

Comparing a-list empire educational software to Khan Academy's: increasing student performance by incorporating artificial intelligence into video-based instruction

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Abstract

The Internet has given rise to a plethora of educational resources that are available to students. These resources come in a variety of formats including downloadable worksheets with answer keys, online problem solving calculators, and instructional software that allows users to learn a topic and solve problems. One of the most popular websites is produced by Khan Academy, which allows users to watch educational videos and then practice what they have learned by solving problems. One weakness in the site is that its interactivity with the student is limited to evaluating the correctness of answers to problems. A human teacher, on the other hand, could review the student's work and see where the student made his/her mistake and then explain to the student how to correct it. Such feedback is valuable to helping a student improve. A-list Empire is a social media website that is creating educational content using a similar format to Khan Academy's. The primary difference is that students are given an electronic worksheet to enter their step-by-step problem solving and artificial intelligence (AI) software then evaluates their work and points out where mistakes are made and how to correct them. An experiment compared the effectiveness of Khan Academy's software compared to A-list Empire's. Students were taught arithmetic operations on complex numbers. Half practiced problem solving using Khan Academy's software and half practiced using A-list Empire's AI-based software. On a post-test, students using A-list Empire's software showed higher performance, and more so for difficult topics, and more consistently high performance than those using Khan Academy's software. The results suggest that AI can improve educational performance when added to the video-based instruction paradigm.

Keywords: educational software, Khan academy's, video-based instruction

1. Introduction

The past two decades have seen an enormous increase in the use of technology to supplement and even replace traditional classroom instruction. Nowhere is this more prevalent than with the Internet where there are now countless sites, many of them free, that offer supplemental educational resources for students. Technology-based education, often referred to as e-learning, has received a lot of attention in the research community. E-learning has increased in popularity over the years because it provides benefits such as: provides time and location flexibility; results in cost and time savings for educational institutions; fosters self-directed and self-paced learning by enabling learner-centered activities; creates a collaborative learning environment by linking each learner with physically dispersed experts and peers; allows unlimited access to electronic learning material; and allows knowledge to be updated and maintained in a more timely and efficient manner (Baloian *et al.*, 2000; Kumar *et al.*, 2001; Piccoli *et al.*, 2001) [3, 10, 12].

One of the most popular forms of supplemental instruction resource is video-based instruction (VBI). VBI is generally well-received by students. Accordingly, much research has been devoted to studying its effectiveness. Adding videos was shown to improve performance in third and eighth graders (Boster *et al.*, 2006) [6]. Videos have been shown to improve educational achievement compared to other formats such as text (Khan *et al.*, 2010) [9], lecture (Siegel *et al.*, 1997) [14], and simulation (Morgan *et al.*, 2002) [11].

One of the reasons why videos may enhance learning is that videos tend to be engaging, which fosters student learning (Roblyer and Edwards, 2001) [13]. Videos lead to higher acceptance and satisfaction among students (Donkor, 2011) [7]. Such engagement and acceptance leads to greater attention to the material being taught and deeper cognitive processing of the material, thus enhancing learning (Balslev *et al.*, 2005) [4].

The effectiveness of videos as part of instruction is enhanced when the videos are interactive as demonstrated by Zhang *et al.* (2006) [17]. Zhang and his colleagues investigated four conditions: a classroom environment, an e-learning environment with no video, non-interactive videos that students had no control over, and interactive videos where users could control what they saw and when they saw it. Results showed that both learning satisfaction and performance was greatest in the interactive video condition.

Perhaps the most well-known e-learning resource in the United States that uses such an interactive video-based instruction is Khan Academy. As in the case of the Zhang *et al.* (2006) [17] study, users of the Khan Academy website have the freedom to select any video they want at any time. The popularity of Khan Academy has even given rise to a classroom that is modeled after it (Bishop and Verleger, 2013) [5].

While websites such as Khan Academy are widely popular and freely available, the very prevalence of such resources gives rise to some very basic questions such as: How effective are they?; How well do they teach all of the students who use

them?; How robust is their teaching effectiveness across the range of content they teach, specifically easy subject matter vs. difficult subject matter? These are important research questions, the answers to which can help educators and users alike make informed decisions in the resources they use.

The questions raised in the preceding paragraph are important because one of the concerns that have been raised as technology-based education becomes more prevalent is “What is lost in terms of educational effectiveness when technology replaces a human teacher?” It is generally assumed that technology lacks the expertise that a human teacher brings such as a deep knowledge of the subject matter, expertise in teaching methods, and an ability to assess a student to see where his or her learning needs are.

Researchers in the field of artificial intelligence (AI) have focused in making technology-based instruction act more like a human teacher by encoding the deep knowledge regarding subject matter, teaching methods, and assessment abilities into the technology itself. This field is often referred to as intelligent tutoring systems (Graesser *et al.*, 2012; Sottolare *et al.*, 2013) [8, 15]. Many intelligent tutoring systems (ITSs) are modeled after John Anderson’s ACT-R theory (1990) [1], which focuses on how people learn to proceduralize the knowledge they are taught so that they can apply that knowledge to practical problem solving. Accordingly, ITSs that are modeled after ACT-R start by giving students lessons that describe the concepts they need to learn and follow this instruction by having the students engage in step-by-step problem solving. A key component of this approach is ensuring that students correctly execute the procedures that they are taught. To accomplish this, the student’s work is recorded and compared to a protocol of correct solutions. When students deviate from the correct approach, they are given feedback on what they need to do to correct their mistakes (cf., Graesser *et al.*, 2012) [8].

The combination of video-based instruction and intelligent tutoring system technology seems promising for an online e-learning resource aimed at a wide audience. The videos offer the chance to teach students in an engaging and effective manner and the ITS technology offers a means to insure that the student is actually learning the procedures being taught. Instead of simply requiring students to enter an answer and check to see if the answer is correct, students can be given the opportunity to enter their work and be shown what their mistakes are and how to correct them. We hypothesize that this would lead to greater learning performance compared to video-based instruction alone. Moreover, we hypothesize that this increased performance would also be reflected across subject matter with the ITS technology being more robust across difficult content than videos alone and across students with the ITS technology leading to more consistently high performance than video technology alone.

In order to test these hypotheses, we compared the e-learning technology of Khan Academy, which uses video-based instruction alone against the e-learning technology of A-list Empire, a social media website that uses a combination of video-based and ITS technologies. The testbed was mathematics. Mathematics was chosen since there is evidence in the literature that ITS technology can lead to enhanced mathematics performance (Steenbergen-Hu and Cooper, 2013) [16]. If these hypotheses are correct, students using the A-list Empire educational technology will show higher performance

that is more robust across difficult subject matter and show greater consistency in achieving high performance than students using the Khan Academy educational technology.

2. Methods

2.1 Participants

Participants were 20 students who were recruited from middle school and high schools in Fairfax and Loudoun counties in Virginia. Each one was enrolled in a geometry math class, which means that they had previously taken Algebra I, but had not taken Algebra II. It was necessary that each student had previously taken Algebra I since knowledge of the distributive property was necessary to learn the subject matter taught in the present study. However, it was also necessary that each student had not yet taken Algebra II since the subject matter of the present study, arithmetic operations with complex numbers, is a topic that is covered in the Algebra II curriculum. We wanted to make sure that participants in the present study had no prior knowledge of this topic. Each participated in the study without compensation.

2.2 Topic taught and educational technology used

The topic used in the present study was arithmetic operations (addition, subtraction, multiplication, and division) with complex numbers of the form $a + bi$, where i is the square root of -1 . This topic is typically part of the Algebra II curriculum. There were two core technologies used. First, for the control condition, there was the video-based lesson that teaches students how to perform arithmetic operations with complex numbers. This video-based lesson can be found on the Khan Academy website, www.khanacademy.org. It consists of seven videos, two that provide an introduction to complex numbers, one on complex conjugates and one each for addition, subtraction, multiplication, and division of complex numbers. The Khan Academy lesson software also includes a set of three practice problems per video (except for the introduction to complex numbers) and a space for entering the answer. Once the student answers an answer, there is a button, which, when clicked, states whether the answer is correct. If the student is unsure of how to do the problem, another button reveals hints, which students can use until they get the solution. These hints are not tied to the student’s work but are general in nature. At no point does the student enter his or her work in solving the problem or is the student’s work evaluated in any way by the Khan Academy software.

The A-list Empire software also presents videos that deliver general instruction on the topic followed by practice problems. The primary difference between the Khan Academy software and the A-list Empire software is that the latter includes an electronic worksheet that allows students to type in their work step-by-step. The worksheet is organized by lines, with one line given for each step. When a student is through typing in a step, s/he clicks on an enter button and the step is evaluated by the AI technology. If the step is correct, the student is notified in a feedback box below the worksheet. If the step is incorrect, the worksheet line the step is on is highlighted in yellow and the feedback box explains why the step is wrong and how the step is should be corrected. When the student completes the problem by entering the correct answer, the students is notified in the feedback box. As with the Khan Academy software, there is a hint button that students can use. In this case, the hints are tied to the step that the student has recently

completed and gives the student information on how to complete the next step. There are three hints available, each at successive levels of detail. For example, in the problems involving division of complex numbers, the general hint tells the students to multiply by 1. The second hint tells the students to try to eliminate the imaginary part of the denominator. The third hint tells the student to multiply by the complex conjugate.

The AI component of the system is based on John Anderson's ACT-R framework (Anderson, 1990) that has formed the basis of numerous AI-based instructional systems. The core of ACT-R is a production rule system where sequential procedures are stored based on the antecedent conditions that trigger them. The system then matches the student's input to the step that is listed in the production rule sequence. A match is considered to be a correct step and a mismatch is considered to be an incorrect step. ACT-R allows for more than one pathway to a solution, which is beneficial to the A-list Empire technology since there is generally more than one way to solve a problem. Typically, people who build AI-based systems for education that are modeled after ACT-R enumerate each problem solving path that is possible for solving the problem. This is done for each specific problem that the system will deliver (cf., Aleven *et al.*, 2006) [2]. This becomes particularly cumbersome if the software will ultimately deliver many problems (as would any large scale educational system) or if the system is intended to be flexible enough to allow students to enter their own homework or test-study guide problems (as we intend to allow in future versions of our system).

Therefore, in order to create a more flexible system that can support any problem within a problem class, we wrote our system to operate on generalized problem types where the numbers used in the underlying production rule model the AI engine uses are parameterized rather than instantiated. For example, a typical ACT-R system might model a simple solution path for adding $(2 + 3i) + (3 + 4i)$ as

Step 1: $(2 + 3i) + (3 + 4i)$

Step 2: $(2 + 3) + (3i + 4i)$

Step 3: $5 + 7i$.

This would require a separate model for every possible problem that the system would deliver to a student. By parameterizing each variable, we create a system that requires only one knowledge model per problem type plus the particular variable values for each problem. Therefore, our solution path for the same problem looks like

Step 1: $(a + bi) + (c + di)$

Step 2: $(a + c) + (bi + di)$

Step 3: $evl(a+c) + evl(b+d)i$. (evl means to evaluate the sum of a+c)

Problem 1: $a=2, b=3, c=3, d=4$, and so on for each problem to be used.

This method means that the system can generate unlimited problems to present to the students and the AI technology can respond to them since its representation of the problem is generic rather than hardcoded. For each possible step, there are multiple pathways that are permissible and we supplemented the algorithm with mathematical expression evaluators that recognize equivalent inputs (e.g., $a+bi$ and $bi+a$ are mathematically equivalent).

For each step in the process, the possible errors a student could make are enumerated. For each error, there is associated text that describes the error and the way to correct it.

Similarly, three hints, each progressively more specific, are also created for each step in the process. The benefit of our parameterized approach to representing the problems is that these hints and feedback can also be written generically and then populated with specifics from the problem. For example, in a standard algebra problem type of $ax+b=c$, if a person subtracts the value of b from one side of the equation and not the other, we can write the corrective feedback as "You subtracted b from one side of the equation and not the other. You need to subtract b from both sides of the equation." This format allows for one general piece of feedback to be used in any problem of this type where the user makes this particular mistake.

2.3 Procedure

The participants were first given a pre-test consisting of five problems to make sure that they did not already know the subject matter being taught in the experiment. The pre-test including problems in addition (one problem), subtraction (one problem), multiplication (two problems) and division of complex numbers (one problem). None of the participants had to be eliminated from the experiment because they already knew how to solve the pre-test problems.

Upon completion of the pre-test, participants were randomly assigned to experimental condition (Khan Academy software vs. A-list Empire software). As a result of the assignment, 10 participants wound up in the Khan Academy software condition and 10 participants wound up in the A-list Empire software condition. The first part of the instructional process was having participants in each group watch the Khan Academy videos on solving complex number problems using arithmetic operations. There were seven videos in all, two that were an introduction to complex numbers, one that taught addition of complex numbers, one that taught subtraction of complex numbers, one that taught multiplication of complex numbers, and two that taught division of complex numbers (one taught complex number conjugates and the other taught division of complex numbers). Since the main difference between the Khan Academy instructional software and the A-list Empire software is the use of AI to evaluate students' step-by-step work and provide hints and corrective instruction as needed, we wanted to keep the two conditions as close as possible. Using the same instructional videos in both conditions eliminates the possibility that any differences in resulting post-test performance could be attributed to differences in the instructional videos rather than the AI software.

After participants completed watching each instructional video (except the introduction), they were given three practice problems to solve for each type of arithmetic operation. In the Khan Academy software condition, participants were only able to enter answers to the practice problems. If they were stuck, they could press the button provided on the Khan Academy website to get general hints on how to solve the problem. These hints were not tied to the actual work done by the students, since the students had no way of entering their work on the Khan Academy website. In the A-list Empire software condition, students were given an electronic worksheet in which they entered their problem solving, step-by-step. If they were stuck, they would press the hint button and receive up to three hints as described in the educational technology section above. When they completed each step of

the problem, they clicked on an enter button and would be notified if the step they entered was correct or would receive feedback on any mistake that they made. Participants then corrected the mistakes before moving on to the next step. The problem was considered complete once the student entered the correct answer.

When participants completed each instructional video and practice problem set, they were given a post-test. The post-test consisted of 20 problems of similar format to the ones taught in the Khan Academy videos. There were five questions each for complex number operations involving addition, subtraction, multiplication, and division. Participants were allowed no additional resources, such as calculators, to assist them in solving the problems. They were given scratch paper and pencils for computations. Also, to insure consistency, participants were not allowed to replay any of the videos.

3. Results

The answers to the 20 questions on the post-test were scored based on whether the correct answer was given. Because participants did not always show their work, no partial credit was given in cases where they did show their work and made careless mistakes even if they did demonstrate that they conceptually understood how to solve the problem. We did not award partial credit, even though this is often done in schools, because we had no way of knowing whether other participants who gave wrong answers and did not show their work made their mistakes because of lack of understanding or careless mistakes. Therefore, to be consistent across all participants, we only looked at total number of correct answers.

Because there were different types of problems based on the arithmetic operation involved, the data were broken out by both condition and problem type so that we could investigate whether there were any interaction effects as well as a main effect due to technology. The mean number of correct answers by participants, broken out by condition and problem type, is shown in Table 1. As can be seen in Table 1, participants in the Khan Academy software condition averaged 49.5% on the post-test. In US schools, this is generally considered to be a failing grade (F). Participants in the A-list Empire software condition averaged 90% on the post-test. In US schools, this is generally considered to be somewhere in the A grade range.

An analysis of variance was performed on the data and revealed a main effect of technology. The difference between the two means was statistically significant, $F(1,72) = 33.53, p < .0001$. This suggests that adding AI technology, as A-list Empire did, to a video-based e-learning system can greatly improve performance. There is a secondary finding that is worth noting to the main effect. In any educational setting, there will always be some students who learn no matter how they are taught and some who will struggle. Therefore, in addition to looking at overall means, it is useful to explore how robust an educational technology is in teaching all of the students who use it. To do this, we examined the variability in scores between the two groups to see the degree to which the technology appears to help all students who use it.

In the Khan Academy group, the post-test scores ranged from 0 to 100, i.e., the full range of possible scores, suggesting that the technology is more effective for some students than others and that it is not particularly robust across students. Five of the Khan Academy students scored below 60 in the post-test (considered an F in most school districts) and with the

exception of the one student who scored 100, no other student scored above 70 (considered in the C grade range in most school districts). In the A-list Empire group, the post-test scores ranged from 80 to 100. This suggested that, while some students did outperform others, in general, all students performed reasonably well. Of the 10 students in the A-list Empire condition, seven achieved scores of 90 or above (considered in the A grade range in most school districts) and the remaining three scored in the B grade range for most school districts. It is probably rare to find an educational intervention that produces performance in the A grade range for the vast majority of the students who use it and no performance lower than the B grade range.

In order to test statistically whether A-list Empire software is more robust across students than the Khan Academy software, we looked at the variability in performance. To do this, we conducted a Levene’s Test for Homogeneity of Scores Variance across the eight different cells (2, technologies x 4 problem types). The results was statistically significant, $F(7,72) = 5.08, p < .001$, indicating that the A-list Empire software showed more consistent performance across students than did the Khan Academy software.

Another way to evaluate an educational technology’s performance is to determine its robustness across the different types of content it teaches. Clearly, some content is easier for students to master than others, so it is no real achievement for an educational technology to claim that it can teach easy content. A review of the means in Table 1, along with a consideration of the procedures involved, suggests that some arithmetic operations involving complex numbers, such as division, are more difficult than others. This was confirmed by an analysis of variance, which revealed a main effect due to problem type $F(3,72) = 3.43, p < .05$.

Table 1: Mean Number of Questions Answered Correctly Based on Question Type and Condition

	Addition	Subtraction	Multiplication	Division	Total
Khan Academy	3.5	3.2	2.4	0.8	9.9
A-list Empire	4.5	4.6	4.5	4.4	18

Given that some problem types are more difficult than others, in order to test how robust the Khan Academy and A-list Empire softwares are with respect to problem type, we look at the technology by problem type interaction. An analysis of variance revealed that this interaction is significant, $F(3,72)=2.74, p < .05$. Looking at the individual problem types, we see a trend in the Khan Academy software condition for performance to drop off as students progressed from addition to subtraction to multiplication to division. In fact, the mean performance on division problems was statistically lower than it was for addition ($p < .01$) and subtraction ($p < .05$) problems. On the other hand, in the A-list Empire software condition, there was no significant difference in the mean performance across problem types. This suggests that the Khan Academy software works better on easier subject matter but poorly on complex subject matter (the mean performance in the division problems was 16%). In contrast, the A-list Empire software worked roughly equally well on both the easiest and most complex subject matter with mean performance ranging between 88% and 92%.

4. Discussion

The primary purpose of the research was to investigate whether adding an AI capability to a video-based e-learning methodology could enhance learning. Since Khan Academy is perhaps the most widely known and used video-based e-learning platform in the United States, it served as an ideal comparison to the A-list Empire technology, which added AI technology to the video-based e-learning paradigm. The results showed both a main effect and an interaction effect.

The main effect is important because it shows that, across the board, AI technology has the potential to improve performance in video-based e-learning systems. Overall, performance between the two groups differed by more than 40 percentage points, which corresponds to the difference between getting an A or an F in school. This difference is not only statistically significant, but also clinically significant as it creates a low-cost, scalable means to improve education. Equally relevant, the A-list Empire technology showed itself to be robust across students, with no student scoring below 80% on the post-test and seven of ten students scoring in the A range. In contrast, the Khan Academy software did not show itself to be robust across students as scores ranged from 0% to 100%, with five of ten students scoring in the F range and only one scoring above a C. These results suggest that a video-based e-learning paradigm without AI is neither particularly effective at producing high performance nor robust across students while one with AI is effective at producing high performance and is highly robust across students.

The interaction effect shown in the present experiment is also noteworthy since it addresses the issue of whether video-based e-learning systems with and without AI are robust across subject matter. The Khan Academy technology, which lacks AI technology, showed a steady drop in mean student performance from 70% to 16% as problem types increased in difficulty. This difference was statistically significant and suggests that video-based e-learning systems without AI are, at best, marginally useful for easier subject matter, but work very poorly for more complex subject matter.

On the other hand, the A-list Empire technology, which includes AI technology, showed consistently high performance across all problems types, with no statistically significant difference in mean performance. This consistency shows that, while adding AI is useful for all subject matter, it particularly shines when the subject matter is complex. Mean student performance rose by about 30% when students used AI-based technology to learn the easiest subject matter (addition of complex numbers), but mean student performance was 5.5 times higher for the most complex subject matter (division of complex numbers).

5. Conclusion

As noted in the Introduction, there is a plethora of educational resources available on the Internet these days. Even when resources are free, there is the opportunity cost of the time investment in using the resources and the potential impact on students' grades as a result of their use. The latter is especially important because grades become increasingly important as students progress throughout school. This is particularly true in the high school years where grades are an important consideration that colleges use in admissions decisions. Therefore, the challenge that students face when looking for

supplemental educational resources is to find resources that actually boost student achievement.

The present findings indicate that a key consideration in designing video-based e-learning systems is the inclusion of AI technology that allows students to enter their work step-by-step and receive feedback regarding the mistakes they make and hints that are tied to the actual work done by the student so far. The A-list Empire technology includes such AI capabilities and was shown to produce high performance across all students and across all content that was tested. On the other hand, the Khan Academy technology, which lacked such AI capabilities, showed much lower overall performance, particularly in more difficult subject matter. Moreover, the performance across students was highly variable, suggesting that only a limited number of students would actually derive benefits from the technology.

While the present study indicated that AI technology shows promise in producing high student achievement across both easy and complex subject matter, additional research should be done. Such research should focus on other grade levels and associated topics within math, and also on other subjects that may be non-computational in nature. Also, of benefit may be the inclusion of authoring tools that allow users to enter their own problems into the software so that they can use the technology to help them with homework and to study for tests. This would enable the technology to more closely align with curricula used in schools and thus make the integration of the technology into the school system easier.

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