# Make shorter videos: Insights into Educational Video Duration from Quantitative Analytics

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## ABSTRACT

### CONTEXT

The use of pre-recorded videos to deliver content in engineering courses has increased substantially in the last decade due to several factors. Many institutions have migrated towards blended or flipped-classroom teaching approaches, replacing or supplementing traditional lectures with pre-recorded video content to deliver core concepts. Students are often equipped with multiple devices that are capable of both watching and recording video content anywhere they go, and have reliable internet connections to online learning management systems and video repositories like YouTube™. The COVID-19 pandemic also saw a forced shift to online learning in many regions, and not everyone has returned to the old modalities of classroom lecturing. Significant research has focused on producing best practice recommendations for video production, with the most common advice being that videos should be short, less than 6 minutes, delivered extemporaneously, and with enthusiasm.

### PURPOSE

This work seeks to quantify the impact of video length on learner engagement, which will be approximated using video audience retention data and view counts as proxies.

### METHODOLOGY

Quantitative viewing analytics data from ~450 videos with a combined total of almost 1 million views, across four mechanical engineering units from two universities, with campuses across two countries, all hosted via the YouTube platform are analysed. Sample units are drawn from a range of instructors and across different sub-disciplines and years of the degree. The analysis primarily examines the effect of video duration on learner engagement via the surrogate measure of audience retention plots (the trending proportion of viewers who are "retained" throughout a video's duration. Factors such as video content type (lectures versus worked examples), video privacy, and scheduling within the semester of study are also investigated for potential trends and confounding effects.

### OUTCOMES

Analysis shows a substantial variation in overall video engagement as a function of video length. Significant variation is also observed with respect to individual units, and unlisted versus publicly available videos.

### RECOMMENDATIONS

Learner engagement with video content in engineering education is sensitive to video length. Where possible, effort should be made to apportion content into short videos to maintain high retention rates.

### KEYWORDS

Video engagement; Lecture videos; Analytics; YouTube

# Introduction

The integration of pre-recorded videos into engineering education has surged in recent years, driven by advances in technology and evolving pedagogical strategies. Educational videos are now widely used in higher education, both as a primary teaching method and as a supplementary resource, offering potential benefits such as increased flexibility and accessibility (Faye, 2014; Tisdell, 2016), and potential drawbacks, such as reduced personal interaction. This shift aligns with the broader adoption of blended and flipped classroom models, utilising video content to complement or replace traditional lectures. Such models aim to enhance student engagement and learning outcomes by allowing students to engage with core concepts asynchronously and use in-person class time for interactive activities (Bishop & Verleger, 2013).

The growing preference for video-based learning among the next generation of students and the decreasing costs of video production suggest that this format will play a significant role in tertiary education (Szymkowiak et al., 2021). Students benefit from the ability to access and interact with educational content from various devices and locations, making learning more convenient and accessible. It also grants students personal agency, allowing them to study based on their individual needs (Dart, 2020). Additionally, the COVID-19 pandemic has accelerated the shift towards online learning environments, with many institutions maintaining the use of video content even as in-person classes have resumed (Marinoni et al., 2020, Hew et al. 2020).

Research has identified best practices for creating effective educational videos, recommending that videos be concise, generally under six minutes, to maximise learner engagement and minimise cognitive overload (Guo et al., 2014). Effective videos are often delivered with enthusiasm further enhancing viewer retention and comprehension (Dart & Gregg, 2021). Despite these guidelines, there is limited empirical evidence quantifying the impact of the type of video and its length on learner engagement.

This study aims to address this gap by analysing viewing analytics from 440 videos with almost 1M total views, across four undergraduate mechanical engineering topics. Hosted on the YouTube platform and spanning two universities, and campuses in two countries, the research will explore how video length affects viewer engagement, which will be estimated via the proxies of view count and video audience retention.

# Purpose

This work seeks to quantify the impact of video length on learner engagement, which will be approximated using video audience retention data and view counts as a proxy. Several other factors such as content type (lecture content versus worked examples), unlisted versus publicly available videos, and scheduling of video content across a 12-week semester will be explored.

# Methodology

## Unit Selection

Four units were selected for this study based on the following requirements:

- The unit is taught in a contemporary undergraduate engineering degree;
- The unit utilises video recordings as the primary method for content delivery, i.e. a flipped classroom approach (Bishop & Verleger, 2013);
- The videos are hosted on YouTube, with engagement metrics that are accessible by the channel owner;
- The channel and videos have been utilised for multiple deliveries of the unit (at least three offerings) and the *average* view count for each video in the unit exceeds 200.

## Data Collection and Coding

YouTube metrics (video duration in minutes, view count and audience retention data) were downloaded and collated for videos from the target units of study using an automated script and the YouTube data and analytics APIs. The audience retention data for each video comprises a series of 100 data values, with each representing the average audience retention fraction (0-1, 4dp), at each percentage point of the video's total duration, from the start to the end. An example of the audience retention data for a single video is provided below with the plot shown in Figure 1. The plot shows drastic decreases in retention near the start of the video due to accidental clicks and playlist auto-play, and also near the end of the video due to outro content.

**Retention data:**

*[0.9964; 0.6902; 0.6580; 0.6365; 0.6661; 0.6741; 0.6741; 0.6786; 0.6938; 0.6822; 0.6688; 0.6607; 0.6598; 0.6705; 0.6876; 0.6831; 0.6795; 0.6705; 0.6777; 0.6965; 0.7037; 0.7055; 0.7278; 0.7278; 0.6965; 0.6965; 0.7135; 0.7171; 0.7431; 0.6723; 0.6544; 0.6356; 0.6276; 0.6079; 0.6141; 0.5801; 0.5837; 0.5694; 0.5685; 0.5568; 0.5810; 0.5953; 0.5703; 0.5667; 0.5765; 0.5667; 0.5953; 0.5971; 0.5927; 0.5936; 0.5882; 0.5622; 0.5524; 0.5595; 0.5604; 0.5425; 0.5470; 0.5372; 0.5264; 0.5273; 0.5354; 0.5318; 0.5246; 0.5452; 0.5201; 0.5380; 0.5246; 0.5291; 0.5148; 0.5184; 0.5192; 0.5354; 0.5255; 0.5488; 0.5649; 0.5810; 0.5739; 0.5801; 0.5774; 0.5748; 0.5560; 0.5631; 0.5568; 0.5756; 0.5676; 0.5568; 0.5542; 0.5703; 0.5533; 0.5577; 0.5774; 0.5783; 0.5739; 0.5676; 0.5595; 0.5712; 0.5479; 0.5237; 0.4942; 0.4270]*

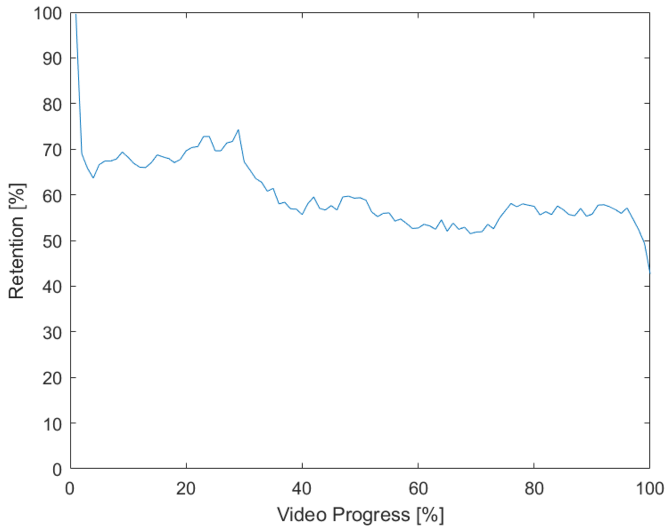



**Figure 1: Video retention vs progress example**

Each video was coded based on: Unit Code (deidentified for this paper); Content Type (Lecture Content or Worked Example), Scheduling within the semester (Fortnight 1 to 6 of our typical 12 week teaching period). Any videos that did not fit the schema for Content Type, or fell outside the scheduled teaching semester were removed from the final dataset, these included offering-specific welcome videos for the units, recordings of project or task information and feedback, and informal help videos, often for engineering software related issues (38 in total).

A MATLAB™ script was utilised to filter the dataset based on the above codes. Filters were also used to bin videos based on video duration, with the average audience retention rates then plotted as a bold line to show trends across the relative video progress. Shaded regions were additionally plotted using the same colour, at ±1 standard deviation distances above and below these mean values, to give an impression of the variability of each set of filtered data (See Figure 2, right).

Bins were generally chosen in increments of 3 minutes based on the precedent established by Guo et al. (2014). The longest videos in the study were sorted into two final bins, 12-20 minutes and longer than 20 minutes, with the longest video in the dataset being 43 minutes.

# Results

## Analysis of all data

An initial analysis of the entire dataset of 440 videos was conducted. Figure 2, left, plots the audience retention rate for each video as a function of the relative video progress for each video. Figure 2, right, displays the same data but in various video duration bins, with the mean retention for each bin, and shaded regions denoting ±1 standard deviation for each bin.

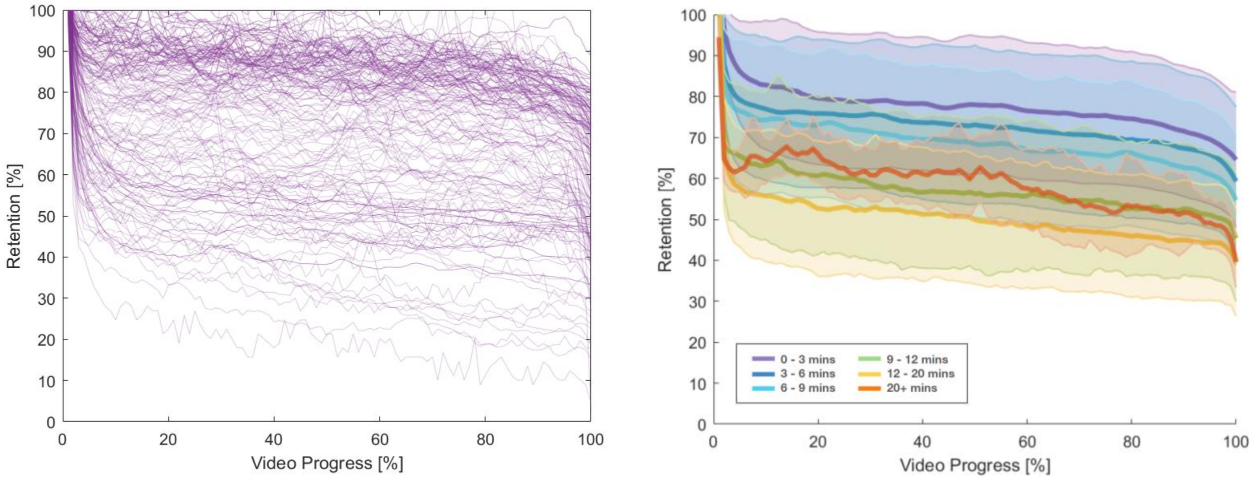



**Figure 2: Video retention vs progress.**
**Left: all videos as individual plots.**
**Right: All videos, binned by duration, μ (mean) plotted, ±1σ (standard deviation) shaded.**

This data shows a clear trend of reducing audience retention with increasing video duration, up until the final bin with video lengths greater than 20 minutes. This last bin, containing only 16 videos, bucks the trend and displays a jump in retention. These videos are drawn from only two of our sampled units and appear throughout the majority of the semester. Further investigation revealed that a large proportion (79%) of these longer videos were worked examples. This potentially explains why their retention averaged slightly higher, with students rewinding and rewatching portions of these longer recordings to follow the workings. This will be explored further below.

The dataset was next filtered based on the nature of the video content. The "Lecture Content" bin contained all formal learning materials that were shared as unit content over multiple offerings of the unit. "Worked Examples" are videos where an example problem is solved or worked through by the presenter, independent of the relevant teaching. This was a common mode of video delivery for the units sampled. The video metrics for this sorting are summarised in Table 1. Both content modalities are binned by video duration and plotted in Figure 3.

**Table 1: Summary metrics for "Lecture Content" and "Worked Example" video categories.**

| Video Content | Number of Videos | Total Views | Average Views per video |
|---|---|---|---|
| Lecture Content | 345 | 674,384 | 1,955 |
| Worked Examples | 95 | 168,488 | 1,774 |
| **Total / Average** | **440** | **842,872** | **1,916** |

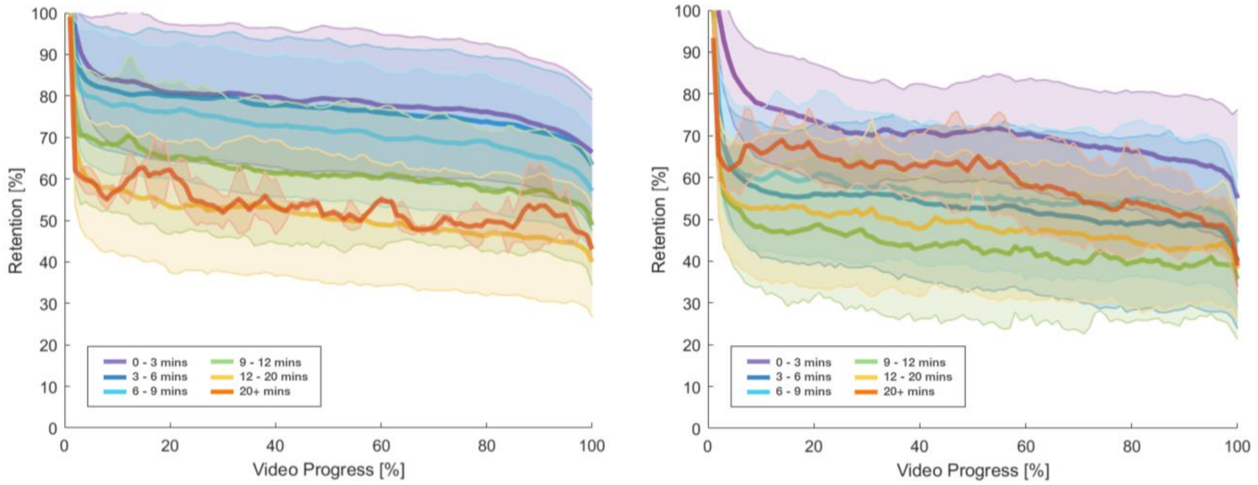



**Figure 3: Videos by type, binned by duration - μ plotted, ±1σ shaded.**
**Left: "Lecture Content" videos. Right: "Worked Example" videos.**

The "Lecture Content" videos show very high and consistent levels of retention for videos up to 6 minutes in length. A slight reduction is evident for videos up to 9 minutes in length, and greater reductions for videos up to 12 and 20 minutes in length. The data is thin for videos longer than 20 minutes but the trend closely follows that of videos 12 - 20 minutes in length. Interestingly, the slope of attrition throughout a video is fairly consistent across all of the binned durations, except for the 20+ min videos, which may be due to the lower number of videos compared to the other bins.

Significant differences in audience retention were observed for the "Worked Example" videos. Retention is very high for videos less than 3 minutes in duration but drops more quickly as duration increases. Surprisingly, the videos in this dataset with durations greater than 20 minutes have higher retention than all other categories, bar those shorter than 3 minutes. This is also the only plot where the average engagement significantly increases in the first 50% of the video duration, which is indicative of rewatching key early portions of these videos.

## Analysis by unit

The dataset was next filtered into its four separate units of study to check for any trends specific to each unit. The summary metrics are presented in Table 2, and the data is shown in Figure 4.

**Table 2: Summary metrics for the videos drawn from each unit/course.**

| Unit | Year of Degree | Videos Released | YouTube Privacy Setting | Number of Videos | Average Video Duration (min) | Total Views | Average Views per Video |
|---|---|---|---|---|---|---|---|
| 1A | 1st Year | 2021 | Unlisted | 180 | 5.68 | 123,594 | 687 |
| 2B | 2nd Year | 2018 | Unlisted | 93 | 8.10 | 97,360 | 1,047 |
| 2C | 2nd Year | 2014 | Public | 82 | 8.48 | 528,817 | 6,445 |
| 3D | 3rd Year | 2015 | Unlisted | 85 | 12.24 | 93,101 | 1,095 |
| | | **Total / Average** | | **440** | **8:00** | **842,872** | **1,916** |

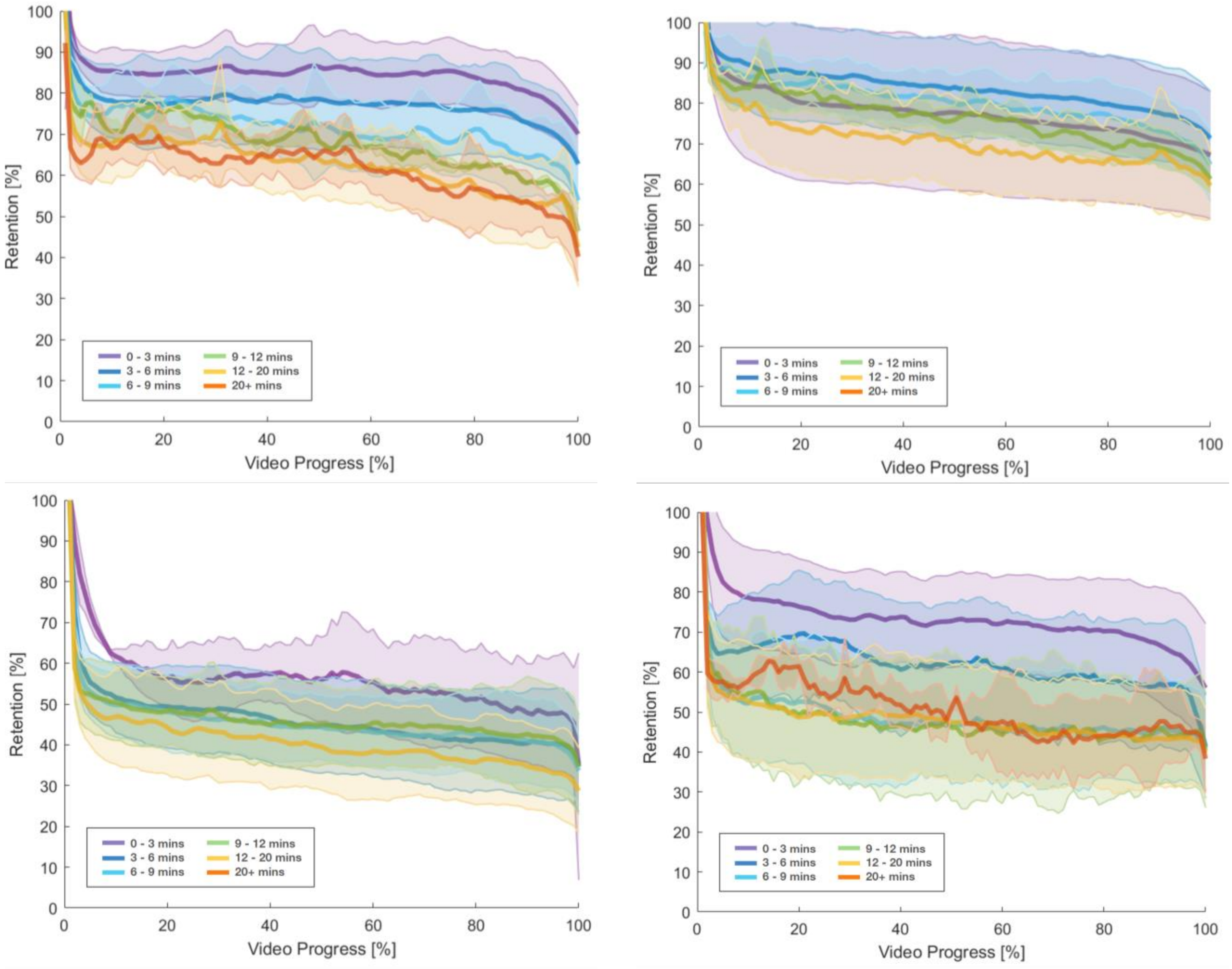



**Figure 4: Videos by unit, binned by duration - μ plotted, ±1σ shaded.**
**Top-left: Unit 1A, Top-right: Unit 2B, Bottom-left: Unit 2C, Bottom-right: Unit 3D.**

Unit 1A shows the strongest retention, in terms of both its mean gradients throughout the videos and the minimal drop evident at the start of the videos. Similar trends are evident in Unit 2B whose videos were produced by the same instructor as Unit 1A. Unit 2C is unusual in that the retention drops much more significantly at the start of the videos. We believe that this is a result of the videos for this unit being listed publicly on YouTube, rather than being unlisted like the other three units. Public listing allows for videos to be included in search results which generates "organic reach". These videos attract viewing audiences far beyond the students in the unit of study through a combination of YouTube searches, suggestions and other means. The YouTube Unit 2C host channel metrics for traffic sources are summarised below in Table 3, showing this organic reach.

**Table 3: YouTube traffic source metrics for the host channel of Unit 2C**

| Fortnight of Semester | Number of Videos | Total Views | Average Views per Video |
|---|---|---|---|
| Weeks 1-2 | 113 | 177,124 | 1,567 |
| Weeks 3-4 | 69 | 98,640 | 1,430 |
| Weeks 5-6 | 81 | 147,701 | 1,823 |
| Weeks 7-8 | 64 | 145,554 | 2,274 |
| Weeks 9-10 | 61 | 139,076 | 2,280 |
| Weeks 11-12 | 52 | 134,777 | 2,592 |
| **Total** | **440** | **842,872** | **1,916** |

Likely direct traffic sources originating from our learning management system are noted by (LMS), these total 60% of views, meaning that ~40% of channel views are organic. We suggest that the likely impact of this organic reach is reduced audience retention, particularly at the start of the video, where casual YouTube viewers might quickly jump away if the content is not to their interest.

Unit 3D exhibits trends somewhere between Units 1A/2B and Unit 2C, with the higher than usual retention evident in the longest videos attributable to the worked example videos discussed previously.

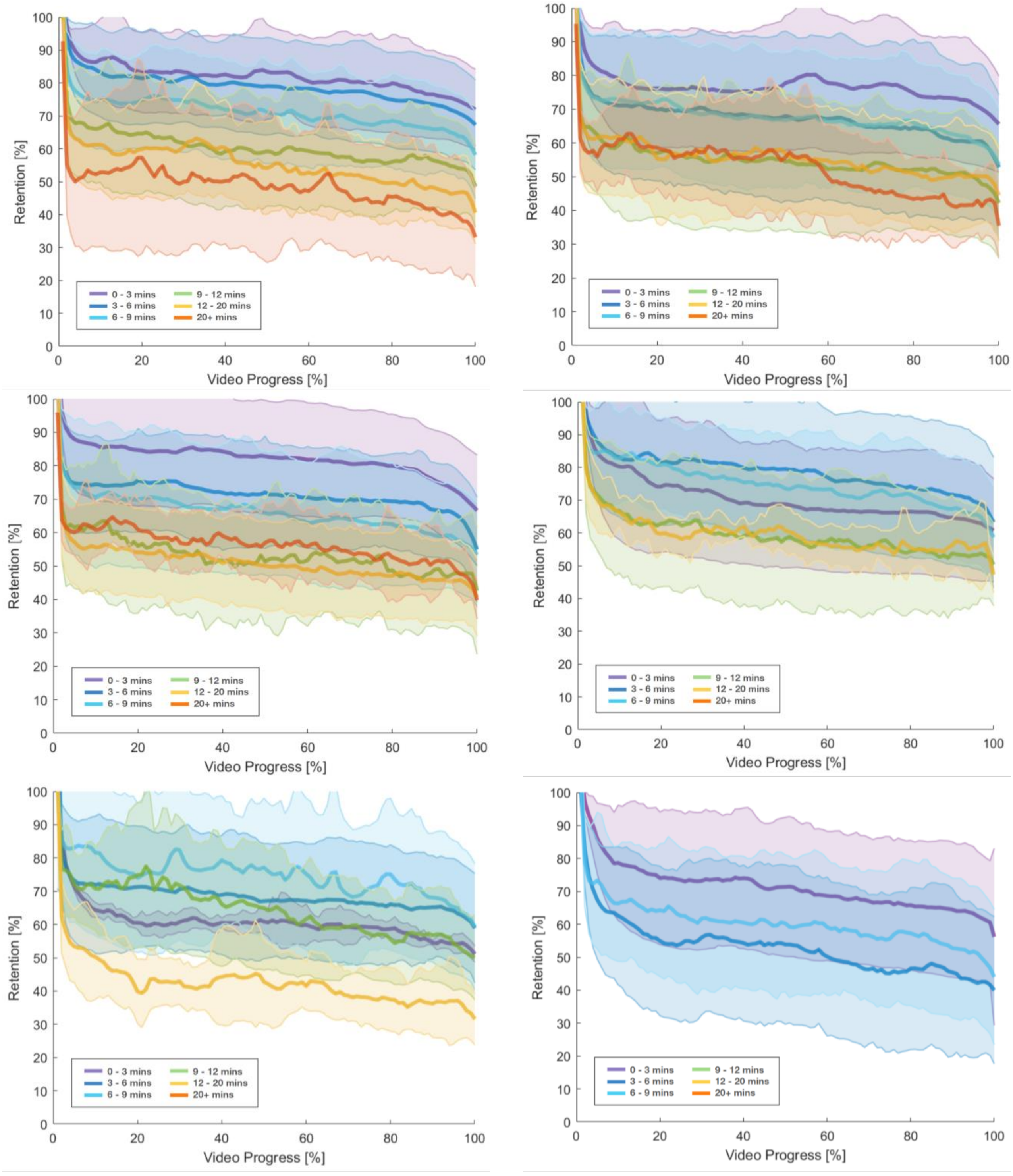
## Analysis by each fortnight of teaching within the semester

The dataset was next filtered by the fortnight in which the content was scheduled for teaching. Given that a 12-week semester is typical for the institutions and units included in this study, this resulted in a total of six bins. The metrics for each of these fortnights are summarised in Table 4, and the data for each fortnight are plotted in Figure 5.

From Table 4, it is interesting to note that the average number of videos released declines over the course of the semester, total views hold relatively steady and average views per video consistently increase. This was a surprising finding, and goes against the anecdotal impressions of the authors that student engagement drops more significantly in the later stages of our units.

| | | | |
|---|---|---|---|
| Playlists (LMS) | 28% | Browse Features | 2% |
| External Links (LMS) | 25% | Other YouTube Features | 2% |
| Youtube Search | 20% | Channel Pages | 2% |
| Suggested Videos | 15% | Embedded Players (LMS) | 1% |
| Direct or unknown (LMS) | 5% | External App (LMS) | 1% |

**Table 4: The number of videos, total views, and average views per video for each fortnight, starting from Weeks 1-2 and ending with Weeks 11-12.**




**Figures 5: Videos by teaching week, binned by duration - μ plotted, ±1σ shaded.**
**Top-left: Weeks 1-2, Top-right: Weeks 3-4,**
**Centre-left: Weeks 5-6, Centre-right: Weeks 7-8,**
**Bottom-left: Weeks 9-10, Bottom-right: Weeks 11-12.**

## Conclusions

Viewer engagement with video content in engineering education is sensitive to video length. Where possible, effort should be made to apportion content into short videos to maintain high retention.

- For lecture content, aim to keep videos less than 6 minutes in duration to maximise audience retention.
- For worked examples, also aim to minimise video duration to improve audience retention, but also know that high rates of retention can be achieved for relatively long examples. Further research is required to confirm the trends observed in this study and understand their root causes.
- View counts for the units surveyed stayed surprisingly consistent over the course of a semester, with average views per video actually increasing steadily throughout the semester.
- Audience retention metrics may be impacted by your choice of listed or unlisted status on YouTube. Over time, listed videos may generate significant organic reach through search results and recommendations, bringing a more diverse, non-student audience to your videos which can skew or cloud your judgement of the student viewing behaviour.

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