Video Resources and Peer Collaboration in Engineering Mechanics: Impact and Usage Across Learning Outcomes

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Abstract

Video resources, largely in the form of recorded lectures or problem solutions, have become fairly commonplace in higher education classroom in the past few years. Video authoring tools and distribution channels are now powerful and seamless, presenting a wide array of new opportunities for faculty to produce sharable educational assets. Video resources, when created using pedagogical and multimedia best practices, are known to be valuable learning tools for students. A variety of studies have enlisted cognitive load theory and/or the worked example effect to demonstrate efficacy in a variety of settings and disciplines.

In this paper, we examine the use of video resources by students in an undergraduate engineering mechanics (dynamics) class, with a specific focus on how video consumption correlates to the achievement of specific learning outcomes. We focus on video solutions to problems, and map student perceptions about the usefulness of the videos onto the learning outcomes for the course. Then, we map each graded assignment (homework, quiz, exam) onto those same learning outcomes, and compute an average score for each student on each learning outcome. We use student background information and data about total video consumption to further enrich the discussion.

The results indicate that some students find video resources crucial to their academic success, across learning outcomes, while other students extract little value from the video resources. These students indicate that they prefer to work alone, with another technology (i.e., the textbook), or in study groups rather than engaging with the technology as a partner for learning. Some learning outcomes within the course, notably those related rigid body kinematics and rigid body kinetics (via Newton's laws), reveal that students perceive high value of the videos regardless of their grade on assignments related to those outcomes. We find significant interplay with other factors reported on student background surveys, especially their views on collaboration. The data suggest that peer collaboration and video usage have a mutually-reinforcing effect, with students actively engaged in both earning better grades in the course.

Introduction

Technology-based innovations in engineering education have a long history, and the relatively recent maturation of social media tools such as blogging and video have accelerated development of new approaches to support student learning. The idea of anywhere, anytime learning, supported by a variety of asynchronous resources, is particularly alluring in this modern era of hyperconnectivity. Giving students learning resources, and allowing them to choose when, where, how often, and with whom they use those resources holds the promise for powerful, personalized learning experiences. The sophistication of the learner matters, however, and it seems intuitive that some students are better at managing their academic environment than others. As such, there are many open questions about how students use technology resources for learning, especially in the context of their full academic workload and their general approach to learning. In this study, we have introduced video technologies within the context of a sophomore mechanics classroom, and *we ask the specific questions*: to what extent do the videos support student learning? Does student usage of the videos vary with learning outcome? Are the videos better suited to enable learning for more complicated topics? And how do students weigh the relative value of learning with videos against the other options available to them (the textbook, their peers, and the instructor)?

Review of relevant literature

Learning by watching experts solve problems. Dynamics belongs to the class of foundational courses for mechanical, aerospace, and civil engineering students, and their mastery of these core concepts is crucial for future success in the curriculum as well as the workplace. Developing mastery often involves a combination of actually solving problems (live, on paper), as well as watching experts solve problems (via pre-recorded videos). Solving problems is both an intuitive and well-worn idea whose value is not disputed, and engineering students are constantly sharpening their problem solving skills by actually solving problems on homework assignments and exams.

The other part of this dyad, watching experts solve problems, leverages the worked example effect[1]–[3] (WE). In brief, WE contends that students can become better at many cognitive tasks by watching experts solve problems via carefully-constructed learning materials. Worked examples can be paper-based or video-based, and in general the literature converges on the idea that studying worked examples can form a powerful approach to learning. Worked example research has focused on all manner of technical topics, including secondary math education[4], electrical engineering[5], and even engineering mechanics[6] and physics[1]. Especially when extended with other pedagogical tools such as self-explanation prompts[7], [8] or other kinds of scaffolding[9], worked examples are known to be a useful tool to support learning cognitively complex tasks with both efficiency and accuracy.

Technology interventions and specific learning outcomes. Much of the worked example literature used a fairly controlled laboratory setting rather than an actual higher education classroom. Some of that literature focuses quite closely on mechanics related learning outcomes. Recent work using controlled eye gaze experiments examined how students learn physics concepts from worked examples[10], with the conclusions supporting the central tenets of both the worked example effect (via cognitive load theory[11]) and effective multimedia design that leverages spatial contiguity principles[12]. Quite a bit of work in similar laboratory settings has focused on quantifying specific aspects of physics or mechanics problem solving using eye gaze technologies and other instruments to evaluate student differences[5], [13], [14]. And again, the preponderance of the literature supports the idea that learning very specific topics can be effectively supported with a variety of worked examples and other technology-based interventions.

Technology interventions in a classroom environment. Studies to evaluate interventions in a classroom environment are more difficult to execute for a variety of reasons, not the least of which is the issue of experimental controls. A recent meta-review[15] of web 2.0 technologies concluded that at least the tools appear to do no harm in classrooms, and in the best cases they can be quite effective (such as when integrated into a full package of engaged pedagogies[16], assessments, and so forth that are self-consistent). Although the authors conclude that strong evidence is still lacking, they nonetheless argue that web 2.0 technologies can be effectively deployed in a variety of classroom contexts. However, a counterpoint emerges[17] when/if students perceive technology interventions to be "added" workload, an additional expectation, or in other ways conflicting with their preferred approach to learning. These two meta-reviews engage the underlying tensions of technology interventions in classroom environments: students perceive tremendous academic stresses on their time, and they make expeditious decisions about how to manage their workload; *they seek to optimize task efficiency with task accuracy*. To the extent that technology interventions clash with student expectations about how they best learn, such interventions may not be successful or even welcome.

The gap in the literature. Taken together, these studies illustrate that technology-based interventions can be powerful aids to learning (the worked example effect), especially for cognitively complex tasks. This has been repeatedly shown in various laboratory environments across different technical subjects. Yet, when deployed in classroom environments, the interventions may expose underlying tensions about how students manage their workload within their educational ecosystem, and what instructional supports they are comfortable accessing. These individual student differences are important and can seriously impact their learning[18]. We therefore observe a gap in the literature that helps to motivate this study: for students in a real classroom environment, what are the usage patterns of the various instructional supports (videos, peers, textbook, instructor) available to them, and in what ways does the ecosystem shape these usage patterns? This paper gives a preliminary look at these issues using data collected during a recent academic semester in a Dynamics course.

Study population, data, and methodology

Student population. The subjects in this study were students in the sophomore-level course *Dynamics* at a large, mid-Atlantic public university during the Spring 2012 semester. Total enrollment in the course was 120 students, drawn mostly from mechanical and aerospace engineering (about 85% of the total enrollment), but also including students from biomedical engineering and other disciplines. The course textbook was Hibbeler[19], and the Mastering platform was also used for online homework (HW) assignments (in addition to traditional hand-written homework assignments). There was a single section of this course offered in Spring 2012. Moreover, many of the students in this course were also enrolled in other single-section courses including Strength of Materials and a mathematics course (either differential equations, or probability and statistics). As such, there were dozens of students in this class who shared nearly-identical technical course schedules, and they therefore could easily form study groups for in-person collaboration. This question about collaboration habits is important and appears later in the paper.

Course content and learning outcomes. This course followed the Hibbeler text in terms of presentation, with one notable exception. Kinematics content was covered at the beginning of the course, for both particles and rigid bodies, with kinetics for each following in sequence. In terms of chapters in Hibbeler, the sequence was: particle kinematics (Ch. 12), rigid body kinematics (Ch. 16), particle kinetics (Chs. 13, 14, 15), and rigid body kinetics (Chs. 17, 18, 19). The course was structured with a total of 21 learning outcomes (LOs) organized into three essential categories (**Table 1**). Due to time constraints during the course, none of the vibrations content [LOs 2(g) and 3(h)] was assessed, leaving 19 LOs explored in the course.

Technology components. The course included two key technology elements that enabled anytime, anywhere learning and collaboration: a course blog instead of a more traditional course management system (CMS), and substantial video content. The ***course blog*** replaced the CMS as an information distribution channel, but it also served as a communication and peer collaboration platform through its posting and commenting features. Students were awarded up to 3% of their final course grade based upon their level of participation on the blog. Video content took two forms: (i) ***lecture videos*** were condensed, efficient coverage of lecture concepts, motivation, and derivations, typically lasting about 15 minutes, and (ii) ***video problem solutions*** were detailed solutions to dynamics problems authored by the course instructor, typically lasting between 5-20 minutes. All videos were authored according to best practices for multimedia content creation[12], [20], and were distributed in compressed format for student use. Our data for this course and many others indicate that students use the *lecture videos* in very targeted ways, for instance if they miss class due to illness or a job interview. Their overall perception of the lecture videos is rather lukewarm; they appreciate having access to them, but do not believe they are exceptionally helpful for their course performance. They much prefer the *video solutions*, which more closely resemble the graded assignments in the course, and we therefore *restrict the discussion in this paper to student perceptions about and use of video solutions.*

Table 1. Learning outcomes for Dynamics.

1. Understand the kinematics of particles and rigid bodies, and describe their motion in quantitative terms.
- 1(a). understand particle kinematics in multiple coordinate systems, including moving systems
- 1(b). understand projectile motion
- 1(c). define absolute and relative motion for particles
- 1(d). understand planar kinematics for rigid bodies, including translation and rotation about a fixed axis
- 1(e). define absolute and relative motion for rigid bodies
- 1(f). apply rotating coordinate system techniques to the solution of planar rigid body problems

2. Relate applied force/moment/torque to translational/angular acceleration using free body diagram methods.
- 2(a). use FBD techniques to derive equations of motion (EOM) for particles
- 2(b). apply Newton's second law to relate force to acceleration in multiple coordinate systems for particles
- 2(c). define moment of inertia for a rigid body
- 2(d). use FBD techniques to derive EOMs for rigid bodies
- 2(e). apply Newton's second law to relate force to acceleration in multiple coordinate systems for rigid bodies
- 2(f). derive EOMs for general motion of rigid bodies
- 2(g). use Newton's second law to derive EOMs for vibrating systems

3. Apply energy and momentum methods to the solution of practical problems.
- 3(a). understand kinetic and potential energy
- 3(b). apply work-energy methods to particle kinetics problems
- 3(c). understand the concepts of conservation of energy
- 3(d). understand impulse, momentum, and impact
- 3(e). apply I-M methods to particle kinetics problems

3(f). apply W-E methods to rigid body kinetics problems
3(g). apply I-M methods to rigid body kinetics problems
3(h). use energy methods to derive EOMs for vibrating systems

Data. From the class, 83 students consented to participate in this study; participation was voluntary and did not impact their grade in the course. The dataset for analysis includes 35 pieces of graded work (each in the form of a mechanics problem to be worked from beginning to end and eligible for partial credit during grading) in all, including 19 hand-written HW assignments of two problems each (only one of which was collected and graded), two quizzes composed of one problem each, and three exams (two mid-terms, one final) composed of 5 problems each (15 problems total). The Mastering data from online homework (another 19 assignments) was included in the student's final course grade, but is excluded from the analysis here for two reasons. First, the Mastering work was meant to encourage low-stakes practice, with multiple submissions allowed for each problem, and *no hand-written work* associated with the Mastering problems was collected. Second, Mastering grading is only granular in the sense of how many attempts a student has taken—not in reference to the quality of their work leading up to submission of their answer. In the absence of any evidence of problem-solving process, we decided to remove the Mastering data from the analysis completed here because it is qualitatively different (i.e., no meaningful partial credit) than the other pieces of graded work in the analysis. Students also completed a small project (5% of their final grade) on a topic of their choice, and they earned class credit (up to 3% of the final grade) corresponding to their level of participation on the course blog. The 35 assignments were mapped onto the course learning outcomes, while the project and course blog content were not (due to the diversity of topical areas covered in both the project and blog contents). Students in this study also completed 3 surveys totaling 91 items throughout the semester (pre-, mid-, and post-) , and these surveys covered a wide range of topics about their perceptions, work habits, collaboration habits, consumption of technology, and so forth. *Many survey questions asked about the overall course experience, but some survey questions targeted specific learning outcomes and/or topical areas for the course.* The surveys were mainly composed of Likert-scale items, with about 12 open response items covered over the three surveys. Surveys were administered during class meetings, on paper, and then recorded into an Excel spreadsheet for further analysis. Because not all consented students attended class on all three days on which surveys were administered, not all 83 participants completed all three surveys.

Methods. For all participants, survey and open response data were merged with gradebook data for the 35 graded assignments described above, plus the project and blog contributions points, into a master dataset that allows us to correlate survey and open responses with academic performance data. The learning outcomes are mapped onto each topical area for the course, and there are 8 of them:

- Particle kinematics (P-K), Hibbeler Ch. 12
- Particle kinetics, Newton's law (P-N), Hibbeler Ch. 13
- Particle kinetics, work-energy methods (P-WE), Hibbeler Ch. 14
- Particle kinetics, impulse-momentum methods (P-IM), Hibbeler Ch. 15
- Rigid body kinematics, including rotating coordinate systems, (RB-K), Hibbeler Ch. 16
- Rigid body kinetics, Newton's law (RB-N), Hibbeler Ch. 17

- Rigid body kinetics, work-energy methods (RB-WE), Hibbeler Ch. 18
- Rigid body kinetics, impulse-momentum methods (RB-IM), Hibbeler Ch. 19

The LOs were then mapped onto both the 8 topical areas defined above, as well as the 35 graded assignments included in the analysis. In each case, one LO was defined as the "primary" LO for that topic or problem, and one or more "secondary" LOs were also defined. This LO mapping allows us to connect specific problems to specific topics and specific LOs. In particular, we matched graded assignments to topical areas if *any* of the assignment's learning outcomes matched the topical area's *primary* learning outcome. This mapping enables us to connect student gradebook data from specific topical areas with their survey responses to examine relationships among student perceptions and their academic performance.

The population in this study is of reasonable size (n = 83 students) but the number of data points related to graded assignments per student can be small, especially for grade calculations related to a specific learning outcomes. For instance, of the 35 graded assignments considered in this analysis, only 3 have learning outcomes that match the RB-IM primary outcome [which is LO 3(h)]. The number of problems included in the analysis across topical areas ranges from a low of 3 (for RB-IM) to a high of 10 (for RB-K), with an average of 5.5 problems. In any event, because to the relatively small number of graded assignments per LO, we use simple descriptive statistics (mean, standard deviation) and trend analysis to illuminate *this LO data*, and we do not rely on more sophisticated statistical techniques. When aggregating over the *number of subjects* in the population or a reasonably large subset thereof, we do use other statistical techniques as appropriate. We also triangulate the data, where possible, with survey and open response data to add texture and meaning to the analysis.

Results

Important and challenging dynamics concepts. In anticipation of these results, we begin by characterizing the expected difficulty of the topic areas listed in **Table 2** in light of the Dynamics Concept Inventory (DCI)[21]. The DCI targets 11 core dynamics concepts, and these concepts were identified through a Delphi process[22] involving expert educators who suggested rigid body dynamics concepts their students struggled with. From this process emerged a set of 11 key concepts that fall into the topical areas here as follows: RB-K (5 DCI concepts), RB-N (3 DCI concepts), RB-WE (1 DCI concept), RB-IM (2 DCI concepts). Results from 2005 suggest[21] that across the items on the DCI, 6 are the most problematic for students; they include two items on RB-K, two on RB-IM, and one each on RB-N and RB-WE. Certainly some of the graded assignments in this course conform to the spirit of DCI problems, and in particular those 6 quite challenging DCI items. Moreover, all students in the course have already completed the mechanics portion of college-level physics, which means that many of the particle concepts in dynamics are partially, at least, review for students. Our conclusion, then, is that we expect students to perform worse in general on the rigid body learning outcomes than they do on the particle outcomes.

Aggregate performance per learning outcome. This analysis focuses on understanding any differences in student attitudes or performance by course learning outcome. **Table 2** describes class averages on the primary learning outcome associated with each topic area, as well as the number of graded assignments used in the score calculation. Each graded assignment represents one problem, and each one is weighted equally in the mean score and standard deviation calculations regardless of whether the assignment was a HW, quiz, or exam question. This approach artificially deflates student scores on the per-topic calculations because a single homework problem is given equal weight to a single exam problem. In the overall grading scheme of the course, and in the calculation for final course average used here, the HW problems were individually weighted quite a lot less than individual exam problems (and the final grades were calculated according to the weighting scheme detailed on the course syllabus). The last column on the table indicates the student perception of usefulness of the video solutions available to them, *by topic area*, averaged across all students who completed the post-survey (which contained this item). Survey responses were on a 0-1-2 scale, with 0 being "low" usefulness and 2 being "high" usefulness. The scores reported on the table support our contention that students would perform more poorly on rigid body concepts than on particle concepts. Not only are the average scores lower for rigid body concepts, but the standard deviations tend to be higher, indicating more scatter in student performance. In the aggregate, students perceive the video solutions to be somewhat useful, and we note that on the topic that students generally find very challenging (RB-K, which includes rotating coordinate systems), they perceive the videos to be more useful.

Table 2. Topic area breakdown of student performance, perceptions of video usefulness, with number of assignments composing each area.

Topic area	*# assignments*	*Mean score (%)*	*St. Dev. (%)*	*Average video usefulness*
P-K	5	88.1	10.9	0.98
P-N	4	88.9	8.9	1.05
P-WE	8	88.3	8.4	1.07
P-IM	6	93.5	7.5	1.07
RB-K	10	83.3	10.5	1.32
RB-N	4	81.0	13.7	1.13
RB-WE	4	85.2	10.2	1.15
RB-IM	3	84.3	9.3	1.15

Individual performance, and complicating factors, per learning outcome. Individual student performance gives further clues about how students use their available support resources to promote their academic success. **Figure 1** illustrates student performance by topic area, their final course grade, and their perception of usefulness of video solutions for that topic area. The figure reinforces the notion that generally students perform better on particle topics than on rigid body topics (as reported in **Table 2**), as the spread in the topic scores seems to be higher for rigid body topics. The colors on the figure also convey the idea that students perceive the rigid body videos to be slightly more useful than the particle videos (due to the presence of less black symbols—low usefulness—on those sub-figures). In the dataset, there were 16 students whose assessments of usefulness were not uniform across all topic areas, and their usefulness assessment averaged 0.48 on particle topics and 1.05 on rigid body topics (on the 0 = low, 1 = medium, 2 = high scale). This again reinforces the notion that students perceive the rigid body material to be more difficult and to derive more use from the rigid body videos. It seems clear that students attached value to the video solutions and recognized that they could be helpful for their learning, especially for more difficult topics in the course.

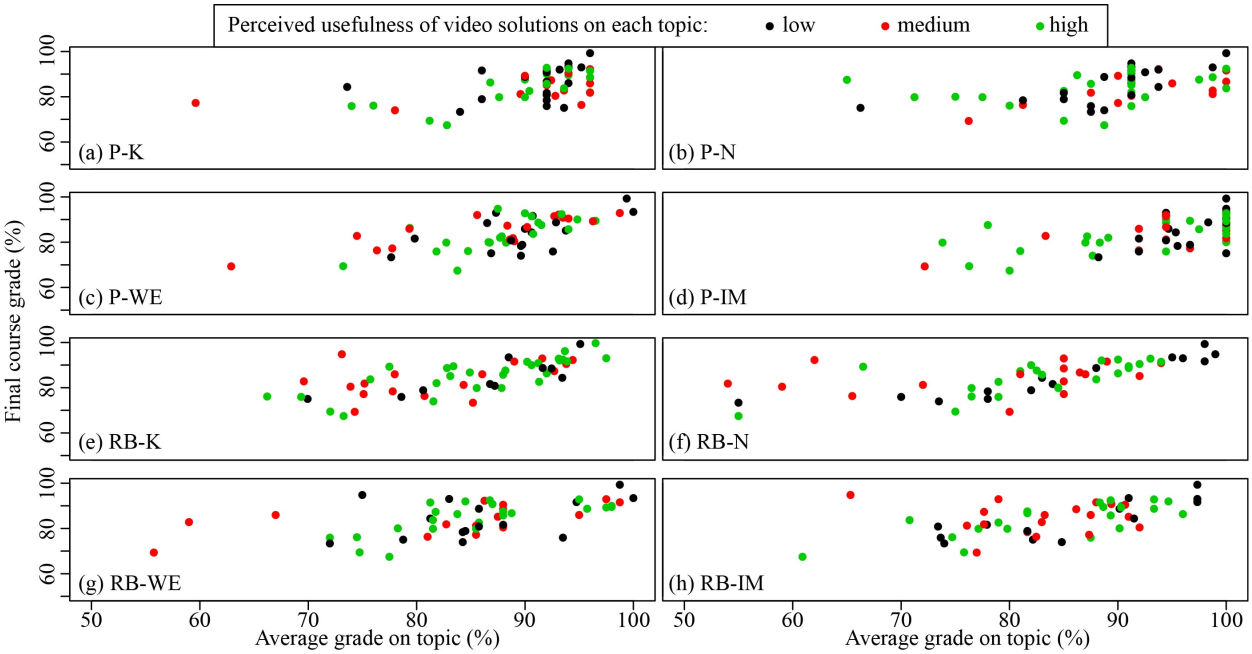

Figure 1. Perceived usefulness of video solutions by topic area, with student grades on assignments related to those topics and overall course grade.

The role of peer collaboration. Much of the research on technology interventions focuses on laboratory work that considers the intervention in the vacuum of the controlled experimental setting. In truth, all educational interventions—technological, pedagogical, and so forth—exist within the ecosystem of each class, and within the student's ecosystem of their overall college experience. Students have many competing demands on their time, and we might rightly ask: *within a real educational context, what mediating factors might influence when/how/how often students use video resources to support their learning?* Our previous research[23]–[25] has shown that attitudes about peer collaboration may be important for students, and we explore this issue next as a mediating factor for video usage.

More granularity on a per-student basis is shown in **Figure 2**, which contains four different sets of data. The two axes of the plot are two survey items from the post-survey: a binary question about whether a student prioritizes peer collaboration, and an item about the perceived usefulness of video solutions on the topic of RB-IM. The bubble radii correspond to the reported total consumption of solution videos by the student (as determined by an item on the post-survey), and the color of each bubble indicates the student's performance on all graded assignments whose primary learning outcome was related to RB-IM. The two axes are categorical data, with two levels on the peer collaboration question, and three on the perceived usefulness question. As such, we have *jittered* the data so that all the bubbles do not fall exactly on top of each other. Jittering is a data visualization technique[26] that adds a small amount of random noise to measurements to avoid having data points fall exactly on top of each other, and it is particularly useful for visualizing the categorical data on this plot. Only the measurements on the two axes are jittered.

The plot contains great depth and richness and requires explanation. ***First***, this plot is representative of the class of plots corresponding to all 8 topical areas listed in **Table 2**. Only the plot for RB-IM is shown here, but the plots for all eight topic areas are qualitatively similar to this one. ***Second***, generally students who perceived higher usefulness (higher on the y-axis) of the videos consumed more of them (larger bubble radius). ***Third***, generally students who consumed more of the videos (larger bubble radius) earned a better score on graded assignments (more blue and green colors). ***Fourth***, generally students who prioritized collaboration (more blue and green on the right side of the figure) outperformed those who did not, regardless of number of videos consumed or perceived usefulness. ***Fifth***, some students perceived high usefulness and consumed many videos, yet did not score very well on graded assignments (large red bubbles).

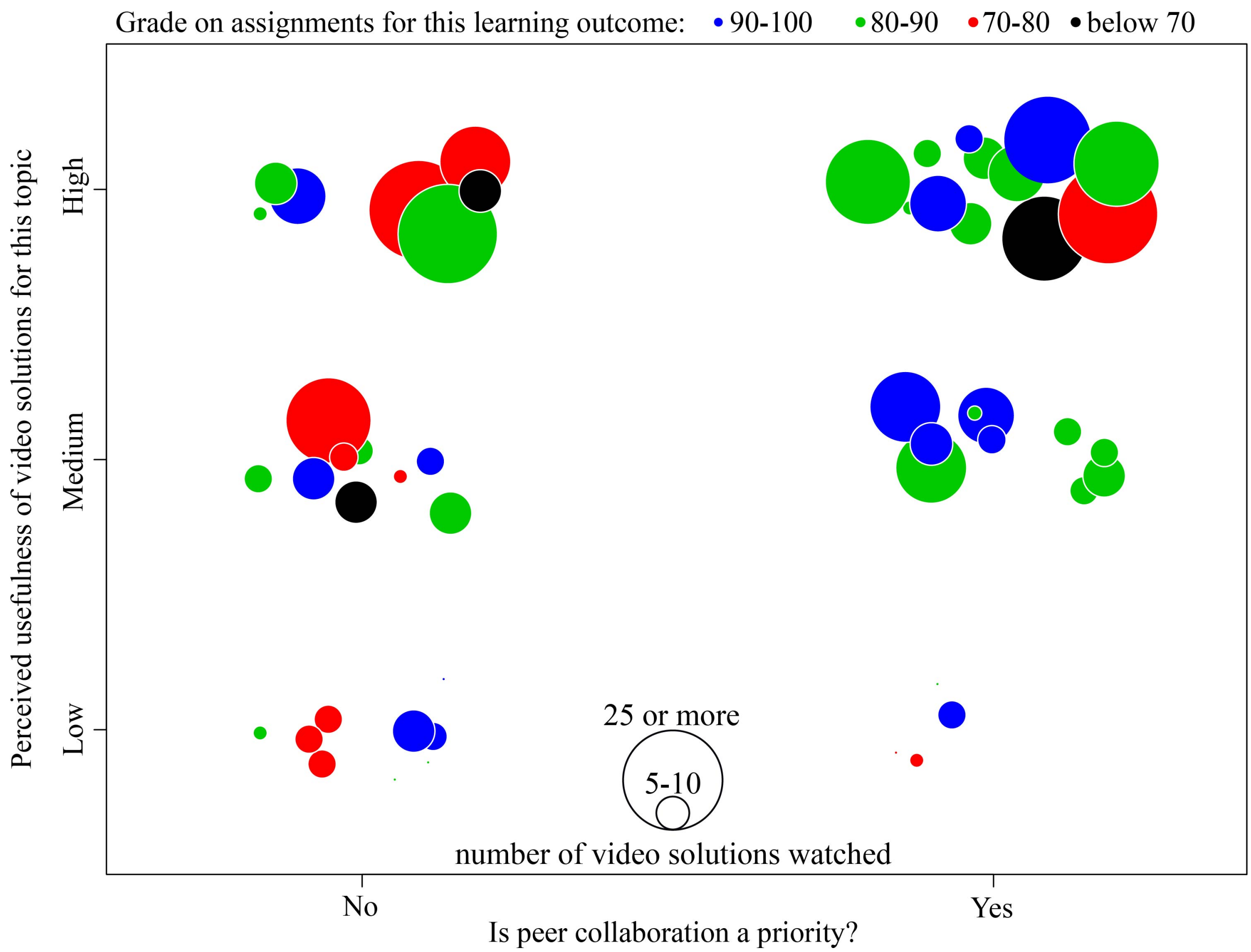

Figure 2. Bubble plot of student attitudes and performance on four metrics: perceived usefulness of video solutions, prioritization of peer collaboration, video consumption, and academic performance on graded assignments. The perceived usefulness and assignment grade correspond to topic area RB-IM.

Mismatch in performance on different learning outcomes. We now introduce a new metric that helps shed some light on student performance across learning outcomes. We define a mismatch parameter $S_{m,i}$ for student *i* as follows:

$$S_{m,i} = \sum_{j=2}^{8} \sum_{k=1}^{j-1} \left| g_{k,i} - g_{j,i} \right| \quad (1)$$

where the $g_{j,i}$ and $g_{k,i}$ are the average grades of student i on graded assignments for topical area k and j as defined in **Table 2**. For the 8 topical areas in this study, there are a total of 28 terms in the mismatch summation for each student, as follows. For area 1, there are 7 other areas available for the mismatch calculation. For area 2, there are 6 others (because its mismatch with area 1 has already been calculated). For area 3, there are 5 others, and so forth, until we arrive at the total of (7+6+5+4+3+2+1 =) 28 terms in the summation.

This mismatch parameter characterizes the variation in student experience/perception of the difficulty of material in the course, relative to himself/herself. A small mismatch parameter means that a student found all the topical areas to be of roughly equal difficulty and their performance was about the same on each area. A high mismatch indicates that a student found some material more challenging than other material, and their performance on graded assignments reflects that. As a practical matter, the minimum value for $S_{m,i}$ is zero (the student performs exactly the same on each topic area) and the maximum mismatch could be as large as 800 or 900 (for a student whose performance is wildly erratic across topical areas). In this study, the minimum mismatch score was 52.5, the mean was 248, and the maximum was over 700. The class average mismatch $S_{m,class}$, calculated via equation (1) using class averages on each topic area in the j and k summations, was about 130, corresponding to just less than ½ letter grade mismatch (130/28 = 4.6 percentage points) on average. A statistical summary of the data, parsed by mismatch score, is given in **Table 3**.

The relationship between mismatch and final course grade is perhaps not surprising: high-performing students earned a strong grade by performing well on each topic area. Poorer-performing students scored more erratically across topic areas. Students with highly-erratic performance scored the worst of all. We intentionally chose a comparison of student performance to himself/herself, rather than to the class as whole, because we were interested in each student's performance as they experienced and perceived different topics of different difficulty in the course. We explored a number of other potential definitions for the mismatch parameter, some involving the class average mismatch, and all yielded qualitatively similar results to those reported here.

We are particularly interested in understanding students with low mismatch scores, those whose experience in the course was fairly level and who performed about the same on each of the topic areas. We further parse this group into two sub-groups: high performers (n_{high} = 16, final course grade > 90%) and low performers (n_{low} = 10, final course grade < 80%). Our question is: do we see any differences in video consumption or collaboration patterns between these two groups?

Figure 3 is a bubble plot comparing performance of students with mismatch parameter $S_{m,i} < 300$. We choose 300 as the cutoff because across the 28 terms in the mismatch summation, a mismatch of 300 corresponds to an average mismatch of just over 10 percentage points, or about one letter grade. The bubble radius indicates each student's reported total usage of video solutions (larger radius = more solutions watched), and the bubble color indicates the student's response to the post-survey item about whether they prioritize peer collaboration (black

= no, red = yes). *The trend is clear*: higher-performing students tend to collaborate more with peers and consume more video resources than lower-performing students. However, the relative value of either form of collaboration, with peers or with the videos, requires more exploration.

Table 3. Mismatch score range and academic performance of students in each range. Final course grades are calculated for students *within each mismatch score range*.

Mismatch score (points)	*# students*	*Final course grade*	
		Mean (%)	*Standard deviation (%)*
0-100	4	95.2	5.1
100-150	16	87.9	6.0
150-200	19	85.5	5.7
200-250	12	85.5	5.8
250-300	4	80.2	2.9
300-350	7	84.0	6.8
350-400	11	80.5	8.7
400-450	5	85.1	6.2
450-500	3	76.1	--
500-600	1	79.8	--
600+	1	74.2	--

The relative roles of video usage and peer collaboration. Our data do not allow us to parse out effect sizes for the contribution of peer collaboration, video usage, or other factors to overall student academic performance. But we can say something about the total ecosystem in which a student experiences each of these and give a qualitative description of what we believe to be the underlying factors impacting technology usage and peer collaboration.

<u>(a) The role of video usage.</u> Laboratory and even some controlled in-class experiments have consistently demonstrated the worked-example effect for students in many different disciplinary areas. The worked-example effect posits that students can learn by studying worked examples, and that their learning is improved through intentional scaffolding of various other instructional experiences around the worked examples. For example, worked examples that include reflective instructional prompts[27] or requests for self-explanations[28] were found to improve student learning. This paper, as well as our prior research, shows the strong suggestion of the worked example effect at work. Generally, students who consume more videos perform better in class, across all topic areas.

<u>(b) The role of peer collaboration</u>. However, there are certainly some students who consume many videos yet do not earn a good result on either specific topics or in the course as a whole. Our data certainly suggest an additive effect in which more peer collaboration, combined with higher video consumption, leads to improved outcomes. There are outliers in the data, to be sure, but the *general trend seems to be positive reinforcement of video usage and peer collaboration*. Peer-mediated learning is widely known to be a potentially valuable strategy for students, so the positive role of peer collaboration is no surprise. However, we do see evidence that students *sometimes prefer peer collaboration to video usage*. In open response items on the surveys, more than one dozen students expressed some version of “I prefer to collaborate face to face, rather than using digital technologies” (which would include both videos and the course blog), so

it is clear that some students simply relied on their peers in study groups to learn the content. This is completely consistent with the observation above that many students are in many of the same (single-section) courses together, so study groups across multiple courses can provide a stable peer group that is valuable and productive.

Taken together, the entirety of the student ecosystem for learning becomes more clear. Within the context of this class, students have finite time and cognitive resources to devote to class activities. Students seek to optimize the time they spend and their usage of available support resources. Students can collaborate with the learning technologies available to them, including the video solutions, the textbook, their peers, the instructional team (office hours), and internet resources. Students therefore attempt to *shape their approach to the course* to emphasize collaboration with whatever resources they are most attracted to.

But our data suggest only mild agility when it comes to *shaping their approach to learning based upon task complexity/learning outcome*. There is very little evidence in our dataset that students alter their approach to use more of less of any one resource in response to a change in difficulty of a course topic. Some of the open response items from the surveys reveal student usage of videos in targeted ways for difficult concepts: "[I use the videos] only when I'm not understanding a matter/subject". And we have presented evidence of differential perceptions of usefulness of solution videos across topic areas. But our data at present do not support the contention that students employ a highly dynamic study strategy that truly optimizes their approach and usage of available resources, by learning outcome or topical area.

This observation may have important implications for how we think about educational interventions, especially technology-mediated interventions. Too often interventions are developed in idealized settings, and their use by students in the full context of their educational experience is not fully considered. Here, we have learned that the video solutions we have developed are: (i) generally viewed by students to be useful (sometimes differentially by learning outcome), **and** (ii) students who use the videos more actively generally perform better on graded assignments, **but** (iii) given the choice of which collaborative resources to use (peers, textbook, videos, or instructor), students may not always prioritize the intervention (the videos) the way we might like or expect. Within the overall educational ecosystem experienced by the students, they make decisions and trade-offs about how they spend their time, with whom, and doing what. Their rationales for decisions about use (or not) of various kinds of educational interventions can be opaque and a complicated function of their workload, peer group, ease of access to the resources, predisposition toward technology, and the difficulty of the material. While there has been a large amount of research about change processes involving faculty adoption of innovations[29], [30], it appears that more research is needed to fully understand student choices about which interventions might afford them a powerful and efficient learning experience.

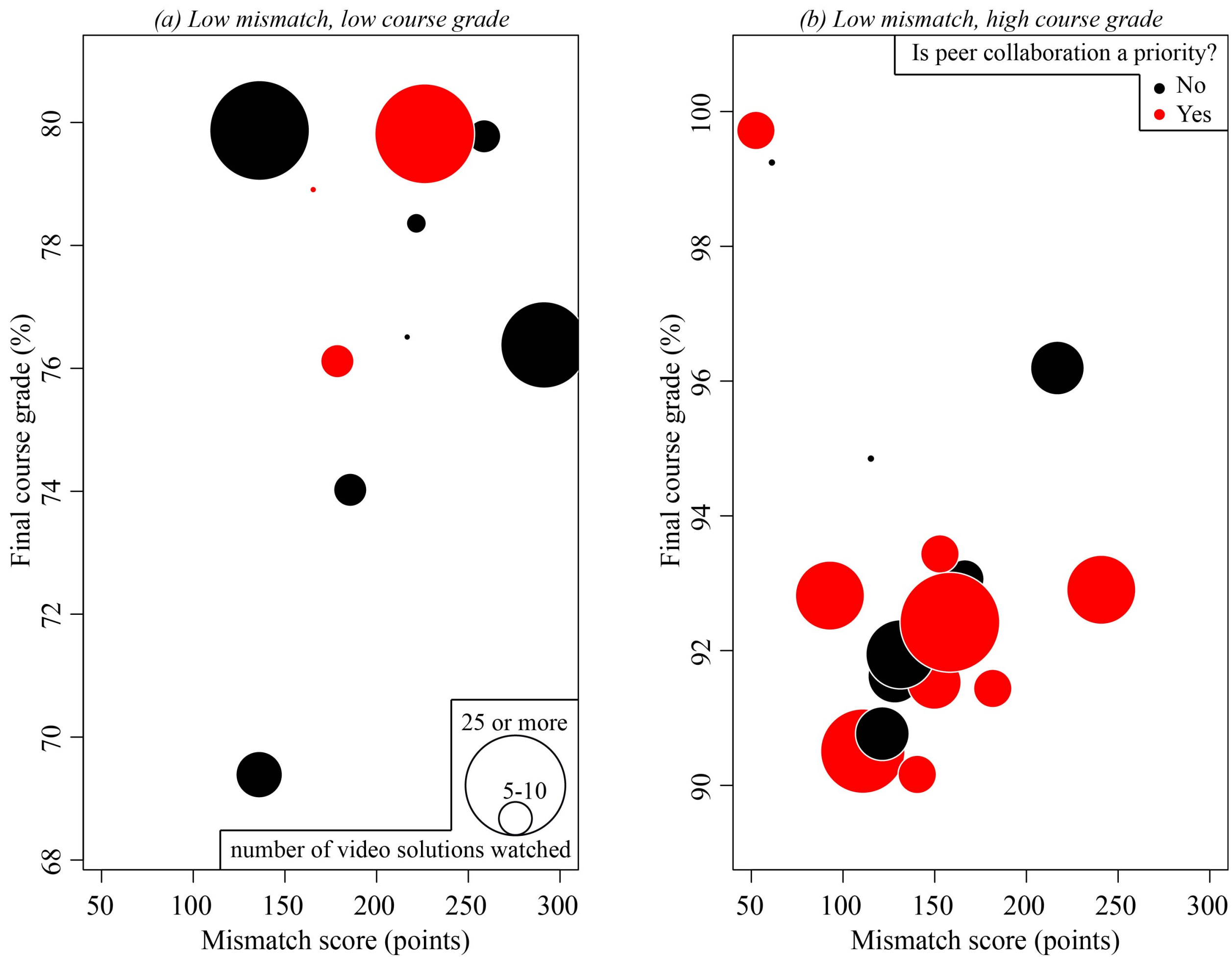

Figure 3. Comparison of video consumption and final course grade for low and high mismatch students.

Conclusions

In this paper, we present recent research results concerning the use of video-based instructional resources in a Dynamics class. Our goal was to examine technology usage and impact as a function of learning outcome in the course, and we used the 8 topical areas across particle and rigid body dynamics as representative of the key learning outcomes. We examined class performance across and within topical areas, as well as video usage, attitudes about collaboration, and perceptions of video usefulness (on a per-topic basis) to develop a description of student usage and decision making about these instructional supports. We generally conclude that students who use the videos more actively perform better in the course, a clear suggestion of the worked example effect at work. In addition, we found that generally students who collaborated with peers more actively performed better in the course, a result consistent with the large body of literature on collaborative- and peer-based learning strategies. We did not find especially persuasive evidence of per-learning-outcome differences in student usage and approach, although some elements of this did appear in open response items on our surveys. Students also perceived some differences in the usefulness of the videos by learning outcome, suggesting that perhaps students viewed some topics as cognitively more demanding than others. The most important outcome of this work is that well-established ideas like the worked example effect, when integrated into an actual classroom environment, co-exist in the student's ecosystem that is filled with competing choices and priorities. Student agility in shaping their learning environment by accessing the full spectrum of instructional support resources appears to be low. Despite the evidence that an intervention may add value in a controlled setting, a classroom environment may introduce irresolvable conflicts to students that may limit adoption or effectiveness of an innovation in practice. More research about these conflicts and their resolution would certainly be a welcome addition to the literature.

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