“A deeper understanding of student preferences for in-class video use: a segmentation analyses of needs, group differences and preference clusters”

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Article abstract:

This study analyzed segment differences of student preference for video use in lecture classes and university use of videos lecture classes. We then conducted novel gap analyses to identify gaps between student segments' preferences for videos versus their level of exposure to in-class videos. MANOVA was used to identify significant factors that explain the gaps. Understanding student expectations and preferences for using in-class videos in live lecture classes, by segment, and contrasted to the level of video use in their classes, including identifying surpluses and deficiencies of video use.
Gap analysis of video preference relative to video exposure showed a bimodal distribution, with an approximately even split between students with an overall deficit (44.5%) and surplus (47%) of in-class videos. Deficit means students preferred to see more videos than what the lecturer showed them. Surplus means the lecturer showed students more videos than they preferred to see. Further analyses break down the deficits and surpluses based on the type of videos shown.
Results are useful as an effective diagnostic tool for education managers because they are not at the individual student level but rather by course level. One implication for educational managers is that a one-size-fits-all approach for all courses will benefit some students and possibly annoy others. This paper extends Alpert and Hodkinson's (2019) findings by identifying preference clusters and performing segmentation analyses based on finer-grained disaggregated data analysis.

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Abstract

Purpose – This study analyzed segment differences of student preference for video use in lecture classes and university use of videos lecture classes. We then conducted novel gap analyses to identify gaps between student segments' preferences for videos versus their level of exposure to in-class videos. MANOVA was used to identify significant factors that explain the gaps.
Design/methodology/approach – Segment differences of student preference for video use in lecture classes and university use of video lecture classes were analyzed. Novel gap analyses were then conducted to identify gaps between student segments' preferences for videos versus their level of exposure to in-class videos. MANOVA was used to identify significant factors that explain the gaps.
Findings – Gap analysis of video preference relative to video exposure showed a bimodal distribution, with an approximately even split between students with an overall deficit (44.5%) and surplus (47%) of in-class videos. Deficit means students preferred to see more videos than what the lecturer showed them. Surplus means the lecturer showed students more videos than they preferred to see. Further analyses break down the deficits and surpluses based on the type of videos shown.
Practical implications – Results are useful as an effective diagnostic tool for education managers because they are not at the individual student level but rather by course level. One implication for educational managers is that a one-size-fits-all approach for all courses will benefit some students and annoy others.
Originality/value – This paper extends Alpert and Hodkinson's (2019) findings by identifying preference clusters and performing segmentation analyses based on finer-grained disaggregated data analysis.

Keywords Lectures, Instructional videos, In-Class Videos Preference Segments, Gaps (Over and Under) in In-class Videos Usage
Paper type Research paper

1. Introduction

In-class videos have long been a part of education. Sometimes they are a 'hit' in that they are met with interest and enhance learning, but at other times, they may be met with disinterest and complaints. These outcomes often puzzle course designers and instructors who have selected the videos for sound reasons and the best of motives. To achieve more reliable outcomes, educators need to understand effective video selection and student preferences better. This research undertakes a range of gap analyses, including actual video use frequency and the frequency preferences of students, and video source preferences. Similarly, it investigates differences between groups of students and between students' preferences at different types of universities.

Such differences are important to understand because, for more than 50 years, the traditional lecture class has been criticized for being, to put it bluntly, boring and thereby turning off students (e.g., Silberman's (1970) book proclaiming a "Crisis in the Classroom"). The response since then has been diverse, with some educators proposing that live lectures be abandoned altogether in favor of the "flipped classroom" (e.g., Bishop and Verleger, 2013), an approach which is claimed to increase student engagement (Tucker, 2012). Other measures have also been suggested to make live lectures more engaging, such as in-class activities to break up the lecture, for example, Kaddoura's (2013) 'think-pair-share' approach. While video has been available for some time, videos are ubiquitous in today's digital era, easier to make and easier to find – although the quality is becoming more varied. Today's students like to watch videos, as evidenced by the enormous popularity of YouTube, so a lecture interspersed with an occasional video is one way to add variety to the lecture class (Alpert 2016) and increase student engagement. Hence, it seems intuitive that many instructors would consider inserting some videos into their lectures.

There is ample evidence of the benefits of using instructional videos in classrooms. Instructional videos are generally considered to be more attractive elements compared to other learning materials. Additionally, the use of instructional videos in classroom lectures has been shown to improve the students' evaluation of both the lecturer and the learning institution, making the student satisfaction less dependent on the talent of the educators (Scafuto *et al.*, 2017). Furthermore, Das *et al.* (2019) found that the instructional videos' quality in the classroom contributes to improvements in learning outcomes and student satisfaction. Instructional videos are often used in classrooms to promote problem-posing and solving abilities. Additionally, lecturers can use the videos to anchor their lectures within a real-world event appealing and meaningful to students. The core idea is to design instructional videos that let students experience the cognitive process that experts go through when solving a real problem in reality (Chiou, 2021).

While there are theories about how videos may assist learning and practical information about making more effective videos (e.g., Brame 2016), there is a gap in the literature relating to actual video usage during lectures and how that compares to student preferences. Similarly, there is a lack of knowledge about differences between students based on their academic context or type of university or personal factors (e.g., gender, or course studied). Knowledge of these issues would assist instructors, learning designers, and university policymakers concerned with higher education teaching effectiveness make better-informed decisions about how videos can best enhance live lecture classes.

The focus or scope of the present paper is on the use of in-class videos in live lecture classes, and the data was gathered strictly on that basis. However, subsequent reflection suggests that the findings apply to other live face-to-face teaching and learning situations where an instructor or facilitator is present and interacting with the students, managing the learning experience and controlling the showing of videos, rather than students selecting when they watch them. Hence, videos viewed outside of class, in any way, are not within the domain of this study. Similarly, recorded lectures, such as in MOOCs, are outside of this study, as are course activity sessions not led by the main lecturer. The specific focus of this paper differentiates it from other articles that study the use and design of videos in other contexts, such as the growing literature on online educational videos and MOOCs relating (e.g., Zhang *et al.*, 2006; Guo, Kim, and Rubin, 2014; Conole, 2015).

In order to make a better-informed decision on how to enhance lectures using instructional videos, it is important to understand how students differ in their preferences of instructional videos used in the classroom. Differences in preference can be attributed to the types of learning outcomes. Instructional videos are more effective at delivering skill-based learning outcomes (Xie, 2021). Students will probably prefer more instructional videos used in courses that deliver skills than theoretical knowledge. On the other hand, differences in the student's preference of instructional videos use in the classroom can also be attributed to differences in the student's learning styles. A prior study found that students with certain learning styles performed better when video material was used, while others performed better when text material was used (Yousef, 2018).

A recent article in *Education + Training* developed an approach for understanding video use during lectures. Alpert and Hodkinson's (2019) study identified the basic parameters, characteristics, and video use issues during lectures. Their approach identified the importance of not just supply-side descriptions (i.e., what lecturers are doing) but also demand-side descriptions (i.e., what students want), at the same time comparing them to identify any discrepancies or gaps between what lecturers are doing and what students want. Their detailed survey was developed based on qualitative exploratory interviews with students, which identified various issues relating to video use during lectures. Their article presented aggregate results (averages for the whole sample). We saw the potential to extend that research by taking their data and statistically analyzing it for *group differences*. Differences investigated included university type and focus, differences by academic discipline and level (undergraduate vs. postgraduate), and differences by students (e.g., age and gender). Our study adds value based on their unique data set by conducting a finer-grained (disaggregated) analysis.

2. Method

2.1. The data

We obtained a copy of Alpert and Hodkinson's (2019) data from the authors. To minimize repetition, we need to explain aspects of the data collection as these must be understood as the foundation for our statistical analysis. For additional details on data collection, see the original presentation of the data (Alpert and Hodkinson 2019). We need to explain the survey data collection, unit of analysis, and measurement as it is the foundation for our statistical analysis. *Students* rather than instructors were chosen for the survey because each student sits through several different instructor's classes and thus is better placed to report on a larger number of classes and instructor's styles. This choice also allows students' perceptions and preferences to be assessed. An online survey of students was conducted to ask how many videos they have seen in their lecture classes and what they preferred from these videos. The question wording was designed to be simple, direct, and comprehensible to obtain reliable and valid measures as per Krosnick (2018). A broad sample was acquired to represent current practices and student views. A commercial market research company (SurveyMonkey) provided the sample. This sampling process yielded 773 high-quality responses from a broad range of students at universities across the USA.

The survey measured four academic characteristics: discipline, type of university, university focus, and type of Degree. There were similar numbers of respondents from the major university disciplines of Arts and Humanities, Physical and Biological Sciences, Social Sciences, and Engineering, with smaller numbers from other disciplines. Regarding the type of university, 66% of respondents were from public universities, 27% private, and 6% public junior colleges. Regarding the focus of the university, 50.71% were from research-intensive universities, 32.73% from teaching-focused universities (32.73%), and the remainder (16.56%) was classified as "other" or "don't know". Regarding degree type, undergraduates comprised 74.77% of the sample, with the remainder being Masters, Ph.D., or "other" Degree students. The sample comprised 54.72% females and 45.28% male students.

The *unit of analysis* is important in survey research. It is a special challenge to measure video usage in lectures concerning participants' inaccuracy of recall and avoiding answers that are generalisations such as, "How many videos have you seen in lecture during the last semester, on average?" Instead, to make their response task simple and clear, the goal was to ask specifically about *recent* video viewing, so the questionnaire (which was administered during a study week) asked about videos “seen in the last week” to elicit accurate reporting of such viewing. However, merely using ‘a week’ as the unit of analysis could be confounding because the number of courses varies between students, so the respondents were asked how many courses they were currently enrolled in as active students. In the sample, 8% reported enrolling in one course, 21.7% in two courses, 22.5% in three, 28.8% in four, and 18.9% in five or more courses. Therefore, the data was collected and analyzed at the level of *each individual course* in the prior week, i.e., separately for each lecture course in which they were enrolled. We believe this is the best available unit of analysis for studying video use in higher education lecture classes.

2.2. Data analysis approach and methods

Whereas Alpert and Hodkinson (2019) presented aggregate results from the data set, our focus is on group differences. We introduce a new segmentation approach based on gap groups, and we conclude with a post hoc segmentation following standard cluster analysis procedures. *Gap analysis* is a classic approach for comparing performance with expectations. Our objective is to identify the largest gaps because the insights they provide offer opportunities of most benefit. Gap analysis is used in the scholarship of teaching and learning studies to compare what universities provide to what students or industry wants, to help guide the direction of actions to improve education (e.g., O'Neill and Palmer, 2004; Wang, Ayres and Huyton, 2010; Lee and Cho, 2017; Abbasi, Ali, and Bibi, 2018). Gap analysis can be more sophisticated and insightful than analysis of merely descriptive results because descriptive results may be less meaningful as it can be hard to know whether the result is high or low or whether it requires improvement or not. For example, the mean number of videos shown per class is interesting but not informative for education concerning specific contexts and the development of optimal educational designs. Our analysis attempts to identify where the most needed actions are by calculating actual (what universities are doing) minus preferred (what students or industry wants), thereby directing attention to the largest gaps that result. Typically, gap analysis research will conduct a t-test to ensure the gap is statistically significant (e.g., Wang, Ayres, and Huyton, 2010; Abbasi, Ali, and Bibi, 2018). Thus, gap analysis provides a dynamic, contextual analysis of results. If gap analysis is less frequently used, it may be necessary to have both data elements (i.e., exposure and preference) available in the Alpert-Hodkinson data set.

Unusually, we *combine traditional gap analysis with segmentation analysis* to provide more insightful results. We identify what we will call "gap segments". Gap analysis has been used to identify and assess clusters in college students learning environment quality. Jackson, Helms, and Ahmadi (2011) defined the service quality of learning environments as the gaps between the students' perceptions and expectations of the environment. They used this definition to identify quality clusters by contrasting and classifying the students by the perception-expectation gap. Mann and Enderson (2017) similarly applied gap analysis to identify differences between marketing students' preference for mathematical formulas and their actual exposure to the formulas. Furthermore, they classified the students based on the differences, either as a surplus or a deficit. The approach helped to provide insights into the students' perception of their academic preparation in these areas.

We identified three types of gaps from the student's expectations and actual exposure to instructional videos in the classroom. The first, a *deficit* gap, indicates that students wanted *more* than what was delivered in the classroom. Second, a surplus gap indicates that the students wanted *less* than what was delivered; in other words, instructors are doing too much of this concerning what students prefer, and third, a *no gap group*, in which what students wanted was more or less exactly delivered – a 'things are just right' group. Having identified the three groups, we can then examine what is driving or determining the size of each group. Understanding what is driving deficit situations or surplus situations in a particular segment provides a deeper understanding of what is happening and is a simple indicator of the remedial action to take. For example, to show more videos if the deficit group is the largest and show fewer if the surplus group dominates.

In terms of statistical implementation of gap analysis, paired-sample t-tests were done to examine the statistical significance of the identified gaps, and ANOVA was used on both video exposure (videos shown by instructors) and video preferences (what students want) to explain what caused the gaps. In addition, multivariate analysis of variance (MANOVA) was used on the overall gap to determine whether differences exist between the preference-exposure gap of students based on their demographics (gender, Degree, age, and experience with MOOC) and university context (field of study, type of university, and focus of university). The effect size was calculated using the η^2 formula To estimate the magnitude of differences (Fritz, Morris, and Richler, 2012).

Finally, a cluster analysis was used to identify segments in the sample based on students' preferences for videos in the classroom. We adopt the two-step cluster analysis, which combined the k-means approach with the hierarchical approach, to classify the sample into clusters based on their preferences incrementally. The two-step approach has similar advantages to hierarchical cluster analysis, but it has the added advantage of not making an initial assumption about the number of clusters in the data (Kulchitsky, 2008). Thus, we conduct gap-segment group difference tests, post hoc cluster analysis for identifying different groups and close with comparing the results.

3. Results

Recall that student respondents reported their experience across different classes they attended within the last week of lectures, with each class treated as a case for analysis. As mentioned, this unique unit of analysis provides a more accurate look at video use. It is important to remember that the unit of analysis is the student class, not the students. Thus, the number of cases in this analysis is much larger than the number of students surveyed. We obtained for this analysis *2544 unique student-class cases* from 773 unique student respondents. The average number of lecture classes per student is 3.29, a plausible mean number of courses taken per academic semester. Table 1 shows the detailed breakdown of the data set based on the students' and the university's backgrounds. It also shows a broad range of students, courses, and universities, which is required for a valid investigation of group differences.

-- Insert Table 1 about here --

3.1. Gap Analysis

Let us look at the gaps between students' preference for videos in the classroom and the actual exposure to videos delivered in the classroom. In order to do this, we classify the cases into three groups based on the differentials between preference and delivery in each case. This gap helps identify which part of videos delivered in the classroom meet students' preferences and which parts could be improved by either increasing *or* decreasing the type and number of videos shown. Classifying these three groups is valuable as an analytical “a priori” segmentation of the students (instead of simply demographics), which we will later compare with a “data-driven” post hoc segmentation through cluster analysis.

A *Deficit Group* in our context means that the students wanted more videos than is delivered in the classroom (Group 1), while a S*urplus Group* means that the students wanted less exposure to videos than the actual delivery (Group 2). The best case is *the Satisfied Group*, in which the students reported an equal level of preference and delivery of videos in the classroom (Group 3). Group 1, deficit, constituted 1133 cases (44.54%); Group 2, surplus, constituted 215 cases (8.45%); and Group 3, equals or just right, constituted 1196 cases (47.01%).

We begin with testing for overall paired sample differences between Exposure and Preference. Results are that there are significant differences between overall Exposure and Preference for videos in the classroom. Surprisingly, a statistically significant surplus of videos is shown relative to the number of videos preferred (mean difference= 0.885, p<.001)! Why is this? Considering types/sources of videos, a more fine-grained analysis finds a large surplus of instructor-created videos (mean difference= 0.1072, p<.001). However, there is a small deficit for videos of the type TV origin or Textbook supplied videos (mean= - 0.142, p<.001). The remaining types of videos, from the Internet and Other sources, showed exposure was not significantly different from preference. No statistically significant difference for the Internet (mean difference= 0.027, p<.358) or Other (mean difference= - 0.025 p<.304), indicating that at the aggregate level, about the right amount of these videos are being shown. Thus, a major overuse (in students’ eyes) of instructor-created videos is driving the aggregate overuse finding. Nevertheless, we must keep in mind that other types of videos are not overused.

Let us now look at the sizes of the three groups for their overall frequency gaps. First, we analyze the overall gap between preference and delivery of video content in the classroom by group, regardless of the type of videos shown. There is an approximately *even split* between students with overall deficiencies (44.5% of cases Group 1) and surplus (47% of Group 2). Only a *small percentage of cases have just the right level of exposure* to videos in the classroom (8.5% of cases for Group 3). The mean gap is also significantly different, with students in the deficit group reported exposures on average of 2.4 fewer videos than preferred, while students in the surplus group reported exposures of 4.2 more videos than preferred per course in the given week. These large gaps of means highlighted the sharp difference between the surplus and the deficit groups. This difference suggests that video preference relative to video exposure has a *bimodal distribution*, with many students wanting more and many students wanting less, but few satisfied that the number of videos shown is just right. A bimodal distribution means that limiting to aggregate analysis does not show the complete picture.

For the total gap (whole sample gap, all three groups combined), though, there is not much difference between the average preference of the deficit and surplus group (the mean difference between exposure and preference = .87). However, there is a large difference between the average exposure levels reported by the two groups, with the surplus group reporting a huge exposure level of 7.37 videos while the deficit group is reporting a mere 1.27 videos exposure. Preferences vary much less between the groups, with the deficit group preferring 3.71 videos and the surplus group preferring 3.21 videos. Thus, differences in the reported exposure contribute more to the video delivery gap than differences in the students' preference. The variability of exposure to video delivery in the classroom is why there is such a big gap between the surplus and the deficit group.

We now examine the content delivery gap for each of the different types of videos, starting with instructor-made videos. Students reported that their exposure to instructor-made videos is *more* than preferred in nearly half of the cases. Nevertheless, more than a fourth of the cases are students who reported deficiencies. However, students in the deficit group reported only a small deficit of instructor-made videos (0.81). On the other hand, cases in the surplus group reported a significant 2.99 more instructor-made videos than preferred per course in the given week. Since the previous analysis by Alpert and Hodkinson (2019) showed that while instructor-made videos were quite popular, it is possible that the surplus groups could be viewing lower quality instructor-made videos, and therefore they wish a lower frequency of them.

Students' preferences are generally between 0 and 1 video per lecture class for instructor-made videos, with an average preference of 0.63 videos. On the other hand, exposure levels are skewed toward surplus, with more than 40% of the cases reported an average of 3.72 times of instructor-made videos delivered in the classroom. This skew suggests that some instructors make and show too many videos. This hypothesis is supported by a difference in the reported exposure, with the Surplus group reporting significantly more instructor-made videos than students in the Deficit and Equal group. Table 6 shows a summary of the group proportion and sample parameters for instructor-made videos. The next analysis will examine the content delivery gap from videos other than the instructor-made videos.

-- Insert Table 2 about here --

We look at the remaining three types of videos using Alpert and Hodkinson's (2019) classifications: videos from the Internet, videos of known sources from TV or Textbook, and Other (videos of unknown source). The same pattern prevails. Total sample analysis shows no statistically significant differences between exposure and preference. However, gap analysis finds large deficit and surplus groups with statistically significant differences between their gaps. These are Internet videos (deficit 43.4% of sample, mean gap -1.27; surplus 35%, 1.49), TV and Textbook (deficit 46.9%, -1.09; surplus 25.7%, 1.42), and Other (deficit 35.9%, -1; surplus 19.4%, 1.71). We will not attempt to interpret the results for Other because future research is required to investigate and classify these videos. Again, the gaps seem to be driven by differences in exposure, with exposure not just higher but much higher for the surplus conditions. Also, the difference in exposure is larger between the deficit and surplus groups than the change in preference between the deficit and surplus groups. Specifically, for Internet videos (deficit mean exposure=.32, surplus mean exposure=2.28; deficit mean preference=0.159, surplus mean preference=.79) and for TV and Textbook videos (deficit mean exposure=0.18, surplus mean exposure=2.1; deficit mean preference=1.26, surplus mean preference=0.68). Interestingly, whereas the largest gap group was surplus of exposure over preference for Instructor-created videos (surplus 43.3% of sample vs. deficit 27.4%), for Internet videos, the reverse was true (deficit 43.4% vs. surplus 35%) and the same for TV and Textbook videos (deficit 46.9% vs. surplus 25.7%). We interpret these results as more students want more Internet videos and TV and

Textbook videos than want less, and more students want fewer Instructor-created videos than wanting more.

3.2. Group differences - Analysis of Variance

After identifying the existence and source of the gaps, this section reports the factors that explain the source of differences. We conducted an Analysis of Variance, with student demographics and educational background as independent variables, to explain students' preferences and exposures to videos in the classroom. We also included interaction effects with gap categories (i.e., surplus, equal, and Deficit) to examine whether these factors explained differences of exposures and preferences by gap categories. That is, testing whether the group differences factors vary in their effect by gap category.

This section reports factors that explain students' overall reported exposure and preference for videos in the classroom. For the overall *exposure*, we tested only the student's educational backgrounds. After adjustment, the model explained 67.5% of the total variance of reported overall exposures. There are different exposures to videos for the field of study, degree program (undergraduate versus graduate), and type of university. Specifically, Arts and Humanities, Business and Engineering have a higher video showing rates than Education or Physical and Biological Sciences; Masters degree programs have a higher video showing rates than Undergraduate degree programs; Private Universities and Public Junior Colleges have a higher video showing rates than Public 4 year universities. The type of university, research universities versus teaching-focused universities, both have about the same rate of videos shown. We did not include student demographics such as gender in the ANOVA for exposure (Table 3a) since it would not make sense to think of gender causing different levels of exposure. However, interestingly, if gender is included in the ANOVA, then the result is a statistically significant difference by gender ($p<.038$), and that eliminates the statistical significance for the field of study ($p<.208$). As you may have guessed, what is happening is that gender is *associated* with fields of study that have different exposure levels. Thus, we would say that both are true, there are different exposures to videos associated with the field of study and gender because gender and field of study are themselves associated, but we emphasize field of study as that is the more causative variable.

For the interaction effect with gap category, only Degree and Type of University are significant. Table 3a shows the result of the analysis of variance for students' exposure to videos in the classroom. If the exposure is separated by the three groups: the *Field of study groups is not significant, and neither is the *Focus of Uni groups, although there is a significant interaction effect between *Degree group for exposure. There are no differences between Bachelors and Masters in the Equal group, but there are differences in the Deficit and Surplus group. As for differences in exposure by Type of Uni*group, there is a difference between research-intensive and teaching-focused for the equal group, but not in the surplus and deficit group.

-- Insert Table 3ab about here --

We included students' demographics in the model to test if gender or age affected video preferences for the overall preferences. The model explained 63.6% of the total variance of reported overall preferences. All the main effects are significant, except for gender and MOOC seen. Specifically, Business students have a higher video frequency per class preference, and three academic disciplines have lower video frequency preference, Education, Engineering, and Physical and Biological Sciences; Masters students prefer a slightly higher frequency of videos per lecture class than do Undergraduate students; students at research-intensive universities prefer slightly more videos than students at teaching-focused universities. However, for the interaction effect, only the interactions with Field of Study and Gender are significant. Table 3b shows the analysis of variance for students' preference for videos in the classroom. In addition to the ANOVA results, we also reported the estimated marginal means of exposure and preference by groups and gap category in Table 4.

There is a significant difference in preferences by field of study*group. Arts and Humanities have the highest preferred number for videos in the surplus group but one of the lowest preferred number of videos in the deficit group. Physical and Biological Sciences and Social Sciences have similar gaps. On the other hand, the number of preferred videos is equal for the Deficit and surplus group for Business and Engineering fields of study. For Education, the number of preferred videos in the deficit group is even higher than those in the surplus group. There is a significant interaction in preference by gender*group. There is no difference in preference between male and female students in the Deficit and equal group, but the male preference is higher in the surplus group than the female one.

Overall, while there is a significant group difference in preference by field of study, there is no group difference in reported exposure. This point is one source of the gap between exposure and preference. There is a significant group difference in exposure by Degree, but no significant group difference in preference by Degree. This point is the second source of the gap between exposure and preference.

-- Insert Table 4 and Table 5 about here --

3.3. Cluster Analysis

Segmentation adds an important deeper understanding to aggregate analysis. In the final analysis section, we used post hoc, data-driven methods to explore without researcher bias for possible segments in the student sample, based on their reported exposure, preference, demographics, and educational background. We used cluster analysis following the method described by Hair, Black, Babin, and Anderson (2014, Chapter 8). We initially set the range of clusters to between two and fifteen clusters, with the final result of two clusters identified using the two-step cluster analysis. Cluster 1 explained 54.8% of the variance, and Cluster 2 explained 45.2%. The cluster revealed a near-linear divide between surplus and Deficit cases, with Cluster 1 representing mostly surplus cases, while Cluster 2 consisted almost entirely of the Deficit cases. The ratio between the largest and the smallest clusters is 1.22, which is fairly balanced. The silhouette measure of cohesion and separation obtained from the clustering is 0.6, above 0.5, which is the conventional indication of a strong cluster structure (Whitson, Ozkaya, and Roxas, 2014).

In addition to the surplus and Deficit divide, we also examined the profile of the clusters based on the demographics and educational background. Most Cluster 1 cases came from male students doing their Master's degree or studying in a private university. Conversely, most of the

Cluster 2 cases came from female students doing their Bachelor's degree or studying in a public university. Table 5 shows a full breakdown of the cluster profile. Overall, Cluster 1 could be described as surplus (Group 2), male, Masters degree, private university, no MOOC experience. Cluster 2 could be described as deficit (Group 1), female, Bachelors's degree, public university, MOOC experience. The consistency of the post hoc cluster analysis with our *a priori* gap analysis earlier provides confidence in these results. The clusters provide rich results, with how they capture multiple dimensions simultaneously to explain where differences in the data arise.

4. Discussion, Implications, and Conclusions

While the initial analyses in this article may appear overly fine-grained, the later macro analyses, especially the clustering, confirm the consistency and homogeneity of the findings throughout the study. These results provide an effective diagnostic tool for educators because the results are not at the individual student level but rather by course, i.e., class and university level. Thus, for simple diagnostic purposes, the results/tables presented in this article should be read in reverse order. First, identify the cluster relevant to the institution to obtain a general insight. University managers can compare their student profiles at the university level to see which cluster the university fits into and adjust their curriculum development. If there is a fit to Cluster 1 or 2, then the university's instructors may be showing videos at the national average rate per this survey, and the students in the courses are roughly reflective of the national study body as per this survey. If this is the case, the cluster preference for more or fewer videos may apply to your university. Of course, the local context must be considered, but the cluster results may provide directions to consider. For example, for a Business program in a public university at the bachelors level with a majority female student enrolment, our survey data shows it may be a deficit in the number of videos being shown in that degree program if the instructors' video use frequently and students video frequency preferences are similar to the national averages as per this survey.

Having obtained insight into the likely relevant cluster at the institution, a course reviewer could then work back through the specific discipline, course(s), and levels that are the subject of consideration. Next, a retrospective audit could be undertaken of the types and frequency of videos shown during a previous semester's course using the Alpert and Hodkinson (2019) categorization scheme. The course reviewer may wish to assume the student preferences reported here apply to the class in question at the simpler level. The reviewer is free to adjust the video frequency and mix accordingly, having completed the diagnostic stage.

One implication for educational managers is that a one-size-fits-all approach for all courses will benefit only one gap segment while harming the other. Some courses at the university may be Deficit and some in surplus, so the optimal number of videos to show may vary by course.

Alternatively, this paper offers a blueprint for a more complex analysis duplicating the processes outlined. While gap segments are more difficult to identify than demographic segments such as gender, they can still be measured with a survey. Furthermore, the pattern of characteristics/demographics that can be associated by each cluster (i.e., Master, Male, Private Uni, No MOOC experience for the surplus cluster, and Female, Bachelor, Public Uni, MOOC experience for the Deficit cluster). In sum, gap-segments are measurable by a simple survey, and if not, there are observable proxies (from the preceding cluster analysis) that can be used to approximate the gap segments.

Though gap segments may not seem as readily available as demographic segments, it is more directly actionable. Most Universities asked students to evaluate their instructor at the end of the semester, so adding a few questions on video exposure and preference will not be too difficult. Then preference can be compared to exposure to identify gaps and create gap segments. If we assume student preferences within a single course and institution are relatively stable, a re-survey may only be required after course changes have been made. The focus here is on actionable feedback. The gap-segment analysis should be done ideally by type of video, although this requires a longer end-of-term evaluation survey.

Future research might empirically investigate the 'why' questions, such as test "why do the cluster characteristics lead to the surplus and gap results found in this survey". Also, future research might investigate what specific types of videos comprise the "Other" category identified in this survey. Is the cause of students' generally wanting fewer instructor-created videos related to student concerns that instructor-created videos are generally of lesser quality from the student perspective, or that students may prefer the instructor to deliver a ‘live’ lecture rather than use pre-recorded videos of their own to present the point?

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Table 1. Breakdown of data set by the student's context

Variables	Category	Total Respondents	Total Case
Gender	Female	423	1374
	Male	350	1170
Field of Study	Arts and Humanities	105	307
	Physical and BioSciences	130	439
	Social Sciences	118	386
	Business	124	434
	Education	41	126
	Engineering	117	403
	Undecided	16	47
	Other	122	402
Degree	Bachelors	578	1901
	Masters	125	440
Type of University	Public University	507	1687
	Public Junior College	45	123
	Private University	207	689
Focus of University	Research Intensive	392	1316
	Teaching Focused	253	828
	Other	128	400
Past Experience with MOOC	No	583	1909
	Yes	131	452
	Do not know	59	183

Table 2. Gap by type of videos

Video Source	Gap			Exposure			Preference		
Instructor	Frequency	Percent	$\bar{x}_{gap}$	$\bar{x}_{exposure}$	Std. Dev.	Std. Error	$\bar{x}_{preference}$	Std. Dev.	Std. Error
Deficit	698	27.4%	-0.81	0.11	0.42	0.02	0.92	0.81	0.03
Equal	745	29.3%	0.00	0.20	0.64	0.02	0.20	0.64	0.02
Surplus	1101	43.3%	2.99	3.72	2.74	0.08	0.74	0.67	0.02
Total	2544	100.0%	1.07	1.70	2.56	0.05	0.63	0.76	0.02
	Gap			Exposure			Preference		
Internet	Frequency	Percent	$\bar{x}_{gap}$	$\bar{x}_{exposure}$	Std. Dev.	Std. Error	$\bar{x}_{preference}$	Std. Dev.	Std. Error
Deficit	1105	43.4%	-1.27	0.32	0.65	0.02	1.59	1.16	0.03
Equal	549	21.6%	0.00	1.03	1.12	0.05	1.03	1.12	0.05
Surplus	890	35.0%	1.49	2.28	1.26	0.04	0.79	0.69	0.02
Total	2544	100.0%	-0.03	1.16	1.33	0.03	1.19	1.07	0.02
	Gap			Exposure			Preference		
TV or Text Book	Frequency	Percent	$\bar{x}_{gap}$	$\bar{x}_{exposure}$	Std. Dev.	Std. Error	$\bar{x}_{preference}$	Std. Dev.	Std. Error
Deficit	1192	46.9%	-1.09	0.18	0.48	0.01	1.26	1.04	0.03
Equal	697	27.4%	0.00	0.50	0.91	0.03	0.50	0.91	0.03
Surplus	655	25.7%	1.42	2.10	1.27	0.05	0.68	0.66	0.03
Total	2544	100.0%	-0.14	0.76	1.18	0.02	0.90	0.98	0.02
	Gap			Exposure			Preference		
Other	Frequency	Percent	$\bar{x}_{gap}$	$\bar{x}_{exposure}$	Std. Dev.	Std. Error	$\bar{x}_{preference}$	Std. Dev.	Std. Error
Deficit	913	35.9%	-1.00	0.15	0.48	0.02	1.15	1.01	0.03
Equal	1137	44.7%	0.00	0.17	0.53	0.02	0.17	0.53	0.02
Surplus	494	19.4%	1.71	2.41	1.54	0.07	0.70	0.79	0.04
Total	2544	100.0%	-0.03	0.60	1.21	0.02	0.62	0.90	0.02

Table 3a ANOVA or student's reported total exposure to videos in the classroom

Tests of Between-Subjects Effects					
Dependent Variable: Reported Exposure					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Model	65631.3[a]	44	1491.6	111.75	0.000*
Field_of_Study	197.9	7	28.3	2.12	0.039*
Degree	141.7	1	141.7	10.61	0.001*
Type_of_Uni	132.9	3	44.3	3.32	0.019*
Focus_of_Uni	40.9	3	13.6	1.02	0.383
catgap_tot * Field_of_Study	235.7	14	16.8	1.26	0.224
catgap_tot * Degree	160.9	2	80.4	6.03	0.002*
catgap_tot * Type_of_Uni	395.6	5	79.1	5.93	0.000*
catgap_tot * Focus_of_Uni	79.4	6	13.2	0.99	0.429
Error	30659.7	2297	13.3		
Total	96291.0	2341			
a. R Squared = .682 (Adjusted R Squared = .675)					

Table 3b ANOVA or student's reported total preference to videos in the classroom

Tests of Between-Subjects Effects					
Dependent Variable: Reported Preference					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Model	29325.652a	56	523.672	74.001	0.000*
Field_of_Study	142.919	7	20.417	2.885	0.005*
Degree	34.682	1	34.682	4.901	0.027*
Type_of_Uni	88.851	3	29.617	4.185	0.006*
Focus_of_Uni	69.706	3	23.235	3.283	0.020*
Age	67.183	1	67.183	9.494	0.002*
Gender	2.610	1	2.610	0.369	0.544
MOOC_seen	15.374	2	7.687	1.086	0.338
catgap_tot * Field_of_Study	185.220	14	13.230	1.870	0.025*
catgap_tot * Degree	26.481	2	13.241	1.871	0.154
catgap_tot * Type_of_Uni	53.521	5	10.704	1.513	0.182
catgap_tot * Focus_of_Uni	81.647	6	13.608	1.923	0.074
catgap_tot * Age	21.856	2	10.928	1.544	0.214
catgap_tot * Gender	55.957	2	27.978	3.954	0.019*
catgap_tot * MOOC_seen	9.424	4	2.356	0.333	0.856
Error	16169.848	2285	7.077		
Total	45495.500	2341			
a. R Squared = .645 (Adjusted R Squared = .636)					

Table 4. Estimated Marginal Means of Exposure and Preference by groups and gap category

Independent Variables	Exposure			Preference		
	Deficit	Equal	Surplus	Deficit	Equal	Surplus
By Field of Study						
Arts and Humanities	1.41	2.52	10.37	2.734	2.573	4.002
Physical and BioSciences	0.69	2.60	9.40	2.802	2.432	3.655
Social Sciences	1.06	2.89	8.99	2.663	2.83	3.388
Business	2.02	2.99	10.70	4.361	3.13	4.397
Education	1.22	2.50	7.60	3.682	2.364	2.724
Engineering	1.59	3.01	9.84	3.579	2.987	3.529
By Type of Uni						
Public University	1.37	2.24	7.33	3.61	2.19	3.19
Public Junior College	1.18	2.55	11.12	3.57	2.76	4.54
Private University	1.65	2.67	8.27	4.07	2.55	4.02
Other	1.10	n/a	11.86	2.15	n/a	3.34
By Focus of Uni						
Research Intensive	1.42	2.51	9.82	3.81	2.64	3.77
Teaching Focused	1.51	1.78	9.61	3.56	1.86	3.76
Others	1.36	1.67	9.37	2.62	1.48	3.73
By Academic Degree						
Bachelors	1.00	2.20	8.61	3.16	2.33	3.27
Masters	1.65	2.78	10.69	3.54	2.68	4.27
By Gender						
Female	n/a	n/a	n/a	3.33	2.70	3.43
Male	n/a	n/a	n/a	3.37	2.30	4.12

Note: Marginal means for preference are estimated with the covariate Age=23.97 years old

Table 5. Breakdown of the cluster profile by exposure, preference, demographics, and educational background

Profile	Cluster 1	Cluster 2
Portion	54.80%	45.20%
Name (Tentative)	Surplus, Male, Master, Private University, No MOOC experience	Deficit, Female, Bachelor, Public University, MOOC experience
Mean		
Exposure	6.64	1.27
Preference	3.07	3.67
Gap_Total	3.56	-2.39
Gap_Instructor	2.08	-0.16
Gap_Non_Instructor	1.48	-2.23
Gap Internet	0.69	-0.90
Gap TV or Text Book	0.39	-0.79
Gap Other	0.40	-0.54
Length Preference (minutes)	21.09	17.83
Age	25.08	23.13
By Field of Study		
Arts and Humanities	62.2%	37.8%
Physical and BioSciences	49.2%	50.8%
Social Sciences	56.7%	43.3%
Business	48.8%	51.2%
Education	56.3%	43.7%
Engineering	54.1%	45.9%
By Type of Uni		
Public University	46.8%	53.2%
Public Junior College	57.7%	42.3%
Private University	57.2%	42.8%
Other	71.1%	28.9%
By Focus of Uni		
Research Intensive	55.6%	44.4%
Teaching Focused	55.3%	44.7%
Others	64.3%	35.7%
By Academic Degree		
Bachelors	48.3%	51.7%
Masters	64.3%	35.7%
By Gender		
Female	49.7%	50.3%
Male	60.2%	39.8%
By MOOC_Seen		
Yes	49.2%	50.8%
No	71.2%	28.8%