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ABSTRACT

Technology facilitates advances in learning and drives learning paradigms. One recent innovation is Twitch™, an online streaming platform often used for video game tutorials but also enables amateur online instruction (Hamilton, Garretson, & Kerne, 2014)). Twitch represents a unique learning paradigm that is not perfectly represented in previous technologies because of its "ground-up" evolution and the opportunity for novice instructors to educate mass audiences in real-time over the Internet while enabling interaction between teachers and learners and among learners. The purpose of this research is to empirically examine the efficacy of Twitch as a learning platform by manipulating each of the key characteristics of Twitch and to understand the conditions in which novice instructors may be beneficial. Drawing from Cognitive Load Theory, we demonstrate the worked-example effect in the Twitch environment by manipulating teacher-learner-learner interactions, live versus recorded streaming, and expert-versus novice-based instruction. Based on a laboratory experiment involving 350 participants, we found that learning performance under novice instructors was at least as good as that of experts. However, an exploratory analysis of learner personalities revealed that extroverts benefit only when learner-learner interaction is enabled. Surprisingly, those who are highly agreeable and less neurotic benefited more from novice instructors.

1. Introduction

Advances in technology have enabled valuable new forms of learning—particularly the ability to facilitate online distance learning (Moore & Kearsley, 2011). Discussion boards and chat rooms allow real-time teacher-learner and learner-learner interactions (Vrasidas & McIsaac, 1999). Traditional YouTube™ and similar platforms allow asynchronous video-based instruction (Duffy, 2007; Moran, Seaman, & Tinti-Kane, 2011) that has been effective for learning—particularly in medical contexts (Azer, 2012) and other procedural memory contexts (Lee & Lehto, 2013) where the curriculum includes motor skills and procedures.

More recently, live-streaming platforms—such as Adobe Connect™, GoToMeeting™, and WebEx™—have become very popular. These technologies are very interesting as learning platforms because of two key capabilities which are known to improve learning in certain contexts: 1) real-time interaction between and among the teacher and learners (Bradley & Lomicka, 2000) and 2) video-based instruction (Duffy, 2007; Moran et al., 2011).

Put in academic terms, these technologies allow large scale distance-based implementations of the *worked-example effect* (Sweller & Cooper, 1985). In other contexts the same phenomenon has been called "vicarious experience" (Achterkamp, Hermens, & Vollenbroek-Hutten, 2016). Teaching by example is one of the most effective techniques for reducing the cognitive load required for early stage learning (Kirschner, Sweller, & Clark, 2006). Implementing worked-example based learning over distances (often referred to as "computer-mediated communication") is not new (Duffy, 2007; Gaudiosi, 2012; Kay, 2012; Shane, Stevens, Harenski, & Kiehl, 2008); however, although prior technologies such as YouTube allow massive scale knowledge dissemination, until recently they have not allow the real-time interactions of live-streaming. To this end, when face-to-face interaction is not possible, other multimedia like videoconferencing have been able to provide a more interactive environment than video alone (Shephard, 2003). Yet, videoconferencing has not been historically

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connected to a large-scale audience like those achieved through YouTube. Technologies like Adobe Connect, GoToMeeting, WebEx, and others allow both live-streaming video and live participant interactions. To our knowledge, these technologies have not been tested empirically for their ability to support worked-example based learning in a live, interactive, and distributed environment.

Most recently, one of this family of technologies has emerged as a unique alterative: Twitch™. Twitch was originally created as a platform for gamers who wanted to share experiences with the gaming community. Researchers have described Twitch as a "virtual third place, in which informal communities emerge, socialize, and participate" (Hamilton, Garretson, & Kerne, 2014, p. 1). Similar to the other technologies, Twitch enables live-streaming and all forms of participant interaction (Hamilton et al., 2014).

There is a unique aspect of Twitch that makes it an interesting focus of research. As opposed to the alternatives, Twitch was created from the "ground-up" rather than produced by mainstream technology companies. It was developed for and adopted by gamers rather than organizations. Twitch is both freely available and often used by amateur instructors—who range from novices to experts—rather than by professional instructors. This distinction makes Twitch particularly interesting to information systems (IS) research because much of the learning that takes place by IS professionals comes from searching the Web or otherwise drawing upon the Internet for *informal* guidance as opposed to corporate training (Vasilescu, Filkov, & Serebrenik, 2013). Indeed, software development is one of the emerging forms of learning that takes place over Twitch (Hamilton et al., 2014). In summary, the research question addressed in this study is *under what conditions might training platforms that enable live streaming and live distributed participant interactions that are free—and therefore include the likelihood of novice instructors—be an effective enabler of worked-example based instruction?* Because Twitch is currently the dominant platform that fits the above conditions, it is the focus of our study. Other similar platforms include YouTube Gaming for games and LiveCoding.tv for programming, among many others.

To address this research question, we experimentally evaluate Twitch by using its various features in an environment of both novice and expert instructors. Our learning context for this experiment is the League of Legends™ video game, once rated the most popular computer game in the world (Gaudiosi, 2012). We recruited a wide variety of skilled, novice, and first-time players who were randomly assigned to one of several tutorials on how to improve their score on an in-game task. Although the learning that takes place while playing video games is clearly not a high priority for most organizations, it offers objective and easily quantified measures of learning performance, making it ideal for experimentation.

Our experiments include gameplay tutorials manipulated based on the level of trainer expertise (expert vs. novice), the presence of teacher-learner and learner-learner interaction capabilities (via the Twitch chat), and live-streamed versus recorded video tutorials. Using a single-subject design, we measured participants' performance before (baseline) and after the treatment.

We found several results, both expected and surprising, from the analysis that suggest positive yet cautionary implications for learning through live-streaming. Most importantly, novice instructors are at least as effective as expert instructors in various conditions. In particular, enabling learner-learner interaction is critical under novice instructors. In addition, we performed an exploratory analysis of personality traits. The results revealed that extroverts benefit from learner-learner interaction, while introverts' learning suffers from the same interaction. Also, those who are disagreeable suffer under novice instructors *unless* interaction is enabled. Similarly, those who are the least neurotic benefit more from novice instructors. In summary, our findings indicate that technologies like Twitch that allow for novice instructors show promise, but care must be taken to enable appropriate interaction for the learning and teaching style present.

2. The Twitch learning context

2.1. Related technologies

Twitch is far from the only technology that provides the capability for real-time interaction between a teacher (streamer) and distributed live learners (viewers). For many educational contexts, there are more presentation-oriented tools than Twitch such as Adobe Connect or Citrix GoToMeeting that allow for quick transitions between different presenters, making it simple to switch from an expert such as a professor to a novice student presenting. These tools also have many built-in options to make the interaction as useful as possible. Some of these include built-in text and voice communication with the option to include a webcam, and the option to record a conference for later viewing. These options make these tools excellent for distance education applications.

Despite the advantages of the more professionally-oriented tools, we are interested in Twitch because of its open nature and free cost to both learners and instructors—making it a less formal alternative that is especially interesting in the context of gaming and game programming. On a given day you might find a dozen people streaming live while they develop games or work on game-related programming projects. Similarly, because anyone can create a Twitch channel, the instructors may be both experts and novices, making it an interesting context for examining the conditions under which novice instructors may be equally effective as experts (Shane et al., 2008).

While Twitch has not been widely adopted for non-gaming training, other technologies such as Adobe Connect™, GoToMeeting™, WebEx™, and YouTube Live are being used by universities (c.f., Wilmington University, 2012), organizations (c.f., De, 2017), and even exercise trainers (c.f., McColl, 2016). Twitch has also recently promoted using their services for more than just gaming content (Carpenter, 2016). Lastly, Twitch has dedicated channels for programming and artistic endeavors.

Although research on Twitch is still sparse, there are several interesting related studies worth noting. As a platform, Twitch has been examined to determine the relationship between viewer gratification, game genre, and content type in the context of live gaming (Sjoblom, Torhonen, Hamari, & Macey, 2017). Related video streaming platforms have been used outside of the gaming context to study learning outcomes and learner behavior. For example, one study used data and text mining techniques to investigate student-instructor and student-student interaction enabled in the live-streaming environment (He, 2013). Themes of discussion as well as types of disciplinary action used in both types of interaction were analyzed. Another live-streaming study enabled participants separated by distance to simultaneously view a baseball game and emote towards the game (Lim, Cha, Park, Lee, & Kim, 2012). The emoting capabilities enabled effectively reduced the psychological distance created by the video-streaming environment. Finally, serious video games have been used in primary and secondary education as a means of developing problem-solving skills (Kang, Liu, & Qu, 2017). Recently, actual gameplay has been examined to better understand the effectiveness of learning in game-based environments. Next, we review relevant theory and research that can explain the effects of the Twitch environment.

2.2. Teacher-learner-learner interaction

The role of the teacher in formal education is increasingly moving from a “sage on the stage” to a “guide on the side” (King, 1993). Teachers are innovating with new ways to help students grow and some of the popular innovations are the role of peer instructors and student-driven discussions (Crouch & Mazur, 2001). The goal of these methods of teaching is to have students apply and practice the material they are trying to understand. This style of teaching hearkens back to an apprenticeship-style of learning common before widespread access to formal education. Therefore, education is evolving from teacher-learner interaction, in which teachers disseminate knowledge to students that can ask clarifying questions, to teacher-learner-learner interaction in which teachers and learners share knowledge and practice with other learners.

There are benefits from learning from experts and novices alike. Experts impart their knowledge to novices and novices learn while observing other novices. Novices learn from making mistakes as well as watching the mistakes of others (Shane et al., 2008). Technologies like Twitch offer novices the opportunity to stream their content to other novices as well as experts. Other novices learn by watching the streaming novice make mistakes and novices in general benefit from expert guidance.

2.3. Learner-learner interaction

The effect of student interaction on learning outcomes in online learning environments has been well-researched. Studies have shown that enabling and encouraging learner-learner interaction in an online setting improves academic performance. Students learn more when they have collaborative, interactive, and real-world tasks (Kearsley & Shneiderman, 1998). In a collaborative environment, students must verbalize their understanding and issues with a task, which leads to increased understanding of the task either through formalization of their understanding or explanation from other team members (Kearsley & Shneiderman, 1998). While completing interactive tasks, students must apply their base knowledge to different contexts to create new products. This process produces tangible deliverables that students can take pride in assembling and are easily understood by family and friends (Kearsley & Shneiderman, 1998). During the completion of real-world tasks, students learn skills that transfer more easily to work settings (Kearsley & Shneiderman, 1998). Real-world tasks give students higher satisfaction than text-book tasks as they can see the impact of their work on people and organizations (Kearsley & Shneiderman, 1998). The inclusion of these three elements in learning activities is hypothesized to maintain learners' active participation in the tasks (Dickey, 2005).

Learning environments in which learners play an active role in the process (e.g., game) are more engaging than learning environments where learners play a passive role in the process (e.g., lecture) (Dickey, 2005). This concept is based on a constructivist view of learning that states that learning occurs when the teacher builds upon the previous knowledge of the student (Bonk & Wisher, 2000; Dickey, 2005). Constructivists believe that students learn better when they discover knowledge on their own as opposed to when it is just given to them (Zhang, Zhou, Briggs, & Nunamaker, 2006).

3. Cognitive load theory

Before examining whether Twitch can improve learning, it is important to theoretically frame the meaning of “improved learning.” In referencing the improved learning of a skill, we are explicitly interested in *procedural knowledge* rather than *declarative knowledge*. Declarative knowledge refers to a mental understanding of the tasks required (Anderson, 1982). Procedural knowledge, on the other hand, is where that mental understanding is translated into action through improved ability to perform the task (Anderson, 1982). Our interest in learning is focused on the acquisition of procedural knowledge, which is translated into improved skill. Procedural learning can be enhanced by reducing the cognitive load associated with the learning process (Pollock, Chandler, & Sweller, 2002). This conceptualization has roots in core psychology research that discovered that humans can only keep a certain amount of information in short term memory at a particular time (Miller, 1956) and that this memory can be improved by “chunking” information together (Chase & Simon, 1973).

Based on these concepts, we draw from *cognitive load theory* (Sweller, 1988, 1994, 2011) and some of its predicted effects to explain exactly how interactive live-streaming may improve learning. The term “cognitive load” (CL) refers to the overall mental effort required in working memory as new material is learned, or in other words, is transferred from working memory to long term memory where it becomes automated and even sub-conscious processing (Baddeley, 2012).

CL can be sub-divided into three types: intrinsic, extraneous, and germane (Sweller, 1994). The *intrinsic* CL refers to the general complexity of the knowledge being learned (Sweller, 2011). Intrinsic CL is unique to the learner and is based on the gap between what they already know and what they are trying to learn (Sweller, 2011). As a result, it is mostly fixed and difficult to affect for a given piece of information during a particular learning task.

In contrast, *extraneous* CL is completely determined by the instructor and the learning materials, channel, and design. Kirschner et al. (2006) offer the example that there are two ways to teach the concept of a square to a student. The teacher can 1) verbally explain the concept of a square or 2) show an image of a square. Because a square is a figure, it should be taught using a figural medium. Using text or a verbal explanation in this case is an example of a poorly-designed material that creates unnecessary extraneous CL and, as a result, increases the difficulty of knowledge transfer from working memory to long-term memory. Similarly, the channel by which learning occurs would also potentially constrain the level of extraneous CL if it doesn't afford the medium suitable to the knowledge being learned. If the teacher and learner are not face-to-face, then a video-only channel (without audio) would create extraneous CL for students learning to sing a song. Likewise, an audio-only channel would create extraneous CL for students learning a procedural technique that is best performed with figures or videos.

Extraneous CL also varies depending on the existing knowledge of the learners (Kalyuga, 2008). In the case of novices learning math concepts, static diagrams can be useful because they allow students to proceed at their own pace and internalize concepts before moving on. Animations are best used for more knowledgeable leaners, as they can provide further information or context not available in a static diagram (Kalyuga, 2008). Providing the wrong instructional materials, or the right materials in the wrong format can increase extraneous CL and reduce learning. In summary, extraneous CL should be minimized wherever possible.

Lastly, researchers later discovered that not only does the quality of materials affect overall CL, but the variability of those materials—such as the worked examples given to students—has an effect on learning (Paas & Van Merriënboer, 1994). In particular, Paas & Van Merriënboer, 1994 found that although giving math problems to students that are very similar decreased CL, it also subsequently decreased learning. Worked examples with high variability lead to higher CL and learning. This variability in worked examples helped learners to generate mental schemas which aid learning. This is referred to as *germane* CL.

In summary, conventional wisdom states that extraneous CL should be minimized to allow for the greatest capacity for germane CL, which should be optimized (Sweller, 1988, 1994, 2011; Chi, Feltovich, & Glaser, 1981; Clark, Nguyen, & Sweller, 2011; Paas & Van Merriënboer, 1994; Sweller & Cooper, 1985; Vasilescu et al., 2013). To the degree that technology (e.g. Twitch) can support these goals, it will enhance learning.

3.1. CL effects

CL theory has been subsequently used to generate several instructional techniques designed and demonstrated to facilitate learning. Several of these "CL effects" are enabled by the Twitch platform and help explain why live-streaming may be a valuable tool for distance learning. The effects have been demonstrated to reduce the time to learn and enhance performance on test problems (those that are similar to those seen during training) and transfer problems (those that are dissimilar to problems seen during training but can be solved by following the same high-level rules).

First, and perhaps most relevantly, Twitch enables the *worked-example effect* (Sweller, 1988). A worked-example is when somebody demonstrates how to perform a task step-by-step to another (Clark et al., 2011). Worked examples teach learners how to 1) identify specific types of problems, 2) recall the steps required to solve them in sequence, and 3) recall how to perform each step without error. Worked examples (e.g. a math problem worked step by step) are desirable when the problem to be solved is relatively complex and requires a series of steps or procedures. By following a worked example, learners are provided with a mental schema and are being directed through a path that reduces extraneous CL and enhances germane CL—thus, improving learning. Clearly, by offering live streaming of video, Twitch enables the worked-example effect for large audiences of learners. This is technique is used in our experimental design.

The *split attention effect* (Sweller, 1994) refers to the situation where learning requires both visual and text components but the two modes are not adequately combined. The working memory required to combine the text and visual elements reduces the amount of working memory available for learning. As a result, separated text and visuals do not necessarily prohibit learning, but reduce the speed and performance of the learning process. Twitch improves the split attention effect by combining live-streaming video and an integrated chat room on the same screen. For example, while video is playing, users can also get text-based instructions from the teacher. Furthermore, the teacher can enable the camera, speak directly to the users, and provide audio instructions.

Fig. 1 depicts an example of all three components being used in Twitch: 1) the chat on the far right among viewers, 2) the gameplay in the large visual, and 3) the streamer in the upper right corner of the gameplay. Twitch will not eliminate split attention effects because these occur whenever both audio/text and visual elements are simultaneously being presented. However, they can be minimized by incorporating them together into a single platform. Lastly, it should be cautioned that Twitch should only provide split-attention benefits in contexts where text and visual materials are needed.

3.2. Hypotheses

Based on the above review of CL theory, it is clear that learning over the Twitch platform (or similar live-streaming services) depends greatly on features that enable presentation of worked examples and better facilitate split attention. There are two features of live-streaming platforms that are informed by CL theory that we manipulated in our research experiment: **1)** watching a live stream versus watching pre-recorded audio and video instruction, and **2)** facilitating teacher-learner versus learner-learner interactions.

However, the ability to reduce extraneous CL—and thus improve learning—also depends on the competence of the teacher. One aspect of live streaming platforms that sets Twitch apart from its alternatives (e.g. Adobe Connect) is uncontrolled viewer participation. In other words, Twitch streaming is an informal event where streamers and audiences form organically-based discussions without formal constraints. This means that teachers (streamers) may be experts or novices. Similarly, learners (viewers) may come from a variety of levels of expertise with varying degrees of interest in learning (versus watching for entertainment value). As a result, we also manipulated **3)** the competence of the instructor.

Our theoretical model (see Fig. 2) explaining the performance of learning based on worked examples over Twitch is based on CL theory (Paas & Van Merriënboer, 1994; Sweller & Cooper, 1985;

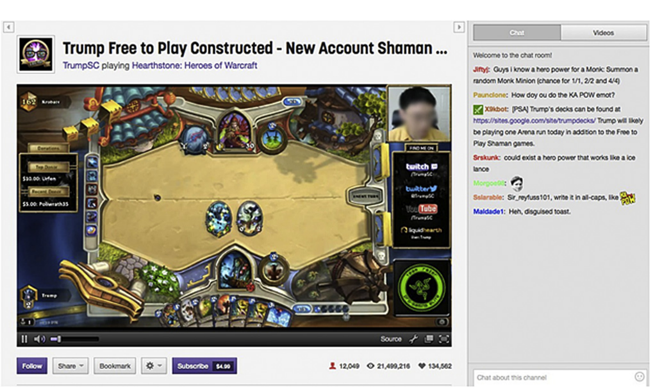


Fig. 1. Twitch live-streaming screenshot.

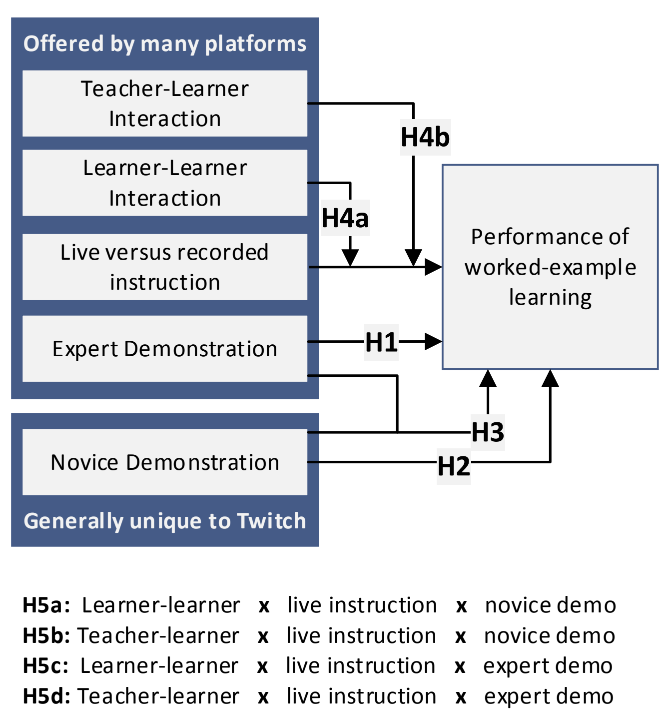


Fig. 2. Theoretical model.

Sweller, 1988) and our specific hypotheses are formulated around the unique characteristics of live-streaming platforms like Twitch. As such, this is not a theoretical model intended to explain the efficacy of all worked-example learning.

3.3. Training from experts

Intuitively, we expect that learning from experts is the most effective way to learn (Hinds, Patterson, & Pfeffer, 2001). Experts become experts through the accumulation of knowledge and/or experience and therefore have information they can provide to learners. Therefore, as experts have extensive knowledge, they appear to be ideal candidates to train others.

Experts have superior and more abstract mental representations of tasks than novices (Chi et al., 1981). A *mental representation* is "a person's knowledge or understanding of how a task functions and how to attempt to obtain a solution to the task" (Giboney, Brown, Lowry, & Nunamaker, 2015, p. 3). Due to increased experiences, experts create more abstract mental representations to account for variance in task processes (Chi et al., 1981). They also explain and demonstrate knowledge in more abstract concepts than novices, who do so in concrete ways (Chi et al., 1981).

As learners receive and assimilate instruction they typically enhance their performance at the task. For the purposes of this paper, performance is defined as the *speed and accuracy at which a person can perform a task* (Speier, 2006). Therefore, when receiving instruction from an expert, learners are expected to increase the speed and accuracy at which they perform the task. Thus, we hypothesize the following:

H1. Learners viewing an expert perform a task will perform better than those who do not receive instruction from an expert.

3.4. Training from novices

It is intuitive to believe that receiving any instruction, even from another novice, will increase learning over not receiving any instruction. This should occur at least to the point where the apprentice learner surpasses the novice master. However, quite a lot can be learned from novices, not only from the knowledge that they convey, but also from the mistakes that they make (Shane et al., 2008). In addition to making mistakes that afford others learning opportunities, novices also explain their knowledge in more concrete ways than experts, allowing for other novices to better understand and follow their instructions (Hinds et al., 2001). The next paragraphs will elaborate on these two concepts.

Humans learn from their experiences by creating mental representations of tasks and activities that allow them to transfer knowledge from one instance of a task to the next and from one task to similar tasks (Simon & Hayes, 1976). Therefore, when humans make mistakes, they transfer that knowledge to avoid making the same mistake in the future. Further, research has demonstrated that the same neural pathways are activated when individuals watch another make mistakes as when individuals make their own mistakes (Shane et al., 2008). Therefore, not only can humans transfer knowledge from their own mistakes to another instance of a task, but they transfer knowledge from the mistakes of others to another instance of a task. Therefore, when novice learners watch other novices perform a task, they learn from the mistakes of novice instructors to improve their own performance.

Not only do novice learners learn from the mistakes of novice instructors, but compared to expert instructors, novice instructors likely explain tasks in more concrete ways (Simon & Hayes, 1976). In fact, research has demonstrated that experts may have trouble teaching novices, as experts convey their knowledge in abstract ways and may have trouble adjusting their teaching style for novices (Simon & Hayes, 1976). As experts have experience with many variations of a task and have dealt with extensive error handling, their knowledge and explanations become more abstract to cover possible variations. Novices, on the other hand, do not have this abstracted knowledge and will explain the task in a very

Fig. 3. In-game screenshot of (1) a player (2) killing a minion to receive gold.

straightforward manner. Because of this we hypothesize the following:

H2. Learners viewing a novice perform a task will be able to perform the task better than learners who receive no instruction.

Lastly, it should be noted that novices and experts are not two ends of the same scale. Different forms of learning can take place from novice versus expert instructors. Therefore, learners who have developed *some* level of expertise—but perhaps are still relative novices—should benefit from the combined tutelage of both novices and experts. Therefore, by combining the ways that experts share knowledge and novices share knowledge, learners should receive a more enriched way to learn.

H3. Learners viewing both an expert and a novice perform a task will be able to perform the task better than learners who view either only the expert or the novice.

3.5. Learning environments

Learner-learner interactions provide the means for learners to interpret, clarify, and validate their understanding (Kraiger, 2008). Interestingly, computer-mediated learner-learner interaction is particularly meaningful and effective (Bergmann & Sams, 2012; Moore & Kearsley, 2011; Roehl, Reddy, & Shannon, 2013). Originally, computer-mediated learner-learner interaction was asynchronous because technologies did not make synchronous distance interactions possible. While this form had certain benefits—such as more democratic outcomes and more reflective discussion (Jonassen & Kwon II, 2001)—it still does not allow the immediate response necessary for many contexts. Smith, Alvarez-Torres, and Zhao (2003) categorized technologies based on their temporality, with synchronous technologies showing more promise in online learning.

H4. Learners in a live interactive environment will be able to perform a task better than learners in a static environment. (a. learner-learner, b. teacher-learner).

There are multiple types of learning environments found in education literature (Kraiger, 2008). Learning environments are "learner-content" when learners must learn the content on their own, "learner-learner" when learners can communicate with other learners as they learn, and "teacher-learner" when learners interact with an instructor as they learn (most typical in education settings). Twitch allows for learner-learner interactions, as viewers can chat with each other during the live stream as well as teacher-learner interactions, as viewers can chat with the streamer and the streamer can respond.

If learner-learner interactions allow learners to discuss their understanding, they will be able to discuss what they learn from experts or novices and be able to learn more effectively.

H5. Learning from a) an expert or b) a novice will be positively moderated by c) teacher-learner interaction and d) learner-learner interaction.

4. Methodology

To examine the efficacy of Twitch-based worked-example learning, we implemented a laboratory experimental design. We selected the video game League of Legends—a popular game with highly detailed and nuanced gameplay that takes time and effort to learn. Although video game learning is clearly not the focus of most organizations, it does provide a useful scenario where learning performance can be objectively measured—through the in-game player score. In addition, the time-pressured environment is very similar to that experienced by software developers that balance the performance of their product (e.g. software defects and speed) against a finite amount of time and resources available. Lastly, much like software development and other forms of technology-based problem solving, video gaming is best learned in worked-example form.

4.1. Game context: League of Legends

The game of League of Legends® is a Multiplayer Online Battle Arena (MOBA) computer game produced by Riot Games. For our purposes, we use a variation of the game that allowed us to measure performance on a particular task with no distractions (number of minions killed). Every 30 s for the duration of a match, waves of minions move from each base toward the enemy side of the map. These minions deal minimal damage, but killing them provides players with significant gold to improve their own abilities. One of the fundamental skills of League of Legends play is to learn how to "last hit" the minions, dealing the critical last hit necessary to kill the minion and thus receive the gold. Unless a player delivers the killing blow to a minion, they do not receive gold for the kill. During the game, each player can see how many minions they, their teammates, or their enemies have killed. The process of killing minions is referred to as "CSing" (pronounced "*SEE-ESS-ing*") in the League of Legends community (see Fig. 3).

League of Legends is one of the most popular games streamed over Twitch. Some people tune in to these streams hoping to improve their own skill in the game by learning from professionals. Our experiment tests various methods of teaching and learning via the interactive style of Twitch.

4.2. Experimental manipulations

The experimental procedure consisted of a control condition and two sets of manipulations. In the control condition (Condition 1 in Table 1) participants completed the CSing task four times with no additional training or external input. The first manipulation related to the interactivity of the training. Participants received training through one of three levels of interactivity. In the lowest level, no interactivity, participants viewed a recorded training video individually via a video player (Conditions 2, 3 and 4 in Table 1). In the next level, learner-learner interaction, participants viewed the same recorded training over Twitch with a cohort of other users with whom they interacted (Conditions 5, 6, and 7 in Table 1). The pre-recorded video was streamed over the Twitch enabling participant chat communication but no interaction with the creator of the tutorial. Finally, in the teacher-learner-learner interaction condition, participants received a live training session streamed through the Twitch interface (Conditions 8, 9 and 10 in Table 1).

Table 1
Experiment conditions.

#	Condition
1	Tutorial only
2	Expert video
3	Novice video
4	Expert video and novice video
5	Expert video with learner-learner interaction
6	Novice video with learner-learner interaction
7	Expert video and novice video with learner-learner interaction
8	Expert Twitch
9	Novice Twitch
10	Expert Twitch and novice Twitch

Using the Twitch chat, participants in this condition interacted with both the teacher (streamer) and other learners (viewers) during the training. Interactivity is represented by the experimental manipulations and not the content of the chat messages produced.

The second manipulation in this experiment was the level of expertise of the trainer. Participants received training on CSing skills from one or both of the following individuals: 1) an expert who has received a high rank in the game, and 2) a novice who began playing the game within a week of the experiment. Both the instructors recorded training sessions for use in the video conditions described above.

Ten conditions were observed overall (see Table 1).

4.3. Measurement

To measure improvement, we used a pre-/post-manipulation comparison of CS (how many minions the participant "last hit" within 10 min. A "perfect" CS score at 10 min into the game is 107, and we can measure change in skill by comparing how close to that number players get before the manipulation versus after the manipulation.

A customized private game was created for each participant during each session to reduce variation between individual sessions. All participants were also directed to use the same in-game character for all sessions and used new accounts created for the experiment to remove any other variation.

To ensure that all participants were completely honest in reporting their CS at 10 min, a program recorded each game in the background, saving it to a file that could be played back later. These recordings were used to verify data.

To create a measure of improvement we subtracted the second game (the last before the training) from the third game (the first game after the training). We chose to use the second game as the baseline because it was the first time playing for many of the participants and we would expect to see a large difference in performance from any new player between their first and second game (see Fig. 4).

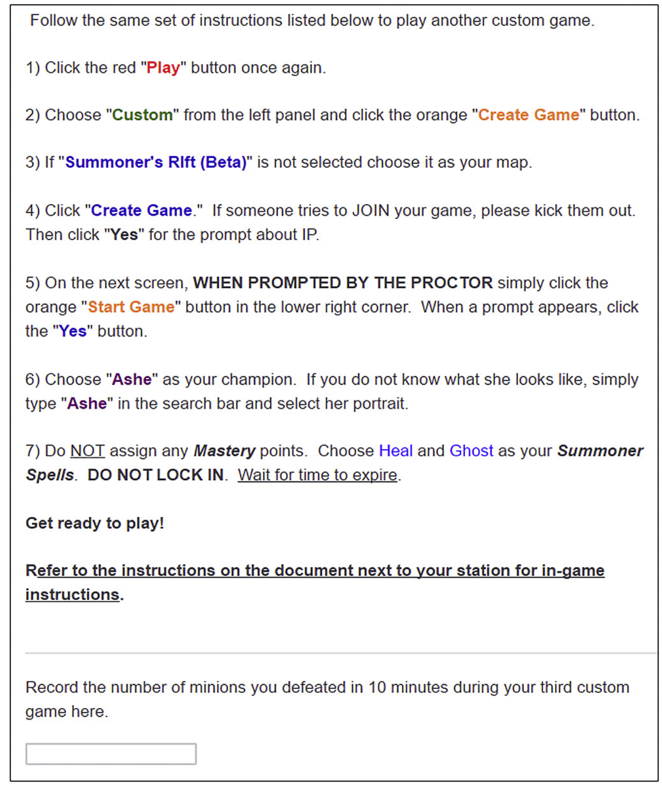
4.4. Experimental procedure

For each experimental session, participants were in a computer lab in groups of up to 25. Experimental conditions were randomly assigned based on session. Each participant was provided with a computer and assigned an anonymous Twitch (if in the Twitch condition) and League of Legends account for use in the experiment. Each then completed a survey of demographic information and gaming-related experience with some specific questions about League of Legends experience (see Table 2).

Each participant then completed the beginner's tutorial. Even participants who had played the game in the past completed the tutorial to ensure that everyone was on approximately the same schedule. Following the tutorial, participants created a custom game and played for 10 min, attempting to get the best CS score possible. Following this and each other game, players recorded their CS score at 10 min in an online survey (see Fig. 4). Following the first game they completed a second game in the same manner.

After the first two games, all participants were instructed to wait until signaled by the experiment facilitator. At this point, participants received their experimental manipulations. The session was instructed to either sit quietly, enter the Twitch room, or view the training video(s) based on their assigned condition.

Following the manipulation, participants returned to the game and played two more private games for 10 min each. Scores for these sessions were recorded in the same manner as the pre-manipulation scores.


Follow the same set of instructions listed below to play another custom game.

1) Click the red "**Play**" button once again.

2) Choose "**Custom**" from the left panel and click the orange "**Create Game**" button.

3) If "**Summoner's RIft (Beta)**" is not selected choose it as your map.

4) Click "**Create Game**." If someone tries to JOIN your game, please kick them out. Then click "**Yes**" for the prompt about IP.

5) On the next screen, **WHEN PROMPTED BY THE PROCTOR** simply click the orange "**Start Game**" button in the lower right corner. When a prompt appears, click the "**Yes**" button.

6) Choose "**Ashe**" as your champion. If you do not know what she looks like, simply type "**Ashe**" in the search bar and select her portrait.

7) Do NOT assign any ***Mastery*** points. Choose Heal and Ghost as your ***Summoner Spells***. **DO NOT LOCK IN**. Wait for time to expire.

Get ready to play!

Refer to the instructions on the document next to your station for in-game instructions.

Record the number of minions you defeated in 10 minutes during your third custom game here.

Fig. 4. Gameplay instructions and score reporting.

Following the fourth and final game, participants completed another survey that included Big Five Personality Trait items (Costa & MacCrae, 1992) and asked about their experiences in the game and sentiment related to the training and the game (see Table 3).

4.5. Participants

We obtained participants through introductory Information Systems courses where participants received course credit for their participation in research studies. In total, we had 350 participants. 279 (79.71%) participants were male. The mean age of the participants was 22.19 (SD = 2.99). For the most part, participants are used to playing games with a mean of 2.27 days per week (SD = 2.50). Two hundred and eighty-one (80.29%) of our participants had never played League of Legends before.

5. Results

To test our hypotheses, we employed analysis of covariance (ANCOVA) using planned contrasts. The ANCOVA tests the effect of specific conditions and covariates on the improvement between games two and three. We have a couple reasons for testing the difference between games two and three. First, for many participants, the first game played was their first time ever playing the game. This leads to many issues with learning the controls of the game and just figuring out what to do and how to do it. As a result, we expect to see improvement between games one and two simply from becoming acclimated to the game. Second, the training intervention was applied after the second game, so the information from that training will be freshest in the players' minds immediately after the training. For these two reasons, our analysis focuses on the change from game two to game three. There was an expected improvement as participants played the games (see Fig. 5).

Table 2
Presurvey questions.

Question	Measurement
What is your gender?	Male/Female
What is your age in years?	Text input
Which of the following do you play or have you played in the past? (Select all that apply)	Mobile App Games, Console Games, Computer Games
How many hours per week do you spend playing video games of any kind?	Text input
How many days per week do you spend playing video games of any kind?	Text input
Please rate your level of interest in each video game genre below (0 low interest, 10 high interest):	Slider 0 to 10
Action, Adventure, Puzzle, Sports, First-Person Shooter, Multi-Player Online Battle (MOBA), Real-Time Strategy, Massively Multi-player Online, Platformer, Simulator	
How long have you been playing League of Legends?	Less than 6 months, At least 6 months, At least 1 year, At least 2 years, At least 3 years, At least 4 years, At least 5 years, I was in Beta.
What is your in-game rank?	Unranked, Bronze, Silver, Gold, Platinum, Diamond, Master, Challenger
How many hours per week do you spend playing League of Legends?	0-1, 1–2, 2–5, 5–8, 8–10, More than 10
If you regularly play League of Legends, what primary role(s) do you play (select all that apply)?	Support, Jungle, Middle Lane Carry, Top, Bottom Lane Carry
What map do you primarily play on?	Summoner's Rift, Twisted Treeline, Crystal Scar, Howling Abyss
Do you usually play against artificial intelligence bots?	Yes/No

Table 3
Post survey questions.

Question	Measurement
I learned useful information from the tutorial about League of Legends	Strongly Disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly Agree
I learned important information from the tutorial about League of Legends	Strongly Disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly Agree
The tutorial about League of Legends helped me perform better in the game	Strongly Disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly Agree
What aspects of the tutorial were most useful to you?	Open answer
What aspects of the tutorial were least useful to you?	Open answer
Your minion kill score many have fluctuated over the course of your four custom games. Please explain why you may have obtained a higher or lower score between different games.	

Out of a possible 107 minions killed, the best score from a participant was 95, so no ceiling effect was present. We also show the summary statistics in Table 4.

We created eight planned contrasts using our hypotheses before running our analysis. The planned contrasts are designed to test certain conditions with other specific conditions. Performing the analysis in this manner allows for direct tests of the hypotheses without conflating the constructs being tested with the conditions. For example, as shown in Table 5, Hypothesis 1 expects expert training to be better than no training. Therefore, Hypothesis 1 is testing conditions 2, 5, and 8—the three expert training conditions—against condition 1—the control group.

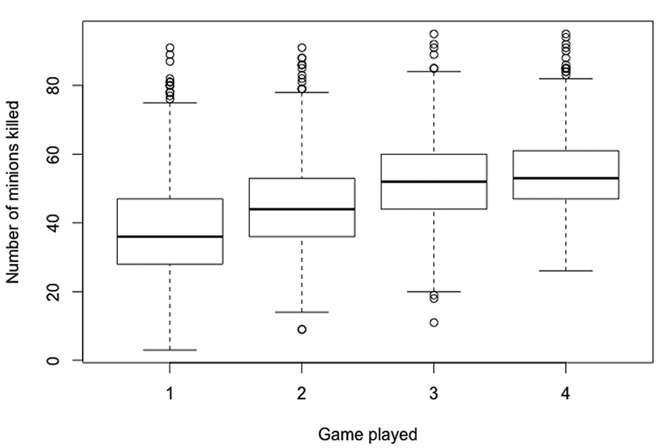


Fig. 5. Performance comparison.

We ran an ANCOVA using R (R Core Team, 2013). We will refer to Table 6 as we discuss the tests of our hypotheses. Fig. 6 demonstrates the adjusted means of improvement by condition for a visual representation of the hypotheses. The adjusted mean estimates the dependent variable by accounting for the independent variables.

5.1. Post-hoc exploratory study of personality

In addition to the results described above, we performed a post-hoc test of the effects of personality on the relationships between trainer (expert or novice) and training type. Thus, we included the Big Five personality traits (agreeableness, conscientiousness, neuroticism, extraversion, openness to experience) (Costa & MacCrae, 1992) in a second ANCOVA. In this second ANCOVA, we interacted the Big Five with the conditions and then, the same as the first ANCOVA, we used planned contrasts to test the exploratory effects. Our goal was to look for personality traits that could help explain conflicting results in our hypotheses and provide deeper insights about the relationships. However, unlike the first ANCOVA, we introduced survey items into the analysis. Before using survey items, it is important to demonstrate the items show reliability and factorial validity. To test for reliability, we calculated the Cronbach's alpha values of each of the constructs. We also conducted an exploratory factor analysis (EFA) to evaluate factorial validity. We removed items that cross-loaded on more than one construct at or above a 0.3-level or that did not load on a construct at or above a 0.5-level. The complete results of the second ANCOVA testing the interaction effects of personality traits on the relationship between the manipulated conditions and learning performance are contained in Table A2 of the appendix. We summarize the significant

Table 4
Summary statistics.

	Construct	Mean	SD	1	2	3	4	5	6	7
1	Age	22.19	2.99							
2	Gender[a] (M = 1, F = 2)	1.20	0.40	−0.24						
3	Years playing League of Legends	0.66	1.62	0.00	−0.19					
4	Novice teacher[b]	NA	NA	−0.07	0.06	−0.16				
5	Expert teacher	NA	NA	0.10	0.03	0.06	−0.24			
6	Learner-learner environment	NA	NA	−0.05	0.06	−0.04	0.19	−0.01		
7	Teacher-learner-learner environment	NA	NA	−0.06	0.07	0.03	−0.02	0.03	0.41	
8	Creep score improvement games 2->3	6.73	9.53	−0.06	0.01	−0.17	0.14	−0.03	0.05	−0.01

[a] Gender is represented as 1 for male and 2 for female.
[b] Constructs 4, 5, 6, and 7 refer to randomized manipulations for which means and std. deviations do not apply.

Table 5
Hypotheses and planned contrasts (reference Table 1).

Hypothesis	Planned Contrast Conditions
H1. Expert training > no training	2, 5, 8 > 1
H2. Novice training > no training	3, 6, 9 > 1
H3. Expert training with novice training > either alone	4, 7, 10 > 2, 3, 5, 6, 8, 9
H4a. Learner-learner training > video training	
H4b. Teacher learner-learner training > learner-learner training and video training	8, 9, 10 > 2, 3, 4, 5, 6, 7
H5a. Novice learner-learner training > novice video training	6 > 3
H5b. Novice Twitch training > novice learner-learner training and novice video training	9 > 3, 6
H5c. Expert learner-learner training > expert video training	5 > 2
H5d. Expert Twitch training > expert learner-learner training and expert video training	8 > 2, 5

Table 6
ANCOVA results.

Construct	Df	Sum Sq	Mean Sq	F Value	Pr(>F)
Age	1	110	109.8	1.278	0.259
Gender	1	0	0.1	0.002	0.969
LoL_Length_Playing	1	957	957.0	11.143	0.001***
Direct Contrasts					
H1. Expert > nothing	1	554	553.7	6.447	0.012*
H2. Novice > nothing	1	520	520.2	6.058	0.014*
H3. Expert & novice > expert or novice	1	35	35.0	0.408	0.523
H4a. Learner-learner > video	1	2	2.0	0.023	0.879
H4b. Teacher-learner-learner > video and learner-learner	1	23	22.8	0.266	0.606
H5a. Novice learner-learner > novice video	1	391	390.6	4.548	0.034*
H5b. Novice teacher-learner-learner > novice video and learner-learner	1	3	3.5	0.041	0.841
H5c. Expert learner-learner > expert video	1	24	23.6	0.275	0.601
H5d. Expert teacher-learner-learner > expert video and learner-learner	1	150	149.9	1.745	0.187
Residuals	337	28,942	85.9		

Significance codes: † < .1; * < .05; ** < .01; *** < .001.

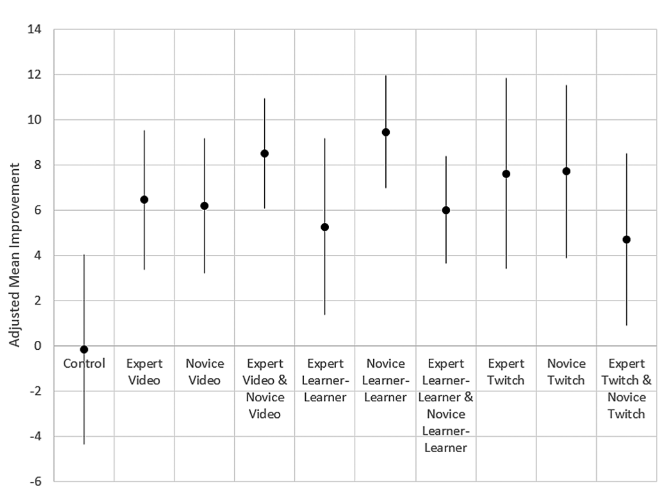


Fig. 6. Adjusted means of improvement by condition.

effects here. We found significant interactions between personality traits and the learning environment, including that extraversion has an interaction with a learner-learner environment. As shown in Fig. 7, extraverts (on the right) and non-extraverts (on the left) improve performance fairly equally in a video environment. However, non-extraverts hardly improve while extraverts improve a lot in a learner-learner environment. Thus, it is clear that non-extraverts are disadvantaged in a learner-learner environment.

We also found that agreeable people learn better from a novice more than non-agreeable people. Fig. 8 shows all of the novice instructor conditions along with the control condition. Not everyone benefited from having a novice instructor. In particular, non-agreeable people tended to fair worse than agreeable people when in a learner-learner or a video condition. The opposite was found in the teacher-learner-learner condition. This result suggests that non-agreeable people should not be placed in learner-learner environments with novice instructors.

Lastly, we found that neurotic people faired far worse with novice instructors than non-neurotic people with novice instructors. Fig. 9 shows the improvement scores for all novice

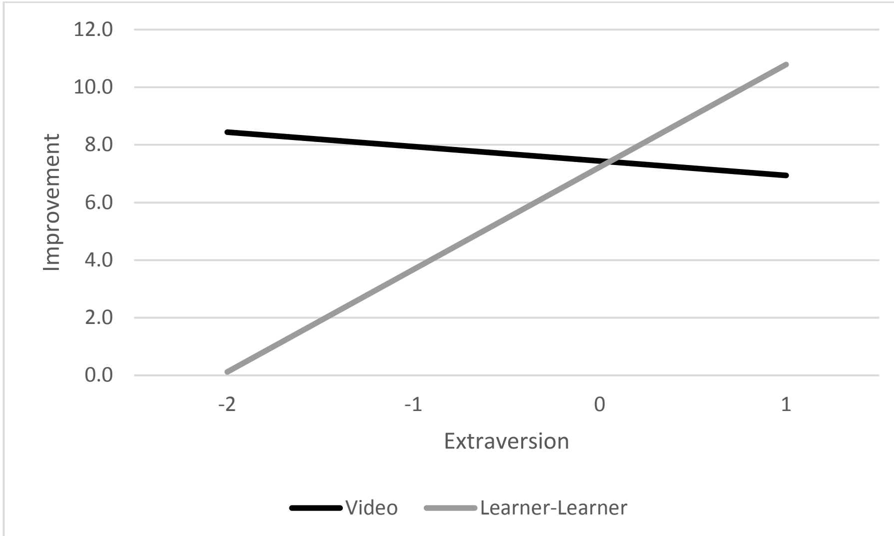


Fig. 7. H4a and extraversion.

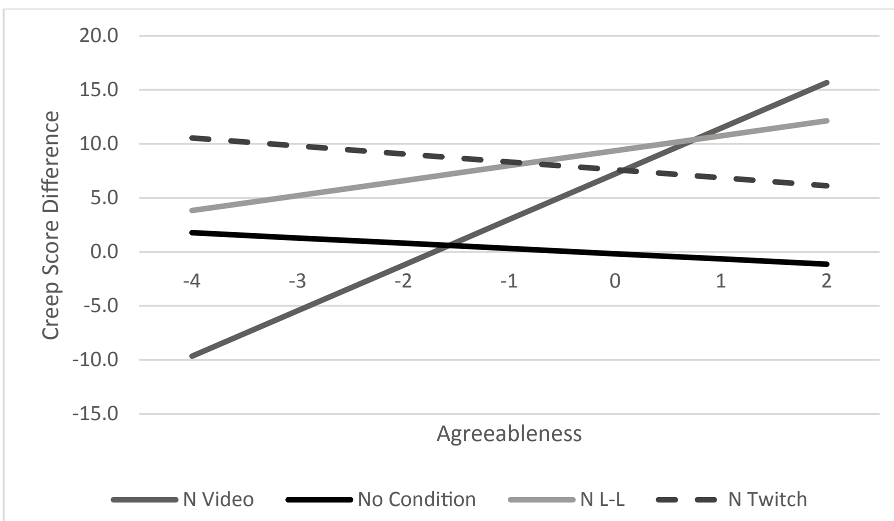


Fig. 8. H2 and agreeableness.

instructor conditions by the participant's level of neuroticism. Less neurotic people (on the left) improved to a much greater extent than more neurotic people (on the right) in all novice instructor conditions. This result suggests that highly neurotic people should not be placed in environments with novice instructors.

6. Discussion

The results of our hypothesis testing reveal that Twitch can have significant impacts on learning performance by enabling online training as well as interaction among learners and teachers during training. However, only certain conditions were impacted in our study. We found that learners can benefit from both expert ($F = 6.447$, $p = 0.012$) and novice ($F = 6.058$, $p = 0.014$) trainers. This is significant in the Twitch context where amateur trainers are commonplace, but also has broad applicability to corporate educational settings were peer-to-peer training is encouraged (Chiu, Hsu, & Wang, 2006). However, our results also indicate that when novice trainers are present, learners benefit significantly from interactions among each other ($F = 4.548$, p = 0.034). In fact, participants in a learner-learner environment learning from a novice had the largest mean improvement than all conditions. The complete hypothesis testing results are contained in Table 7.

It should be noted that several of our experimental manipulations did not result in statistically significant learning improvements. For example, there was no additive effect of expert and novice training (H3). Also, absent a live trainer, learner-learner interactions did not improve learning performance overall (H4a). However, novice instruction improved participants' performance during learner-learner interactions over video interactions (H5a).

6.1. Observations

To gain additional insight and provide context for our findings, we also analyzed comments, chat, and post-experiment interviews with participants. As predicted, participants that

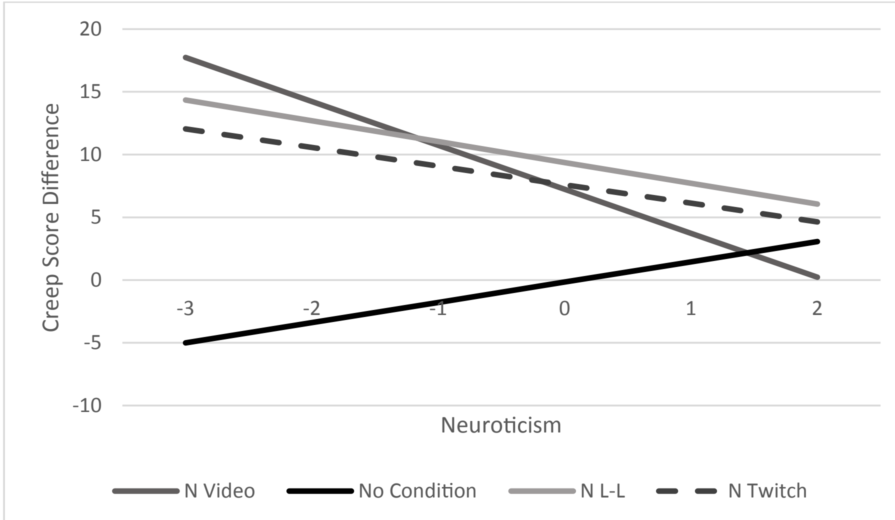


Fig. 9. H2 and neuroticism.

Table 7
Hypothesis testing results.

H	Description	Supported?
H1	Participants who receive instruction from an expert will perform better than those who do not receive instruction	Yes
H2	Participants who receive instruction from a novice will perform better than those who do not receive instruction	Yes
H3	Participants who receive instruction from both a novice and an expert will perform better than either alone	No
H4a	Participants who are in a learner-learner environment will learn better than those watching a video	No
H4b	Participants in a teacher-learner-learner environment will learn better than those not in a teacher-learner environment	No
H5a	Participants who receive instruction from a novice and in a learner-learner environment will learn better than participants receiving instruction from a novice through a video alone	Yes
H5b	Participants who receive instruction from a novice in a teacher-learner environment will learn better than participants receiving instruction from a novice in a learner-learner environment or just a video	No
H5c	Participants who receive instruction from an expert in a learner-learner environment will learn better than participants receiving instruction from an expert through a video alone	No
H5d	Participants who receive instruction from an expert in a teacher-learner environment will learn better than participants receiving instruction from an expert in a learner-learner environment or just a video	No

received training from either an expert or a novice performed better at the CSing task than those that had no training. Comments from participants related to useful components of training included "instructions on last hitting" and "learning that I only get the kill if I'm the last person to hit the minion." Participants' performance increased after viewing both an expert and a novice tutorial. However, although the performance data indicates that participants improved even from notice instructors, comments indicated that participants clearly did *not* believe they benefitted *at all* from viewing the novice tutorial. Although surprising, learning without awareness is not a new phenomenon (Thorndike & Rock, 1934). Although learning without realizing that one is learning can even occur with explicit (a.k.a. "declarative"; or knowledge "about" things) knowledge (Eriksen, 1960), it is even more commonly associated with implicit or "procedural" knowledge (Reber & Squire, 1994). Our video game context is clearly more closely aligned with procedural knowledge, or knowledge about how to "do" something (a.k.a. "motor skills") (Squire, 2004). But, as stated above, even declarative knowledge—e.g. facts, figures, etc.—can be learned unconsciously. As a result, the use of novice instructors in the Twitch environment may be effective across other contexts outside of the present study.

Our post-hoc analysis of personality traits also indicates some interactions that can be detrimental for learners in certain environments. Introverts do not perform well in a Twitch-like environment. Also, agreeable people and non-neurotic people can learn well from novices, but their counterparts cannot. This is an important concept for trainers and educators to understand because mandatory corporate training can force all employees into one training environment that may not be ideal for everyone. Our study demonstrates that it may lower the performance of some people at their tasks.

Additionally, while receiving instruction from a novice over a live stream in a teacher-learner-learner environment did not significantly improve performance, there was a significant difference when these conditions interacted with the amount of time the participants previously played League of Legends. Viewers that had previous experience with the game communicating during this condition often mocked the streamer for lack of expertise, which may have resulted in a loss of attention from other less-experienced viewers.

Finally, participants viewing a video over Twitch of an expert with only learner-learner interaction did not perform better than those not in this condition, but rather performed significantly worse. Post-experiment interviews with participants indicated that they felt lost after watching the expert tutorial with no ability to communicate with the expert live during the stream.

These results support the application of worked-example theory in a live-streaming environment under the right conditions and suggest that learners may not appreciate the effectiveness of the learning environment that they are in despite improved performance.

6.2. Implications and limitations

One benefit of recent technological advancements is the ability of instructors to prepare highly engaging course materials for use by students outside of class. Use of these materials to introduce students to new course content outside of the classroom is commonly described as "flipping the classroom" (Bergmann & Sams, 2012; Milman, 2012). In a flipped classroom, pre-recorded videos, podcasts, and other multimedia are used prior to classroom sessions to give students the opportunity to familiarize themselves with concepts. This allows face-to-face class time to be used for integrating and understanding ideas, rather than introducing them. This type of format can be used to enhance teacher-student mentoring as well as peer-to-peer collaboration between students (Roehl et al., 2013) and can be very beneficial to learning. While most research to date has focused on student perceptions (Bishop & Verleger, 2013), studies on learning outcomes have shown positive results for the flipped classroom approach (Amresh, Carberry, & Femiani, 2013; Bradford, Muntean, & Pathak, 2014).

Recent growth in distance education has fueled further interest in multimedia and online teaching pedagogies. The 2015 Survey of Online Learning from the Babson Survey Research Group found that 28% of U.S. higher education students take at least one distance education course, a 3.9% increase over the previous year (Moran et al., 2011). The survey also concluded that academics are generally more positive about blended courses—classes featuring a combination of online and face-to-face instruction—than they are about online-only courses.

Technologies like Twitch that enable interaction between users can be used to enhance distance learning by encouraging real-time interaction between instructors and learners. This interaction can be either teacher-learner or learner-learner interaction in which students can answer each other's questions. Our results demonstrate that technologies like Twitch can be useful tools for the classroom flip.

A limitation of this study is that we used interactivity only as a manipulation of the learning environment (i.e., condition) of participants. We did not use actual text communications as a measure of interactivity, so it is possible that some participants in a highly interactive environment did not in fact have a very interactive experience. Future research should look more deeply into the individual interactive experiences of the participants.

7. Conclusion

In this study, we investigated the potential of live-streaming technology as a platform for improving learning from instructors of different levels of expertise. We used the context of the game League of Legends to measure performance on an in-game task and found that under certain conditions, live-streaming technologies like Twitch do have potential as a platform for interactive learning. Specifically, we observed that the worked-example style of learning could be adapted in the live-streaming environment. Additionally, we found support for the effectiveness of learning from novices' mistakes in the live-streaming environment. Participants' improved performance coupled with comments that they did not feel that a novice's advice was useful suggests that learners may not recognize their own optimal learning conditions. We would like to further investigate the conditions under which live-streaming technology can improve learning and better understand why learners do not recognize the optimal conditions for improvement.

Appendix

Table A1
Factor Loadings of Scale Items (loadings below .3 hidden)

Scale Item	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
EXT1	0.64				
EXT2	0.83				
EXT3	0.55				
EXT4	0.86				
EXT5	0.73				
EXT6	0.57				
EXT7	0.72				
EXT8	0.62				
EXT9	0.58				
EXT10	0.76				
AGR4		0.74			
AGR6		0.55			
AGR9		0.71			
CON2			0.73		
CON4			0.66		
CON6			0.68		
NEU1				0.58	
NEU4				0.62	
NEU6				0.66	
NEU7				0.78	
NEU8				0.82	
NEU9				0.71	
NEU10				0.74	
OPE1					0.59
OPE3					0.66
OPE4					0.61
OPE6					0.56
OPE8					0.55
OPE10					0.66

Table A2
Big Five ANCOVA Results

Construct	Df	Sum Sq	Mean Sq	F Value	Pr(>F)
Age	1	110	109.8	1.334	0.249
Gender	1	0	0.1	0.002	0.968
LoL_Length_Playing	1	957	957.0	11.633	0.001***
Extraversion	1	238	238.1	2.895	0.090†
Agreeableness	1	104	104.4	1.269	0.261
Conscientiousness	1	150	149.8	1.821	0.178
Neuroticism	1	174	173.7	2.111	0.147
Openness	1	43	43.0	0.522	0.470
Direct Contrasts					
H1. Expert > nothing	1	554	553.7	6.731	0.010**
H2. Novice > nothing	1	520	520.2	6.324	0.012*
H3. Expert & novice > expert or novice	1	35	35.0	0.426	0.515
H4a. Learner-learner > video	1	2	2.0	0.024	0.877
H4b. Teacher-learner-learner > video and learner-learner	1	23	22.8	0.278	0.599
H5a. Novice learner-learner > novice video	1	391	390.6	4.748	0.030*
H5b. Novice teacher-learner-learner > novice video and learner-learner	1	3	3.5	0.042	0.837
H5c. Expert learner learner > expert video	1	24	23.6	0.287	0.593
H5d. Expert teacher-learner-learner > expert video and learner-learner	1	150	149.9	1.822	0.178
Direct Contrasts * Extraversion					
H1. Expert > nothing	1	66	66.5	0.808	0.370
H2. Novice > nothing	1	171	171.4	2.084	0.150
H3. Expert & novice > expert or novice	1	12	12.2	0.148	0.701
H4a. Learner-learner > video	1	647	646.9	7.864	0.005**
H4b. Teacher-learner-learner > video and learner-learner	1	25	25.4	0.308	0.579
H5a. Novice learner-learner > novice video	1	238	238.2	2.896	0.090†
H5b. Novice teacher-learner-learner > novice video and learner-learner	1	95	95.1	1.156	0.283
H5c. Expert learner learner > expert video	1	1	0.7	0.008	0.929
H5d. Expert teacher-learner-learner > expert video and learner-learner	1	204	203.8	2.477	0.117
Direct Contrasts * Agreeableness					
H1. Expert > nothing	1	26	26.2	0.318	0.573
H2. Novice > nothing	1	333	332.8	4.046	0.045*
H3. Expert & novice > expert or novice	1	12	12.4	0.151	0.698
H4a. Learner-learner > video	1	186	185.9	2.260	0.134
H4b. Teacher-learner-learner > video and learner-learner	1	111	111.2	1.351	0.246
H5a. Novice learner-learner > novice video	1	2	1.8	0.022	0.882
H5b. Novice teacher-learner-learner > novice video and learner-learner	1	61	61.3	0.746	0.389
H5c. Expert learner learner > expert video	1	67	67.2	0.817	0.367
H5d. Expert teacher-learner-learner > expert video and learner-learner	1	27	27.2	0.330	0.566
Direct Contrasts * Conscientiousness					
H1. Expert > nothing	1	5	5.2	0.063	0.802
H2. Novice > nothing	1	258	257.6	3.132	0.078†
H3. Expert & novice > expert or novice	1	17	17.1	0.208	0.649
H4a. Learner-learner > video	1	10	10.3	0.125	0.724
H4b. Teacher-learner-learner > video and learner-learner	1	80	80.0	0.973	0.325
H5a. Novice learner-learner > novice video	1	21	21.4	0.260	0.611
H5b. Novice teacher-learner-learner > novice video and learner-learner	1	26	26.0	0.316	0.575
H5c. Expert learner learner > expert video	1	13	13.1	0.159	0.691
H5d. Expert teacher-learner-learner > expert video and learner-learner	1	6	5.5	0.067	0.795
Direct Contrasts * Neuroticism					
H1. Expert > nothing	1	11	11.1	0.135	0.714
H2. Novice > nothing	1	432	432.3	5.256	0.023*
H3. Expert & novice > expert or novice	1	22	22.5	0.273	0.602
H4a. Learner-learner > video	1	32	31.6	0.384	0.536
H4b. Teacher-learner-learner > video and learner-learner	1	260	259.9	3.160	0.077†
H5a. Novice learner-learner > novice video	1	31	30.5	0.371	0.543
H5b. Novice teacher-learner-learner > novice video and learner-learner	1	47	47.1	0.572	0.450
H5c. Expert learner learner > expert video	1	282	282.3	3.432	0.065†
H5d. Expert teacher-learner-learner > expert video and learner-learner	1	18	18.1	0.219	0.640
Direct Contrasts * Openness					
H1. Expert > nothing	1	125	124.7	1.516	0.219
H2. Novice > nothing	1	78	78.1	0.949	0.331
H3. Expert & novice > expert or novice	1	11	10.8	0.132	0.717
H4a. Learner-learner > video	1	115	114.6	1.393	0.239
H4b. Teacher-learner-learner > video and learner-learner	1	14	13.8	0.168	0.683
H5a. Novice learner-learner > novice video	1	29	29.2	0.355	0.552
H5b. Novice teacher-learner-learner > novice video and learner-learner	1	263	263.0	3.197	0.075†
H5c. Expert learner learner > expert video	1	43	43.1	0.524	0.470
H5d. Expert teacher-learner-learner > expert video and learner-learner	1	90	89.7	1.090	0.297
Residuals	287	23,608	82.3		

Significance codes: *** < 0.001; ** < 0.01; * < 0.05; † < 0.1.

Table A3
Post hoc summary statistics.

	Construct	#	Mean	SD	Alpha	Rel.	AVE	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Age	NA	22.19	2.99	NA	NA	NA	**NA**												
2	Gender	NA	1.20	0.40	NA	NA	NA	−0.24	**NA**											
3	Years playing LoL	NA	0.66	1.62	NA	NA	NA	0.00	−0.19	**NA**										
4	Novice teacher	NA	NA	NA	NA	NA	NA	−0.07	0.06	−0.16	**NA**									
5	Expert teacher	NA	NA	NA	NA	NA	NA	0.10	0.03	0.06	−0.24	**NA**								
6	Learner-learner environment	NA	NA	NA	NA	NA	NA	−0.05	0.06	−0.04	0.19	−0.01	**NA**							
7	Teacher-learner-learner environment	NA	NA	NA	NA	NA	NA	−0.06	0.07	0.03	−0.02	0.03	0.41	**NA**						
8	Creep score improvement games 2->3	NA	6.73	9.53	NA	NA	NA	−0.06	0.01	−0.17	0.14	−0.03	0.05	−0.01	**NA**					
9	Extraversion	10	0.00	1.04	0.90	0.90	0.69	0.04	0.00	−0.17	0.07	−0.12	−0.02	−0.02	0.11	**0.83**				
10	Agreeableness	3	0.00	1.14	0.70	0.71	0.67	0.04	0.14	−0.07	0.01	−0.01	0.00	0.03	0.08	0.21	**0.82**			
11	Conscientiousness	3	0.00	1.14	0.74	0.73	0.69	0.03	0.04	0.04	0.00	0.03	−0.12	−0.08	0.05	−0.10	0.04	**0.83**		
12	Neuroticism	7	0.00	1.06	0.86	0.87	0.70	0.05	−0.17	−0.02	0.01	−0.03	−0.05	−0.04	−0.01	0.28	0.09	0.11	**0.84**	
13	Openness	6	0.00	1.12	0.76	0.78	0.61	0.08	−0.09	0.02	0.00	−0.08	−0.01	0.06	−0.01	0.27	0.14	−0.01	0.06	**0.78**

Square root of the AVE is shown in bold on the diagonal.

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