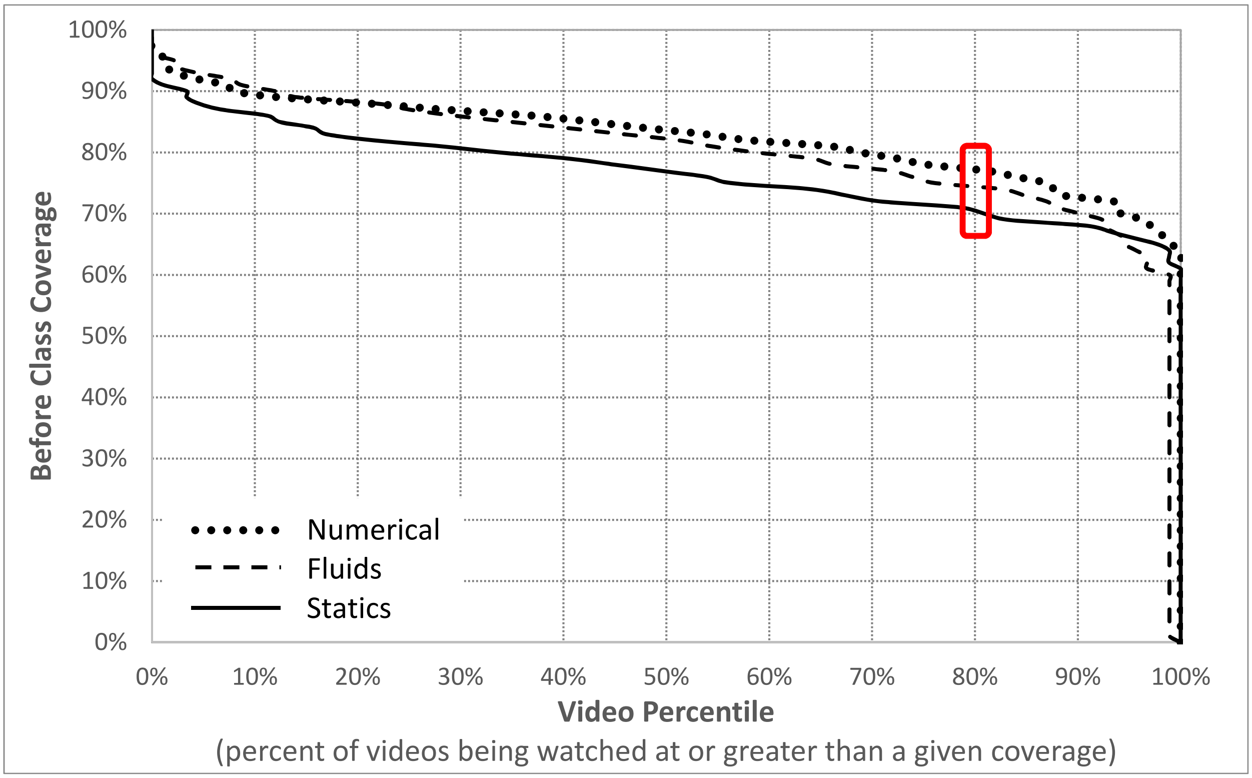

Figure 2. *Before Class Coverage* of pre-class videos. The points on the three curves enclosed within the red rectangle can be read as "80% of the videos had a *Coverage* of at least 77/74/70% before class for Numerical/Fluids/Statics respectively".

Figure 2 shows that the *Before Class Coverage* plots curve substantially above the diagonal. This implies that the number of 'high coverage' videos are many more in number than 'low coverage' ones and this is shown in Table 5. In this table, 'Low Coverage' represents *Coverage* $\leq$ 20%, 'Somewhat Low Coverage' represents 20 < *Coverage* $\leq$ 40%, and so on. All videos (100%) for all three courses are categorized as 'Somewhat High Coverage' or 'High Coverage' videos i.e. they have *Before Class Coverage* > 60%. Similar conclusions hold for *End of Semester Coverage.*

Table 5. Categorization of students/videos based on *Coverage* for the three courses

		Before Class (*End of Semester*)				
Viewing metric	Course	Low Coverage	Somewhat Low	Moderate Coverage	Somewhat High	High Coverage
Percent of videos with	*Numerical*	0% (0%)	0% (0%)	0% (0%)	31% (30%)	69% (70%)
	Fluids	0% (0%)	0% (0%)	0% (0%)	41% (36%)	59% (64%)
	Statics	0% (0%)	0% (0%)	0% (0%)	66% (64%)	34% (36%)

By almost every measure, *Coverage* is greatest for *Numerical* and least for *Statics,* with *Fluids* in-between (Table 4 and Figure 2). One cause for this could be the academic level of students (freshman, sophomore, junior, senior) that typically take these courses. At UGA, *Statics* is a pre-requisite for *Fluids* – hence students take *Fluids* after taking *Statics,* but not too much later because *Fluids* itself is a pre-requisite for other courses. *Numerical* is not a pre-requisite for any course and so students have the freedom to wait until later to take this course. It is expected that students become more disciplined with their studies with increasing academic level and are more aware of what is required to succeed in their college courses, and this might explain the greater *Coverage* in courses that are taken later in their undergraduate years. Another cause for this could be the significantly shorter duration of videos in *Numerical* (see mean duration of videos in Table 3) facilitating higher *Coverage* in *Numerical* compared to *Fluids/Statics*.

Effect of day of week

Videos were typically assigned at the end of a class period, and students were expected to view them before the beginning of the next class period. Table 6 shows video duration and *Before Class Coverage* statistics for videos assigned on different days of the week. Note that while there was no statistically significant difference in video durations over the different days for all three courses, there was a statistically significant difference for *Before Class Coverage* for *Statics* (but not for *Numerical* and *Fluids*) as determined by a one-way ANOVA. A post-hoc Tukey HSD test for *Statics* showed a statistically significant difference between Monday and Wednesday only.

Table 6. Significance of day of week that pre-class videos were assigned on

Numerical	Tue (67 videos)		Thu (71 videos)		*p*
	Mean	S.D.	Mean	S.D.	
Duration (min)	12.5	5.37	12.6	5.22	0.932
Before Class Coverage	82%	6.6%	83%	6.6%	0.496

Fluids	Mon (36 videos)		Wed (33 videos)		Fri (22 videos)		*p*
	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Duration (min)	20.9	10.3	24.4	11.5	26.0	9.12	0.165
Before Class Coverage	83%	7.4%	80%	8.7%	80%	6.9%	0.218

Statics	Mon (36 videos)		Wed (28 videos)		Fri (25 videos)		*p*
	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Duration (min)	18.8	12.0	21.6	12.0	22.6	15.9	0.502
Before Class Coverage	79%	6.2%	74%	6.7%	76%	6.8%	0.014*

* significant at 0.05, one-way ANOVA

Because of tests and holidays, not all videos that were assigned on Tuesday/Thursday were due on Thursday/Tuesday respectively, and similarly not all videos that were assigned on Monday/Wednesday/Friday were due on Wednesday/Friday/Monday respectively. Hence, the significance of day of week could be different based on whether we consider days that videos were assigned or days by which they were due to be watched. Table 7 shows similar statistics based on when the videos were due to be watched. In this instance, while there was no statistically significant difference in video durations over the different days for all three courses, there was a statistically significant difference for *Before Class Coverage* for *Fluids* and *Statics* (but not for *Numerical*) as determined by a one-way ANOVA. Post-hoc Tukey HSD tests showed statistically significant difference between Wednesday and Friday only for both *Fluids* and *Statics.*

Table 7. Significance of day of week by which pre-class videos were due to be watched

Numerical	Tue (77 videos)		Thu (61 videos)		*p*
	Mean	S.D.	Mean	S.D.	
Duration (min)	12.7	5.83	12.3	4.51	0.624
Before Class Coverage	82%	6.4%	83%	6.9%	0.739

Fluids	Mon (28 videos)		Wed (39 videos)		Fri (24 videos)		*p*
	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Duration (min)	24.1	9.00	21.3	10.1	26.0	12.6	0.218
Before Class Coverage	81%	6.5%	83%	7.4%	78%	9.0%	0.031*

Statics	Mon (23 videos)		Wed (39 videos)		Fri (27 videos)		*p*
	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Duration (min)	24.6	16.2	18.3	11.7	21.1	11.9	0.186
Before Class Coverage	76%	7.2%	79%	6.1%	74%	6.8%	0.026*

* significant at 0.05, one-way ANOVA

Note that videos due on Wednesday/Friday are typically assigned on Monday/Wednesday respectively and so for *Statics* the significant difference existing between videos assigned on Monday and Wednesday matches the significant difference existing between videos due on Wednesday and Friday. The fact that day of week that videos were due to be watched has a significant effect on *Fluids* and *Statics* (versus the day of week assigned having a significant effect on *Statics* only) might suggest that it is the day when videos are due that affects students' viewing behavior more than the day when they are assigned.

Considering only *Fluids* and *Statics,* it is interesting to note that *Before Class Coverage* is maximum for videos assigned on Mondays and minimum for videos assigned on Wednesdays as shown in Table 6 (or maximum for those due to be watched by Wednesdays and minimum for those to be watched by Fridays as in Table 7). This trend was mentioned in [7] for *Statics* and it seems to hold for *Fluids* too. So the reason specified in [7] – that students might start a week after having caught up with pending work over the weekend and have more time to watch videos at the beginning of the week (videos assigned on Mondays or due by Wednesdays); whereas they get busy with other work by the middle of the week – seems to hold true at least for classes meeting Mondays/Wednesdays/Fridays.

It is a bit surprising that day of week (either assigned or due) had no significant effect on *Coverage* of videos in *Numerical.* Given that videos assigned on Tuesdays typically needed to be watched by Thursday (i.e. within just 2 days), while those assigned on Thursdays typically needed to be watched only by the following Tuesday (i.e. within 5 days), we would have expected day of week to have a significant effect on *Coverage*. While we can speculate that the difference in academic level between students taking *Numerical* versus those taking *Fluids* and *Statics,* or the substantially shorter videos used in *Numerical* compared to the other courses might be reasons for this, we do not have enough data to corroborate this.

There was no statistically significant difference in *End of Semester Coverage* between the days of week that videos were assigned/due for any course (data not shown), and as stated in [7] this is expected because the much longer timeframe over which *Coverage* is measured (from the day a video was assigned/due to the last day of the semester) makes the effect of the day irrelevant.

Effect of week into semester

Figure 3 shows the weekly average of *Coverage* both before and after class by week into the semester for all three courses. Over the course of the semester, the *Coverage* trendline in *Numerical* and *Fluids* appears to remain almost flat with only a small decrease for *Fluids*. The trendline for *Statics* however, shows a greater dip dropping from 83% during week 1 to 72% during week 17. It was postulated in [7] that the drop in coverage in *Statics* may be attributed to external factors such as students getting busier with other classes/activities and a general decrease in student motivation/discipline over the semester, but if this was true, similar drops would be observed for *Numerical* and *Fluids* (which does not seem to be the case).

Figure 4 shows the average duration of videos assigned each week throughout the semester with trendlines showing neutral, slightly increasing and clearly increasing trends for duration of videos in *Numerical, Fluids* and *Statics* respectively. Interestingly, these trends appear to be inverse of the trends for *Coverage* shown in Figure 3 that depicts neutral, slightly decreasing and clearly decreasing trends for the respective courses. *Coverage* being inversely related to average video duration is somewhat understandable and so increasing average video duration may be a cause of decreasing *Coverage.* However, there is no such relation between the trendlines of *Coverage* and total duration of videos assigned per week (data not shown).

An observation made in [7] about *Coverage* increasing after the first test but decreasing after subsequent tests seems to generally hold true over all three courses. Note from Figure 3 that *Coverage* increases in the week immediately following Test 1 for all three courses and as stated in [7], this is likely because the first test usually serves as a wake-up call for many students who had not realized the effort required to do well in these courses (Test 1 scores are historically the lowest of the test scores). Similarly, the decrease in *Coverage* in the week immediately following Test 2 for *Numerical* and *Fluids,* and immediately following Test 3 for *Fluids* and *Statics* might be explained by the easing of studying after a major test (though the increase in *Coverage* in the week immediately following Test 2 for *Statics* cannot be explained by the above reasoning).

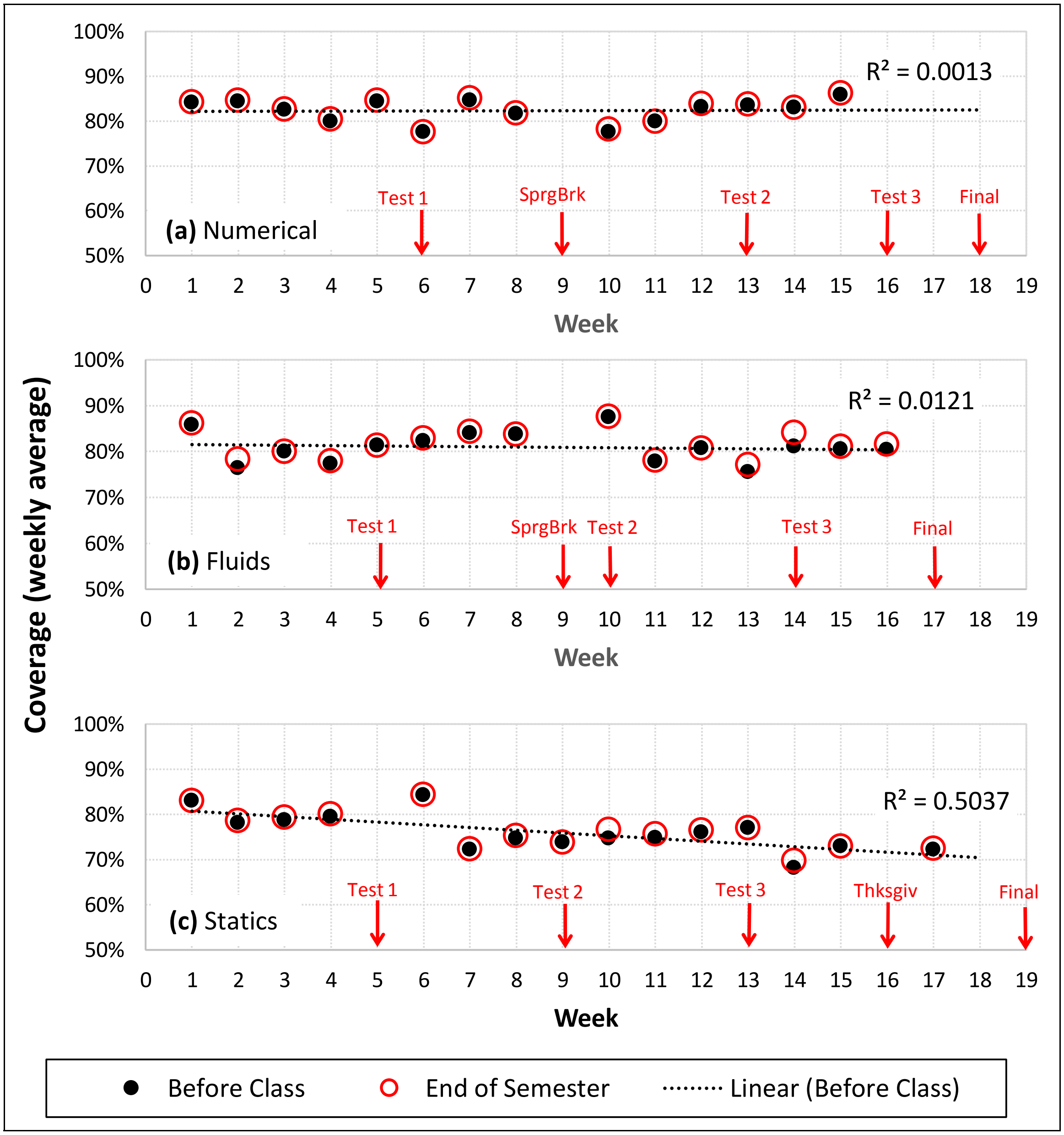

Figure 3. Weekly average of *Coverage* over the 16-18 week semesters for pre-class videos for the three courses. Correlation for *End of Semester* is similar to that for *Before Class*. Note the neutral, slightly decreasing and clearly decreasing trendlines for *Numerical, Fluids* and *Statics* respectively. Only the correlation for *Statics* is statistically significant ($p = 0.003$).

Effect of video duration

Figure 5 shows the change in *Coverage* with increasing duration of videos. There exist clear statistically significant negative correlations between *Coverage* and video duration for all courses, implying that longer videos are viewed to a lesser extent than shorter videos. Short (<20 min) /medium/long (≥40 min) videos had mean *Before Class Coverages* of 84/72/–% respectively for *Numerical*, 86/78/72% respectively for *Fluids*, and 79/73/71% respectively for *Statics* (note that there were no long videos in *Numerical*).

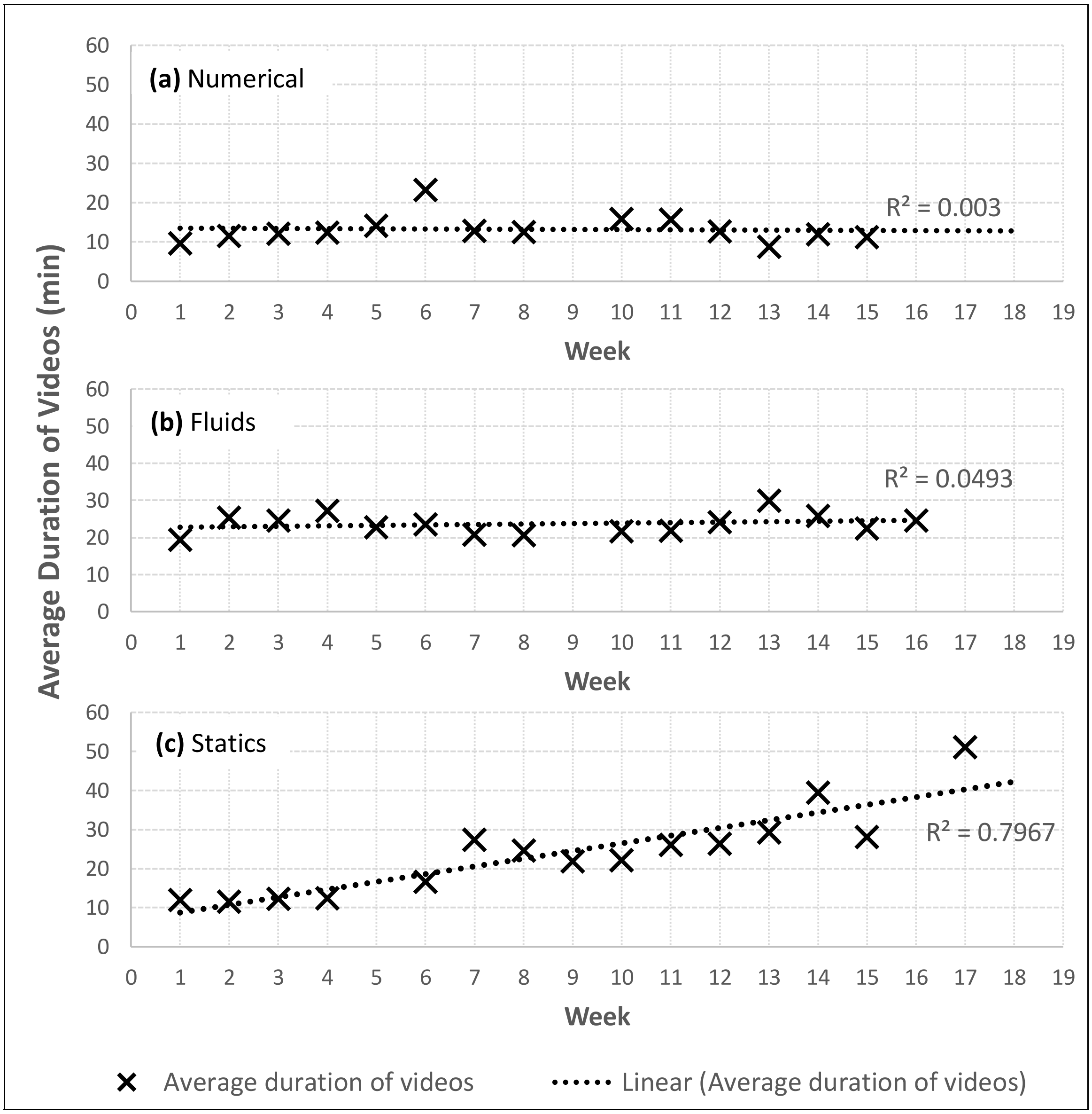

Figure 4. Average duration of pre-class videos assigned over the semesters for the three courses. Note the neutral, slightly increasing and clearly increasing trendlines for *Numerical, Fluids* and *Statics* respectively. Only the correlation for *Statics* is statistically significant ($p < 0.001$).

In [7] we had noted that for *Statics, Coverage* decreased with increasing week into semester (Figure 3-(c)) and with increasing average duration of videos (Figure 5-(c)). However, since average duration of videos increased with increasing week into semester (Figure 4-(c)), it was not clear whether the decrease in *Coverage* was due to increasing week into semester (due to external factors like increased activities or decreased motivation as the semester progressed) or due to increasing duration of videos. The data for *Numerical* and *Fluids* point to the more likely cause for decreasing coverage being increased average duration of videos (because when the average duration is relatively constant or increasing slowly, the *Coverage* remains relatively constant or decreases slowly as seen by directly comparing Figure 4-(a)-(c) to Figure 3-(a)-(c)).

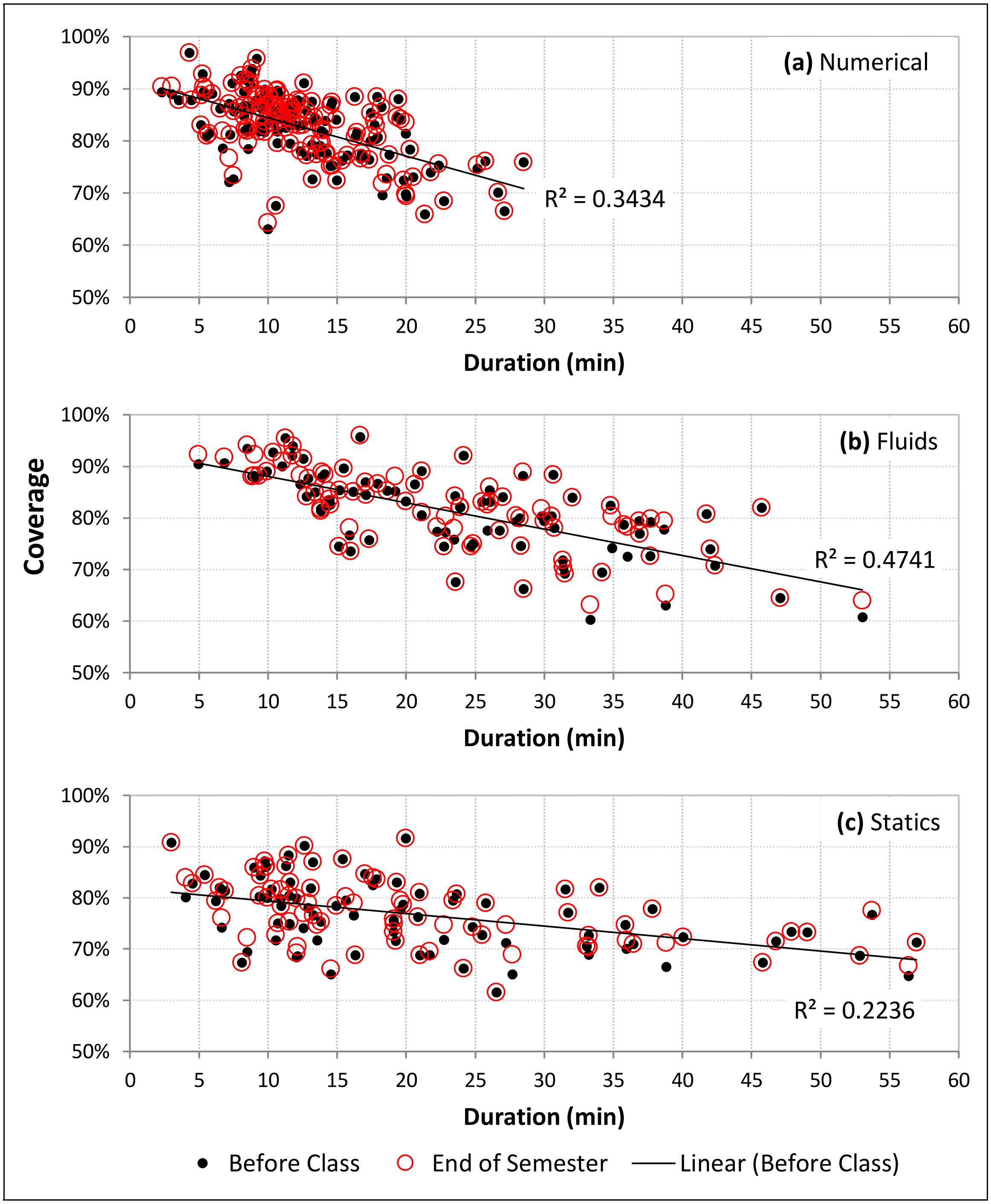

Figure 5. Variation of *Coverage* with pre-class video duration. Correlations for *End of Semester* are similar to that for *Before Class*. All correlations are statistically significant ($p < 0.001$)

A final observation is that even though videos in *Numerical* were significantly shorter, the drop in *Coverage* with video duration is comparable to the drops in *Fluids* and *Statics* (see Figure 5). This might suggest that it is not the absolute duration of videos, but the relative duration of videos (relative to other videos in the course) that effects *Coverage*. That is, a few videos with durations of 20-30 min may seem long in a course where a majority of videos are less than 15 min in duration (like in *Numerical* where less than a tenth of the videos have durations ≥20 min and almost three quarters have durations <15 min), but videos of 20-30 min duration may not seem long to students exposed to much longer videos (like in *Fluids* and *Statics*).

Limitations

The limitations listed in [7], namely coarse-grained data sampled at the end of each day and data being insufficient to conclusively prove hypotheses, still exist. Data on *Participation* and *Full Viewings* is not presented in this paper (unlike in [7]) mainly so that we can focus on the more important *Coverage* metric. Only correlations are presented here – deeper statistical analyses on the data is pending. Effects of gender, pre-course GPA and numerical course grade on *Coverage* are not explored. No attempt was made to determine directly the reason for the trends in *Coverage* (e.g. by surveying students), but this is planned for future studies.

Conclusions

The data presented in this paper on the extent of video viewing of pre-class videos (as measured by the *Coverage* metric) in three flipped undergraduate engineering courses (numerical methods for engineers, fluid mechanics and engineering statics) with almost identical course structures that were taught by the same instructor, suggest the following:

- Mean *Before Class Coverage* for all three courses was relatively high (72-83%). Roughly speaking, this translates to: whenever a video was watched before class, it was watched to three quarters of its duration by every student who watched it. *End of Semester Coverage* is only slightly higher than *Before Class Coverage.*
- Between the three courses considered here, greater *Coverage* is seen in courses that have students at higher academic levels (freshman, sophomore, junior, senior)
- For courses meeting thrice a week (on Monday/Wednesday/Friday), there was statistically significant difference in *Coverage* between videos due on Wednesdays and those due on Fridays – *Coverage* was higher for videos due to be watched earlier in the week. For the course meeting twice a week (Tuesday/Thursday), there was no significant difference in *Coverage* between the days of the week.
- *Coverage* did not drop in all three courses as the semester progressed. Variation in *Coverage* with week into semester was inversely related to average duration of videos; when the average duration of videos remained relatively constant/increased slightly/increased substantially as the semester progressed, *Coverage* remained relatively constant/decreased slightly/decreased substantially.
- *Coverage* was inversely correlated to video duration and this correlation was statistically significant for all courses. Longer videos generally had lower *Coverage* than shorter videos, but this could be based on relative (not absolute) durations. Videos that were relatively long compared to other videos in the same course had lesser *Coverage* even though their durations might not be long in absolute terms when compared to videos in other courses.

Mean *Coverages* reported here are very similar to those reported in [4] for 2015 data and [6], but high compared to those reported in [5]. The presence of graded activities to ensure video viewing (like participation grades, in-class quizzes on video content, or auto-graded pre-class problems) is the common factor between [4] (2015 data), [6], and the present work, and this is perhaps the likely cause of greater *Coverage* (such graded activities were missing from 2014 data in [4] and in [5], and both showed substantially lower *Coverage*). No significance of day of week was found in [5] but pre-class viewing was generally low in their course compared to the courses presented here. *Coverage* dropped as the semester progressed in [4] but only when there were no participation grades/automatic reminders/feedback on segments viewed; *Coverage* dropped drastically in [5] as the semester progressed and this is probably due to lack of procedures to ensure video viewing (like graded activities based on video content, reminders etc.). No significant correlation was found between *Coverage* and video duration in [5] and [6].

Acknowledgements

We wish to thank Mr. James Castle, Lead Instructional Designer at UGA's Office of Online Learning, for facilitating collection and interpretation of viewing data recorded by Kaltura.

References

[1] J. L. Bishop and M. A. Verleger, "The Flipped Classroom: A Survey of the Research", in *Proceedings of the 120th ASEE Annual Conference and Exposition*, Atlanta, GA, USA, June 23-26, 2013. Available: https://peer.asee.org/22585

[2] J. O'Flaherty and C. Phillips. "The use of flipped classrooms in higher education: A scoping review." *The Internet and Higher Education*, vol. 25, pp. 85-95, Feb. 2015, DOI: 10.1016/j.iheduc.2015.02.002

[3] L. Christopher, "The flipped classroom in further education: literature review and case study", *Research in Post-Compulsory Education*, vol. 20:3, pp. 265-279, Aug. 2015, DOI: 10.1080/13596748.2015.1063260

[4] S. L. Dazo, N. R. Stepanek, R. Fulkerson and B. Dorn, "An empirical analysis of video viewing behaviors in flipped CS1 courses", In *Proceedings of the 2016 ACM Conference on Innovation and Technology in Computer Science Education,* ITiCSE '16, Arequipa, Peru, July 11-13, 2016, pp. 106-111, DOI: 10.1145/2899415.2899468

[5] S. P. Gross and D. W. Dinehart, "Pre- and Post-Class Student Viewing Behaviors for Recorded Videos in an Inverted Sophomore Mechanics Course", In *Proceedings of the 123rd ASEE Annual Conference & Exposition*, New Orleans, LA, USA, June 26-29, 2016. Available: https://peer.asee.org/25924

[6] B. Ahn and D. D. Bir, "Student Interactions with Online Videos in a Large Hybrid Mechanics of Materials Course", *Advances in Engineering Education*, vol. 6(3), Spring 2018

[7] B. K. Morris and S. Savadatti, " Analysis of Basic Video Metrics in a Flipped Statics Course ", In *Proceedings of the 125th ASEE Annual Conference & Exposition*, Salt Lake City, UT, USA, June 24-27, 2018. Available: https://peer.asee.org/29800

[8] H. L. Radunovich and S. Acharya, "If You Flip It, Will They Watch? Case Evaluation of a Hybrid Course", *NACTA Journal*, vol. 62(1), pp. 84–88, March 2018.

[9] S. Chapra and R. Canale, *Numerical Methods for Engineers*, 7 ed., McGraw-Hill Education, 2014.

[10] B. R. Munson, A. P. Rothmayer, T. H. Okiishi, and W. W. Huebsh, *Fundamentals of Fluid Mechanics*, 7 ed., Wiley, 2012.

[11] R. C. Hibbeler, *Engineering mechanics. Statics*, 14 ed., Boston: Prentice Hall, 2015.