

StreamWiki: Enabling Viewers of Knowledge Sharing Live Streams to Collaboratively Generate Archival Documentation for Effective In-Stream and Post-Hoc Learning

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Knowledge-sharing live streams are distinct from traditional educational videos, in part due to the large concurrently-viewing audience and the real-time discussions that are possible between viewers and the streamer. Though this medium creates unique opportunities for interactive learning, it also brings about the challenge of creating a useful archive for post-hoc learning. This paper presents the results of interviews with knowledge sharing streamers, their moderators, and viewers to understand current experiences and needs for sharing and learning knowledge through live streaming. Based on those findings, we built StreamWiki, a tool which leverages the availability of live stream viewers to produce useful archives of the interactive learning experience. On StreamWiki, moderators initiate high-level tasks that viewers complete by conducting microtasks, such as writing summaries, sending comments, and voting for informative comments. As a result, a summary document is built in real time. Through the tests of our prototype with streamers and viewers, we found that StreamWiki could help viewers understand the content and the context of the stream, during the stream and also later, for post-hoc learning.

CSS Concepts: • **Human-centered computing** → **Collaborative and social computing** → Collaborative and social computing systems and tools

KEYWORDS

Live streaming; knowledge sharing; knowledge building; collaborative documentation; learning

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1 INTRODUCTION

Live streaming, or the online, real time ‘broadcasting’ of video, has recently gained worldwide popularity. Facilitated by affordable digital video and audio recording devices, high speed Internet access, and the popularity of social media websites, live streams are created by end users and are widely shared by viewers. Previous research has found that the content of live streams is highly varied, often focusing on video gaming [16], celebrity gossip [50], live events [15,51], civic engagement [9], live performances [31], or the selling of goods [46]. Recently, Lu et al. reported

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on the emergence of China-based knowledge sharing live streamers and their communities [34]. The streamers were found to share their knowledge for personal satisfaction and financial gain, and were considered to be “experts” in some topics, even though they were typically unaffiliated with traditional learning institutions. Although these streamers often had large and devoted fan bases, they typically had no effective tools to support peer learning amongst viewers because most streaming platform features, e.g., gifting and leader-boards [31], were designed for entertainment.

Online video has been widely used for educational purposes. Massive Open Online Courses (MOOCs) typically use pre-recorded video lectures and other similar materials to enable students to access content at their own convenience. Archives of knowledge sharing videos on websites such as *YouTube* and *Vimeo* also serve as an important source for online learning, with online discussion boards to engage viewers and content creators in discussions. Although similar in content and style to MOOCs and educational online videos, knowledge sharing live stream (KSLS) has a unique characteristic: *concurrency*. Video content is created live by streamers while many concurrent viewers are watching and actively posting comments. It dynamically changes the direction of information flow among the viewers and between the viewers and the streamer, and thus enables an engaging and interactive learning experience. Although some MOOCs use live video as a pedagogical tool, it is usually in the form of a live lecture in a classroom setting [45] or an ‘office hour’ where students ask questions and the instructor answers via a live broadcast [18]. These live video formats often fail to leverage the co-presence of learners in a way that facilitates community building and peer learning [18].

Like other forms of video-based learning, KSLS is limited by the linear nature of video browsing, i.e., the difficulty of compiling an overview of the video content and skimming through it [32,43]. This is a crucial challenge for KSLS as viewers cannot pause or navigate through the live video without becoming out of sync and thus losing the real-time interactivity of the live stream [15,16,34]. Although several methods have been proposed to annotate and/or summarize non-live videos to leverage the crowd or viewers’ participation [26,43,53], they all require the video to be paused while the task is completed. As annotations and summaries created during live streams can benefit viewers both in-stream and post-hoc, we present a new method for creating in-stream summaries and annotations by leveraging the collaborative activities of a large number of concurrent viewers while minimizing the disruptions to their viewing experiences.

Inspired by Lu et al. [34], we extend their results by interviewing knowledge sharing streamers (N=6) and their moderators or viewers (N=7) to better understand motivations, practices, and challenges while broadcasting, moderating, or watching KSLS. Our investigation revealed several practices and challenges of KSLS, such as (i) KSLS *moderators* often assist streamers in preparing and archiving, in addition to typical comment moderation tasks [16], (ii) it is challenging for viewers to get up to speed on a live stream if they join mid-stream or become distracted, (iii) viewing archived KSLS content is neither efficient nor engaging, due to idle moments and segments that lack useful comments and (iv) streamers already make great effort to edit archive video to support viewers in post-hoc learning, however, comments are often not included due to the additional effort for filtering useful comments.

From these findings and our iterative design process, we designed *StreamWiki*, a web-based tool to support the real-time collaborative creation of archival documentation of KSLS videos and contemporaneous online discussions. StreamWiki takes advantage of a large number of concurrent viewers who are actively participating in a live stream by posting comments, and moderators who are voluntarily helping streamers. On StreamWiki, a streamer or a moderator

creates small tasks and viewers complete microtasks that can potentially benefit their understanding of the stream without needing to pause the video. Viewers can write summaries, vote for summaries, and propose improvements to existing ones. Viewers can vote for their favorite comments to be archived and shown on the video as a moving text, also known as Danmaku [35], so that these comments can draw more attention. StreamWiki also visualizes comments and keywords in the stream in real time. This design enables viewers to actively engage in the process of building knowledge together with peer viewers in live streams, and progressively access an interactive document of the content of the video stream afterwards, which can then be leveraged for further referencing or discussion. StreamWiki can embed live video streams from most streaming platforms via the Streamlink API [61], which enables streamers to use StreamWiki with their favorite live streaming platforms to maintain their fan base.

StreamWiki was deployed for use by four knowledge sharing streamers along with their moderators and viewers. We recruited 25 viewers of these streamers to participate in 6 streams, asked them to use StreamWiki, and collected both quantitative and qualitative data about their experiences. Through our deployment, we found that although using the tool required additional effort from viewers, they generally did not find it to be intrusive or distracting. Viewers thought that using StreamWiki improved their understanding of the streamed content, and saw the documentation process as a way to support streamers, moderators, and the knowledge-sharing community. In addition to providing a useful archive, the streamers found that the resulting document and the usage data on commenting, voting, and summarized content provided insights about viewers' interests and points of confusion during the stream, which could be valuable to improve future streams but could not be gleaned from traditional streaming services today.

2 BACKGROUND AND RELATED WORK

StreamWiki builds on the findings from the live streaming studies and the insights from research on facilitating learners' participation and enabling efficient video navigation for online learning.

2.1 Leveraging Live Video for Knowledge Sharing

Early research in HCI and CSCW has explored how to support the sharing of knowledge amongst distributed audiences using interactive video. Forum by Isaacs et al. [22] and TELEP by Jancke et al. [23] both enabled speakers to broadcast live video and slides, and enabled audiences to interact with the speaker and other audiences using speech or votes. Although relevant, these systems were designed for an institutional setting, which was a smaller scale compared to KSLs, and they did not address the archival of comments.

With the proliferation of live streaming services, users have begun to share a variety of forms of knowledge in live streams [34]. In 2015, Twitch.tv started the 'Creative' category for artists, crafters, and builders to broadcast their creative processes [40]. On *Yizhibo.com*, one of the most popular streaming platforms in China [4], approximately 21.6% of users watch educational live streams [5]. On *Douyutv.com*, another similar site, there is a category of educational streams, with hundreds of streamers regularly sharing knowledge [62]. Lu et al. found a variety of topics that were shared in live streams in China, including foreign languages, college-level mathematics, and history [34]. Haaranen reported on the emerging phenomenon of live streaming programming, in which programmers code and interact with viewers in live streams, and envisioned that it had the potential to impact formal computing education [14]. Such research has

revealed the potential of live streaming, however, little research has explored the needs of knowledge sharing live streamers, moderators, and viewers, the challenges they face, and how KSLs community deal with these challenges. The work aims to understand these questions through a user study and to guide the design of tools to better support KSLs.

2.2 Facilitating Participation in Online Learning

Early research in situated learning has found that novice learners must fully participate in the sociocultural practices of a community to master knowledge and skills [29]. From this perspective, the learning process takes place not only in an individual context, but also in socially situated contexts [17]. Recent research on MOOCs and online learning holds that active participation and engagement in the knowledge community are critical to an online learning process [20,44,49]. Learners can participate in online learning using both asynchronous and synchronous media, which have different effects on their participation [19]. Asynchronous media (e.g., blogs and forums) afford reflection and discussion, while synchronous media (e.g., video conferencing and text chat) foster more conversation between learners, provide social support [19], and increases the learner's perceived social interactivity [30]. Another line of research explored online "backchannel" chatrooms, which allow participants to discuss during a lecture or presentation [37,56]. Although such backchannels may distract learners, they encourage knowledge sharing through self-motivated participation and engagement [56], and can provide additional feedback about learners to instructor [3]. Building on these findings, we aim to further understand how KSLs using synchronous media and having concurrent learners' real-time comments, influence learners' participation and learning processes.

Previous research in Computer Supported Collaborative Learning (CSCL) has explored various ways to better support online learning by creating collaborative learning environments and supporting collaborative annotations and discussions. Classroom 2000 captured course content in multiple media, including audio, video, slides, and notes, to provide a persistent collaboration space for students to access class recordings and continue discussions after class [1]. NB was a collaborative document annotation system which significantly increased the amount of online student-to-student discussions [60]. SynTag [21] allowed viewers to provide real-time feedback for live presentations via simple tags. TraACE [8] enabled learners to leave spatiotemporal anchored annotations of video and discussions in an online learning space, where learners interacted with instructors or peers in meaningful ways. Mudslide [13] supported spatially contextualizing students' points of confusion in online video, which benefited both students and instructors. Korero [6] facilitated the complex referencing of multiple and specific referents in discussions of online courses. LiveMâché [17] supported sharing context and participation in online learning through the collaborative and synchronous curation of multi-media, including live video, text, images, and sketches. The design of StreamWiki synthesizes ideas from these systems to leverage real-time participation of viewers for anchored annotations, feedback, and discussions, and is situated within the context of live streaming to enable educational content to reach an audience that may not be the typical target of these prior systems, e.g., users who are less committed to formal learning.

Previous work has also investigated the needs and motivations of both learners [58] and instructors [59] to inform the design of MOOC systems. We have a similar perspective, which views KSLs as an eco-system that involves multiple stakeholders, including streamers, the moderators who not only moderate discussions but also voluntarily help the streamer prepare the content, and the viewers who actively engage in the community built by the streamer.

2.3 Enhanced Video Interfaces for Online Learning

Videos on MOOCs or websites such as YouTube or Vimeo provide a rich online learning experience. However, the linear video navigation makes it hard for learners to gain an overview of the video or locate content of interest [43], or to meaningfully construct knowledge [12].

Previous work has explored various user interfaces to better support video-based learning. Kim et al. [26] proposed a data-driven method which leverages user interaction data for video navigation. NoteVideo [39] identified conceptual objects in blackboard style videos and supports the direct navigation of them. Other research focuses on supporting the knowledge construction of viewers. Video Digests [43] provided structured summaries of informational videos that were organized into chapters and sections with thumbnails to enable viewers to browse and skim a video. Weir et al. [53] proposed a system that leverages the crowd to generate sub-goal labels for how-to videos to scaffold learning. ConceptScape [32] leveraged the crowd to generate a concept map of lecture videos to support concept-driven navigation of a video.

These enhanced video interaction tools are mostly intended for use with pre-recorded videos. Due to the liveness of KSLs, it is challenging to directly adopt these tools for KSLs, because most of them require viewers to complete tasks that can be too demanding without pausing the live video. Inspired by these systems, we explore how to support KSLs viewers to better understand content and meaningfully construct knowledge during live streams via less demanding tasks.

3 FORMATIVE STUDY

3.1 Interviews with KSLs Streamers, Moderators, and Viewers

To better understand current practices and challenges of KSLs, we conducted semi-structured interviews with six regular knowledge sharing streamers (i.e., 4 males, S1-S6, Table 1) from China, five moderators (i.e., 3 males, M1-M5) who not only watched streams but also voluntarily helped streamers, and two viewers (i.e., 1 male, V1-V2) of S2 and S3. All the streamers created live streams at least twice a week and had at least three months of knowledge sharing experience on live streams. We interviewed more moderators than viewers to gain insights from these more active and engaged users. They all had at least three months of experience watching KSLs.

3.1.1 Method. We recruited the interviewees by sending messages to streamers on the live streaming platforms, reaching out to their moderators and active viewers, or by the chat groups of fans. The interviews were conducted remotely using video calls from July 2017 to Jan 2018.

Table 1. An overview of the 6 streamers we interviewed.

Streamer & Moderator	Streaming Platform	Topic	Typical number of viewers	Streaming styles
S1 M1	Douyu.tv	Artificial intelligence	~200	Slides + talking head
S2 M2	Douyu.tv	Chemistry	~300	Slides + talking head
S3 M3	Douyu.tv	Chinese history	~12,000	Slides + talking head
S4	Douyu.tv	Mathematics	~10,000	Talking head + whiteboard
S5 M4	Huajiao.tv	Chinese culture	~4,000	Talking head
S6 M5	Momo	English learning	~3,000	Talking head + whiteboard

Each interview lasted about 50 minutes, with questions probing current practices of sharing or learning knowledge using live streaming, the motivations for sharing knowledge (for streamers)

or helping the knowledge sharing streamers (for moderators), and the challenges they face using today's technology platforms. Interviews were conducted in Mandarin, audio-taped, and transcribed and translated by the research team who conducted the interviews. The open coding method was used to code the transcription data and identify main themes [48].

3.1.2 Findings.

Seven themes emerged within the data, which alluded to the motivations, practices, and needs of these knowledge sharing streamers, moderators, and viewers. These themes are also presenting some design opportunities and challenges.

F1: Context loss. The interviewees mentioned that one of the biggest problems with live streaming for learning is that it is hard to understand the current context if someone joins mid-stream [M1, M2, V1, V2], or after one is distracted [V1, M3, M4], since the live video cannot be paused or navigated, *“sometimes if I miss the first few minutes of a stream, I would skip the whole stream since I find it hard to continue without knowing what has been taught”* (V1). Although they could ask the streamer or other viewers about the context by commenting, they felt unwilling to ask, because it might interrupt the streamer or other viewers [V1, V2, M3, M4], *“I would avoid asking what is going on in the stream if I missed some parts. With so many comments, the streamer may not see my question or respond to it”* (V2). It was also difficult for viewers to understand the context from comments [M5] because many comments were about emotions or crowdspeak [11].

F2: Challenges of dealing with many comments. All the interviewees noted that one of the biggest differences between KSLs and video lectures is the real-time interactions between viewers and the streamer. Some streamers would like to see a large volume of comments and thought that having many comments meant the viewers were interested in the topic [S1, S3], *“I often encourage my viewers to comment more in my streams. For example, I ask them to comment ‘I if they understand the concept I am teaching. I think the more comments, the more engaged they are”* (S3). However, meaningful discussions can be easily buried by other comments, making it hard for streamers to identify and address critical questions [S3-S6] and viewers to focus on reading meaningful comments [M2, M3, V2]. Some streamers sometimes did not read comments to keep focused, e.g. *“to keep myself in the flow, I sometimes temporarily ignore any comment and focus on the content. I look back at them afterwards”* (S4). They might have looked back at comments after a demanding moment had passed, but often ended up missing some critical comments [S2, S4].

F3: Moderators do more than moderate. All the moderators' duty in the knowledge sharing community was not only to moderate the comments, but also to assist the streamers in preparing streaming materials (e.g. slides, text, videos, or images), edit archived video, or distribute documents for reference to those who are interested. They seem to be 'teaching assistants' in the knowledge sharing community, who take on the duty voluntarily. *“I feel that I share similar life goal with him [the streamer], and I would like to help him with such a career, which will also be an achievement for myself”* (M2). They also noted that *“sometimes the workload is too much for me to work alone”* (M3), and although some viewers expressed their willingness to help, coordinating amongst different people from diverse backgrounds and balancing the workload are challenging.

F4: Effort to archive the video. The interviewees mentioned that they made huge efforts to 'clean up' the recorded video and make an archive video [S1-S4, M1, M4, M5]. They did not upload the entire recording of the live video, but rather edited the video at a later time by going over the entire video recording to decide which parts to edit, a very time-consuming process [S1, S2, M1], *“I usually note the segments of idle moments or less engaging conversations when watching the stream, which are references when I edit the video. But I still have to go over the video afterwards”* (M3). Since some streamers and their moderators were not physically co-located, they had to discuss and collaborate on such tasks remotely [S4, M4], which was inefficient.

F5: Losing meaningful comments in archived video. Since archiving the video already took up much of their time, the streamers and moderators did not choose to handpick meaningful comments to preserve in the archive, but rather discarded all the comments [S3-S5, M1, M5]. Although they had the option to preserve all the comments in the archive, they did not since they thought viewers would not be interested in them because the liveness of the conversations had passed [S1, S2, M1], “since we post-process the video to make it more focused, some conversations during the stream will make the viewers at sixes and sevens, so we don’t include any comments in our archived video” (M1). Because of this, the thoughtful comments are not preserved in the archive, which is a loss for the knowledge sharing community [S3, S4, M1, M2].

F6: Hard for follow-up discussions to refer to the video. The interviewees noted that after the live video, follow-up discussions about the topic continue, especially in the fan groups of streamers [34] [S1, S2, M1, M3, V1, V2]. However, it is always hard to refer to certain part of the stream or certain comments, and even harder for those who were absent for the live stream to join in on the discussions, because the context information and the link are not easily accessed [S2, M3, V2]. “The discussions in the fan group are often casual. We can’t refer to a specific part of the stream or a comment, so that we seldom have deeper follow-up discussions” (V2).

F7: Need to collect feedback from individuals. Streamers value the feedback from viewers, with the primary source of feedback coming from the comments made during the stream and chat messages in their fan groups. Some streamers reflect on these discussions after the stream to make sense of what viewers are most interested in [S1, S2, S4]. This feedback is largely collective, e.g., frequently asked questions or topics that aroused a vivid discussion. Some streamers would like to get more individual rather than collective feedback, e.g., the participation level of a certain viewer during the whole stream or across previous streams, especially for “super fans” [S1-S3, S6]. “When a viewer joins my stream, I would like to see information of his participation history, for example, how long he has been watching my streams, so that I can adjust some content to better fit him” (S6). Since viewers come from diverse backgrounds and have different knowledge and skills, the collective feedback may not work well for them [S2]. The streamers desired information from different individuals to try to satisfy as many viewers as possible [S1, S2, S6].

3.2 Design Goals

Based on aforementioned findings, five goals were identified to guide the design of StreamWiki.

G1: Provide Content and Context Information. Viewers should be able to gain the context of a live video or content that has been talked about if they join mid-stream [F1]. This information should become available in nearly real time during the stream, and archived after the stream.

G2: Support the Documentation of Content and Follow-up Discussions. Viewers should be able to quickly review the salient content of a live video by browsing or skimming through it after the live stream [F4, F6]. They should be able to search for, and navigate to, content that is of interest. They should also be able to resume discussions about the topics in the streams and have access to the context after the streams [F1, F6].

G3: Highlight and Archive Meaningful Comments. Meaningful discussions should be highlighted, archived [F5], and grouped according to relevance, so that viewers can read them without being distracted by other messages [F2], both during and after the stream. The analytics of these meaningful comments (e.g., who posted and how many were posted) should also be available to provide insights about viewers’ understanding of content to streamers [F7].

G4: Off-load the Workload of Moderators and Support for Collaboration. Streamers and their moderators are already occupied with many tasks before, during, and after streams [F3]. When possible, tasks such as annotating the important key points in a stream, highlighting meaningful comments, questions, or discussions, and real-time collaborations on these tasks between viewers who are enthusiastic and willing to help, should be supported [F3].

G5: Support Streamers in Reflecting on their Stream. Streamers can gain feedback from both the whole community and individual viewers, by looking into the analytics and usage data about their reactions and discussions provided by the system [F7]. The system should thus support sensemaking to assist streamers in looking into viewers' data at different levels, and support them in quickly finding useful insights, in terms of content and style, to improve future streams [F7].

4 STREAMWIKI

Based on the findings from the interviews and the design goals, StreamWiki was designed to support knowledge sharing via live streaming. We used an iterative process throughout the design, involving the streamers, moderators, and viewers we interviewed to get their opinions on the design. StreamWiki adds two elements to live video: the ability to gather input from viewers and the ability to display context information written and organized by the viewers. Viewers can add summaries of the content and give feedback on comments and summaries while watching the live video. Content summaries are displayed and updated in real time during the live stream so that all the viewers can better understand the current context. After the live stream, the summaries and the comments become a summary document with the archived video that can not only help viewers understand the content, but also provide a way to navigate the archived video.

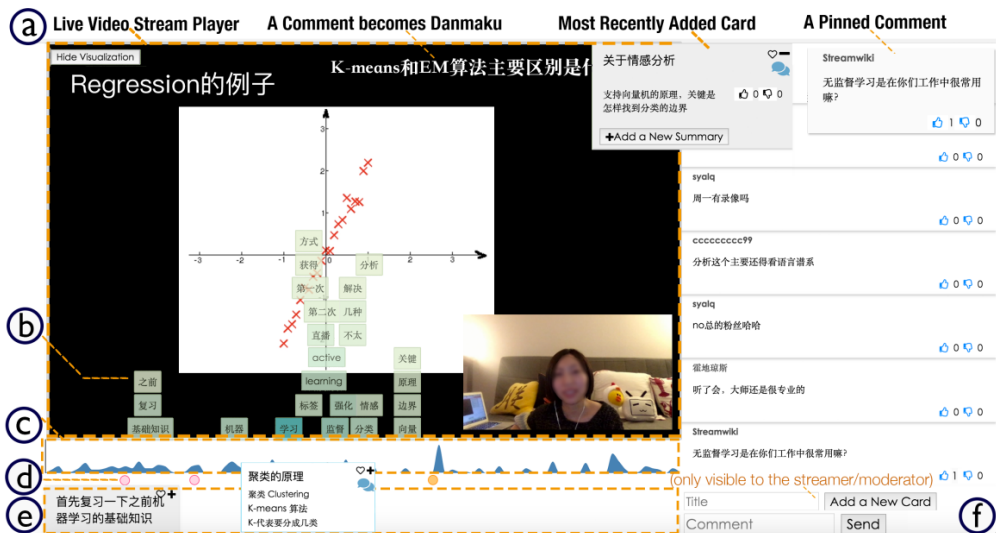


Fig. 1. StreamWiki web interface. (a) Live video stream player. (b) Real-time keyword visualization of the summaries and archived comments. The horizontal position of the keyword indicates the average time at which it occurred. (c) Real-time visualizations of the volume of comments from viewers. (d) Timestamps of cards shown on the timeline. (e) Previously added cards, ordered chronologically. (f) The Comment Window.

StreamWiki consists of three main components – a *video player* that shows the live video (Fig. 1a) with real-time visualizations of the volume of comments and key words of the content (Fig. 1b,c), a *comments window* that allows real-time voting (Fig. 1f), and a *document window* that archives and shows all the summaries that the viewers have written (Fig. 1e). Video player (Fig. 1a) and comments window (Fig. 1f) mimic typical UIs of most Chinese live streaming platforms. These three components are always visible. Herein, we describe SteamWiki’s key features and components, and explain our design process and rationales.

4.1 Summary-Writing Workflow

As viewers cannot pause the live video, it can be challenging for them to write summaries using a recursive summarization workflow as in Wikum [57] or a multi-step concept-mapping construction workflow as in ConceptScape [32]. Accelerated Instant Replay (AIR) methods [24] may not work well for live streams due to a lot of idle moments. Our design prioritizes the reduction of time to write summaries over obtaining a high-quality summary to minimize viewer distraction during the stream. In StreamWiki, the streamers or moderators can create summary-writing tasks at any moment of the stream, and the viewers can then start writing summaries or propose improvements to the summaries written by others. Viewers can also provide feedback on the quality of summaries by upvoting or downvoting them.

To enable such a workflow, we designed a card widget as a shared visual medium, which all viewers can write summaries on (Fig. 2a). The widget has an inline text input field which appears when needed. The most recently added card can be moved around by dragging the mouse. The previously added cards are shown at the bottom of the window, ordered chronologically (Fig. 1e). Viewers can read summaries and archived comments on these cards and add content to them. The cards can also be minimized to only show their titles when not needed.



Fig. 2. (a) The card widget interface where viewers write summaries or propose changes to summaries. The list of archived comments can be invoked by clicking on the icon. (b) The keywords visualizations allow viewers to explore the content of the stream. Hovering the cursor over a keyword visualizes when the keyword appeared in the summaries or archived comments and also highlights the cards related to it.

4.1.1 Initiating a Card. During a stream, a streamer or a moderator can initiate a new card if they think a new topic has just started or if they think a new card should be added to collect summaries from viewers. They can click the “Add a new card” button to initiate a new card, which will be visible to all the viewers and serve as a medium where viewers complete microtasks of writing and voting summaries. They can input the title of the card before submitting, or leave it untitled and let viewers do so after the new card is initiated and shown. The title of the card serves as a high-level overview of the upcoming content of the stream. The

streamers and the moderators we interviewed agreed that other viewers who are not authorized by them should not be able to initiate a card because it will be a mess if too many viewers initiate cards. Automated card initiation based on context might be useful, but is beyond the scope of this work.

4.1.2 Adding Summaries on the Card. Viewers can write their own understanding of the content of the stream on the card by clicking the “Add a summary” button and then typing in the in-line text box that appears. When submitted by clicking the “Save” button or hit the “Enter” key, the summary will appear in all the viewers’ interface in real time. They can also drag and drop a comment in the comment window to add it as a summary, as some comments reflect the stream.

4.1.3 Proposing Improvements to Existing Summaries. Viewers can propose improvements to summaries written by others if they think the summaries are incorrect or missing important details. When hovering the mouse over the summary they want to propose an improvement to, the “Propose an improvement” button appears under the summary. The viewer can click the button and type in the text box that appears. The proposed summary will be shown under the original one to all the viewers in real time, with a “→” symbol on the left indicating that it is an improvement for the original one.

4.1.4 Up-voting and Down-voting Summaries. To introduce a form of social moderation to the microtasks of writing summaries, viewers can also upvote or downvote the summaries on the card. The summary improvement with the most net votes (i.e., the number of upvotes minus the number of downvotes) will be listed on the first line if an original summary has several proposals for improvement. The number of upvotes and downvotes are visible to all viewers.

4.2 Comments Archiving and Danmaku

On most live streaming platforms in China, comments are often displayed as Danmaku, i.e., text overlaid on the video, which is popular in Asia [35]. Danmaku has potential in improving online video learning [55], although may be distracting for KSLs. To extend the current design of Danmaku to better accommodate KSLs, and to facilitate the archiving of meaningful comments, in StreamWiki, only comments with more upvotes above a certain threshold are shown as Danmaku. In this way, we reduce the distractions created by a large volume of Danmaku, emphasize meaningful comments, and archive them for later discussion or reference.

Viewers can upvote or downvote the comments in the comment window. When a comment is upvoted, it will be shown as a pinned comment on top of the comment window. If no one else upvotes it, it will disappear after 7 seconds, similar to the design of Conversational Chat Circle [38]. If a comment gets upvoted several times and reaches a threshold, the comment will be displayed as a Danmaku, moving from the right to the left of the video. In the current design, the threshold is set as 10% of the number of the live viewers or three if there are less than 30 viewers. The Danmaku will be archived to a comment list on the card which represents the current part of the video. The list can be invoked by clicking the speech bubble button on the card (Fig. 2a). All the comments on the list are chronologically ordered, and viewers can directly reply to the comment on the list by clicking the “reply” button next to it. The reply will also be archived in the thread of the comment. This serves as a place for more focused discussion both during and after the live stream [G2, G3]. Since upvoting in real time is challenging, different comment displaying mechanisms could be explored in the future, e.g., instead of showing all comments and a list of pinned comments, we can show a single list but rank the most recent comments by votes.

4.3 Visualizations of Content and Context Information

We also include a component that visualizes the context and content of the stream in StreamWiki to provide high-level information to both viewers and streamers. The features were inspired by several information visualization projects [7,36] and SocialStreamViewer [42]. The visualization changes as the live stream continues and updates in real time when new information is added.

4.3.1 Comment Volume and Cards Timestamp Visualization. StreamWiki visualizes viewer's commenting behavior to provide information to both viewers and streamers [G1]. The system counts the number of comments being sent in a 10-second time window and visualizes the volume of comments using an area chart (Fig. 1c). It also visualizes the timestamp of each card being initiated on the timeline via pink circle (Fig. 1d) to provide information about the topics being streamed at certain times for viewers who may have missed important information. The comment volume visualization helps streamers quickly get a sense of viewers' reactions during the stream. Combining the information on the cards with the comment volume enables streamers to further reflect on viewers' interest and the effectiveness of their story-telling or teaching strategies after the stream [G5]. The 10-second time window was tested effective using the streams of S1 and S2, however, the window size could be normalized to the overall rate of commenting in the future.

4.3.2 Keywords Visualization. We visualize keywords from the content that viewers provided during the stream, including summaries, proposed improvements of summaries, archived comments, and replies to the archived comments. We only use the comments that are upvoted and archived, as many comments may not be meaningful and will only introduce more noise. The visualization is designed to help viewers by displaying an overview of content if they join the stream in the middle or miss part of the content.

The design is inspired by the visualization of talks on OpenVis 2016 [63], where keywords or key concepts in talks are visualized and serve as anchors to navigate the video of the talks. We take a similar approach to visualize the keywords of the content collected from the viewers. The keywords are visualized as tags overlaid on the bottom half of the video player, with their background set at 80% transparency (Fig. 1b). The visualizations can be hidden by a viewer.

To visualize the keywords, our backend server keeps updating a list of keywords extracted using the dictionary, and calculates a score of the number of times it appears multiplied by its TF-IDF in our dictionary for each keyword. A higher score indicates the keyword is more important or appears more in the stream. We chose to show only the first 25 keywords in the list with high scores, to avoid visual clutter in the visualization. The score for each keyword is mapped to the background color of the keyword tag, with darker background colors indicating higher scores. The horizontal position of a keyword tag is determined by calculating the average timestamps of the appearances, so that those tags that appeared early in the stream are positioned on the left, and the later ones on the right. Keywords with higher scores occupy lower positions, and those with lower scores stack above those with higher scores if they share the same horizontal position.

When the mouse cursor hovers over a keyword tag, several connector lines appear and create paths to circles on the timeline, each circle representing the timestamp of the appearance of the keyword in the summaries or archived comments (Fig. 2b). The archived cards with the selected keyword are also highlighted with a white background color and orange outline, and the color of the corresponding circles on the timeline becomes darker. When the cursor moves over an

archived card or circle representing it on the timeline, the visualization only shows the keyword tags that are relevant to the card and hides the others.

4.4 Browsing Archived Video with StreamWiki

After the live stream, all the information gathered during the stream is archived, including the video, the comments, the votes, the summaries, and the other content on the cards. StreamWiki leverages this information for more efficient browsing and navigating of the archived video. When a viewer clicks on a card or a circle representing a card on the timeline, they can navigate the archived video to the time when the card was initiated. When they click on a keyword tag, several connector lines and small circles that visualize its timestamps show up, and they can click on the circles to navigate to specific time spot of the video. The comment volume visualization allows viewers to select a range on the timeline. This range will restrict what information is shown, so that only cards and comments related to that time period are shown.

5 SYSTEM IMPLEMENTATION

We implemented StreamWiki system guided by two considerations, 1) compatibility, so that streamers can keep using the streaming service of their choice; 2) accessibility, so that viewers watching on many different platforms can use the system. The StreamWiki system consists of a front-end web interface and a backend server. The front-end web interface is built with React, Javascript, D3.js, HTML and CSS. The video-react third-party library was used to render the video on the front-end web interface [64]. The backend server is built with Node.js and a Mongo DB database. The front-end and the backend communicate with each other using a WebSocket to transmit data and HTTP requests to access APIs. The web interface can run in modern web browsers including Chrome, Firefox, Safari, and Edge, which should enable many viewers to use StreamWiki, even with mobile devices such as iPads.

As StreamWiki enables streamers to stream using their accounts on existing streaming services, the URL of the stream video is retrieved in the m3u8 format using Streamlink, open source software to capture video URLs on most popular video or live streaming websites [61]. The API currently supports the retrieval of the live video sources from YouTube Live, Twitch, YouNow, Live.me, Douyu.tv etc. [61]. We also collect comments using the official comment APIs for YouTube Live and Twitch, and using a third-party open source library douyu-danmu for Douyu.tv [65], and display the comments in the comment window on our web interface.

The keywords visualization feature was implemented with nodejieba [66], an open source tool for parsing Chinese text with Node.js. We fine-tuned the default dictionary with a corpus of text from Weibo [33] to get a better TF-IDF for short text in Chinese, and used the fine-tuned dictionary for keyword extraction in StreamWiki. To support other languages, this module can be replaced by other Node.js natural language processing tools.

6 EVALUATION

We deployed our prototype with four knowledge sharing streamers and their viewers to see how viewers would use StreamWiki to watch KSLs and contribute to building knowledge. We invited two streamers from our formative study (S1 and S2) and recruited two additional Chinese streamers (S7 and S8) with the same criterion and method as the formative study. We first conducted five natural deployments with three streamers, their moderators, and volunteer viewers from their fan groups, in March 2018.

Table 2. The streams used in the pilot trials and deployment studies.

Type	Topic (listed in chronological order)	Streamer	Moderator	Viewers in StreamWiki (incl. paid)	Recruited and paid Viewers	Viewers on Douyu.tv
Natural deployments	Practical NLP for Dummies I	S1	M1	55	-	75
	Forensic Chemistry I	S2	M2	21	-	135
	Practical NLP for Dummies II	S1	M1	49	-	68
	Forensic Chemistry II	S2	M2	18	-	121
	Economics in Everyday Life I	S7	M7	13	-	66
Deployment studies with paid viewers	Practical NLP for Dummies III	S1	M1	47	4 (P1-P4)	73
	Practical NLP for Dummies IV	S1	M1	53	4 (P5-P8)	65
	Forensic Chemistry III	S2	M2	19	4 (P9-P12)	108
	Forensic Chemistry IV	S2	M2	22	4 (P13-P16)	112
	Introduction to HCI	S8	M8	18	5 (P17-P21)	56
	Economics in Everyday Life II	S7	M7	11	4 (P22-P25)	67

These initial deployments revealed that many viewers were not actively using StreamWiki features, so we then ran six deployment studies in which we paid viewers to make use of StreamWiki, with four streamers, their moderators, and viewers in April 2018. Details about all the streams are shown in Table 2.

6.1 Methodological Challenges and Limitations

As shown in previous research, a large number of viewers hired through Amazon Mechanical Turk tend to be more active than volunteer viewers to watch live events [51]. This work, however, was interested in the behaviors of intrinsically motivated viewers who have an interest in the streamer or the topics of KSLs. Most popular streamers in China have their own communities i.e., fan groups, and the members in the community communicate with each other and the streamer differently as their relationships grow over time [34]. To ensure existing relationship growth was a part of the evaluation, instead of recruiting viewers from MTurk or running a controlled study, we chose to invite the streamers' regular viewers to participate. This also allowed viewers to compare their experiences on StreamWiki with their current practices watching KSLs.

Another challenge of conducting evaluations in the wild is that many popular streamers (e.g. S3 and S4) have signed contracts with streaming platforms or companies [34]. What can be mentioned in streams is highly restricted, so although some streamers may have been willing to participate, they could not promote StreamWiki in their streams, as the software requires the viewers to navigate to our website instead of the streaming platforms. Although we tried to reach viewers in fan chat-groups, the response rate was very low, since without the help of the streamers, viewers may not have incentives to participate in our study. Moreover, many streaming platforms in China reward viewers who intensively use their applications with in-app benefits (e.g., badges). This could have further prevented users from volunteering in our study.

Due to the methodological challenges of running a study at scale, we chose to run a small-scale deployment study. Our studies could simulate a situation where there are several motivated viewers, and provide insights into the usability of StreamWiki and some preliminary results on its usefulness for KSLs users, though larger studies are needed in the future to understand the

full potential of StreamWiki and challenges at a larger scale. For example, trolls who abuse comments have been found in live streams [16,34], so we may need to implement a mechanism to prevent trolls abusing the summary cards. Another limitation is that the study was conducted with Chinese livestreaming users because of the prevalence of KSLs in China. Our results may not generalize to other demographics due to cultural differences and different popularity of KSLs.

6.2 Method

To evaluate our prototype, we conducted five natural deployments with volunteer viewers and six deployment studies with paid viewers. Before the study, we first demonstrated how to initiate cards and how the visualization works to the streamers and the moderators through video calls and a live remote demonstration, to let them become familiar with StreamWiki. For each deployment, we worked closely with the streamer to invite all his/her viewers from fan groups to go to our prototype web application to watch the live stream. We instructed the interested viewers about how to use StreamWiki through a live stream that showcased the UI for 15 minutes and provided a link to the video of detailed demonstrations of system features before the streams. The streamers also emphasized the key features of our system at the beginning of their streams. In all the deployments, we collected user logs from StreamWiki that recorded the number of viewers, the duration that they watched, the comments and summaries from viewers, and all the interactions of viewers using StreamWiki. The live stream video and audio were recorded.

6.2.1 Natural Deployments (Pilot Trials) with Volunteer Viewers. The five natural deployments helped us test our prototype with real users, familiarize the streamers and viewers with StreamWiki, and refine our evaluation method. These natural deployments informed us about how viewers would use StreamWiki when they had limited exposure to it and had inherently limited motivation, and suggested ways in which we could evaluate StreamWiki. Based on the preliminary findings, we decided to recruit and pay several well-motivated viewers in each deployment study so as to mimic situations where there could be multiple well-motivated viewers that are familiar with StreamWiki, engaged with the community, and willing to contribute summaries.

6.2.2 Deployment Studies with Paid Viewers. Although all the viewers from the streamer's fan group were welcomed and allowed to use StreamWiki, for each deployment study, four viewers were recruited by reaching out to them through the fan groups of the streamers. Each viewer was given a 15-minute training session on how to use StreamWiki and was then encouraged to freely explore the system features and write summaries while they were watching the live stream. After the stream, we collected survey responses about various system features (i.e., writing summaries, upvoting for Danmaku, and the visualizations), viewers' perceptions of KSLs, how StreamWiki influenced watching and learning experiences, what viewers liked and disliked, and what each viewer would like to improve about the experience. The survey also asked participants to use their own language to write an overview of the stream they had watched, although they were allowed to refer to the document constructed using StreamWiki. These deployment studies provide the research team with data about how well-motivated viewers would use StreamWiki to watch KSLs and their reactions to it.

6.2.3 Post-stream Interviews with Streamers and Moderators. To better understand the potential use of StreamWiki for streamers and moderators, after the deployment studies, we interviewed the four streamers and two moderators (M1, M2) to get their feedback. For each interview, we first showed them the outcome of StreamWiki, including all the cards, the

comments and the visualizations, and the UI for archived video. We also shared some user logs about how the viewers interacted with StreamWiki. The interview was semi-structured, audio taped, and lasted about 30 minutes. We focused on how they foresaw the features of StreamWiki benefitting them and how they would like to improve the design of StreamWiki.

Table 3. System feature statistics by stream of deployment studies

	NLP3	NLP4	FCHE3	FCHE4	HCI	ECON2
# of viewers using StreamWiki	47	53	19	22	18	11
Total # of summaries	113	52	72	124	28	104
Total # of comments	137	136	28	99	63	67
Total # of cards	6	4	7	10	6	7
# of viewers who wrote summaries	7	8	8	7	6	6
# of viewers who upvoted summaries	6	7	8	4	6	5
# of times summaries were upvoted	33	30	68	47	35	42
# of viewers who posted comments	18	15	6	8	10	9
# of viewers who upvoted comments	14	9	5	5	3	9
# of times comments were upvoted	82	55	23	62	18	25
# of comments that became Danmaku	15	4	5	22	2	3

6.3 Participants

Although we did not recruit any paid participant for the natural deployment studies, there were 156 volunteer viewers who used StreamWiki. For the 6 paid deployment studies, a total of 25 viewers (i.e., 11 males, ages 19-55, *Mean*=26) were recruited, including twelve enrolled undergraduate students, four post-graduate students, five general staff (including workers or administrative staff), and four working professionals (including engineers, journalists and teachers). They were regular viewers of the streamers we invited and watched KSLs at least once a week. Each recruited viewer was paid 50 CNY for their time. There were 145 volunteer viewers who also used StreamWiki in the paid deployment studies (Table 2). Since the streamers streamed on their existing streaming service (*Douyutv.com*), and other viewers could have watched the stream using *Douyutv.com*, we also list the number of viewers who watched using *Douyutv.com* in Table 2 for context.

7 RESULTS OF DEPLOYING STREAMWIKI WITH STREAMERS

Building on the results from our five natural deployments with volunteer viewers, we deployed our prototype with four frequent knowledge sharing streamers, their moderators, and their viewers for six streams (Table 2). The average duration of the six streams was 80.7 minutes (*SD* = 8.1), ranging from 69 to 91 minutes.

7.1 Use of the System

In the five natural deployments, only a small portion of the viewers actively used the system. For example, in Forensic Chemistry I (FCHE1), the moderator contributed the most summaries. In terms of the other viewers, although 11 viewers commented, only 3 upvoted comments, 2 wrote summaries, and no one upvoted any summaries. From the informal feedback from viewers and streamers, many viewers did not feel strongly motivated to contribute summaries, mostly due to

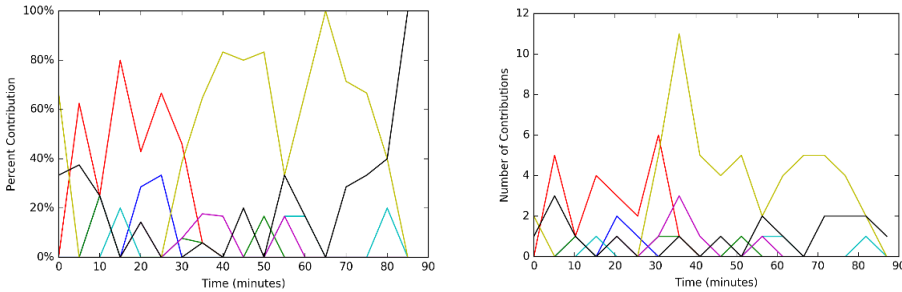


Fig. 3. The relative contribution (i.e., the ratio of the number of individual contributions to the contributions of all viewers, left) and number of contributions (right) of writing summaries from each of the seven viewers in the stream ‘NLP3’ over time. Line colors indicate each viewer.

being unfamiliar with StreamWiki because of their limited exposure to it, them being afraid to make mistakes or mislead others, being unsure about the benefits of using StreamWiki, and preferring to let others contribute rather than contribute themselves while watching. This behavior may have been due to the ‘cold start’ problem, i.e., in online spaces participants are reluctant to be the first to contribute to an empty space. When deployments had paid viewers, the paid viewers seemed to provide the seeding necessary for StreamWiki, thus encouraging unpaid viewers to begin to use StreamWiki features. For example, in Forensic Chemistry III (FCHE3), among the 15 unpaid viewers, 4 wrote summaries and 3 upvoted summaries.

The results of the log analysis inform us about the dynamics when some portion of the viewers were recruited while others were intrinsically motivated in our paid deployment studies. From the log data (Table 3), we can classify streams into 3 different categories: Streams with far more comments than summaries (NLP4 and HCI), streams with far more summaries than comments (FCHE3 and ECON2), and streams with a balanced number of summaries and comments (NLP3 and FCHE4). From informal feedback the streamers got from their viewers, the streams with balanced summaries and comments got the most positive feedback. These two also got more Danmaku promoted, indicating the active participation of viewers. We conjecture that the balanced pattern indicates that the viewers are engaged in both writing the summaries and interacting with others and the streamer, and the two kinds of activities supplement each other to improve engagement while learning. With far more comments than summaries, a stream may suffer from distractions, while with far less comments than summaries, a stream may become boring and less engaging.

The log data also provides information about viewers who contributed summaries on cards. For each of the six streams deployed with paid viewers, there was typically one to three viewers who contributed the majority of summaries during the streams (see Fig. 3 for an example). To our surprise, these viewers were not always the recruited viewers, for example, two were big fans of a streamer. Other viewers only occasionally wrote summaries. Most viewers typically did not propose improvement to summaries written by others, but often wrote a new summary, even though it might overlap previous ones. However, there were three viewers who only proposed improvements to summaries written by others without writing any new summary. This indicated that viewers may prefer to take on different roles in the task of writing summaries.

We also noticed differences in the time span of making contributions. Those who contributed more summaries than average wrote summaries from the beginning to the end, lasting over one hour. For others, the time span between their first summary and the last one was about thirty to

forty minutes, indicating that they only wrote summaries during part of the stream. The level of attention the viewer had throughout the stream might have influenced this. Since some viewers might not be fully engaged, their attention level might drop significantly after watching the stream for half an hour. However, some viewers still engaged in posting or upvoting comments, even if they no longer wrote summaries.

By looking into the summaries and comparing them to the archived video and the streamers' outlines or slides, we identified that 471 of the 493 summaries (95.5%) somewhat represented content in all the six streams. Twenty-two summaries were not related to the content, including off-topic questions (6), streamer-related (5), jokes (4), UI related questions (2), greetings (2), digressing (2), and trolling (1). They were also distributed unevenly among streamers, indicating that they might be dependent on the style of the streamer's community.

Although only 51 comments were promoted as Danmaku, 43 (84.3%) closely related to the stream, including asking questions (28), answering other viewer's questions (10), and making request to the streamer (5), such as asking the streamer to cover certain topic or to repeat something. Eight Danmaku were off-topic, including making fun jokes (5), expressing excitement or emotion (2), or asking for instructions regarding the UI (1).

7.2 Feedback from Viewers

The 25 recruited viewers provided ratings for the usability of StreamWiki (5-point Likert Scale, with 1-strongly disagree, and 5-strongly agree) after they watched a stream. Viewers agreed that StreamWiki was easy to use (*Median* = 4, *IQR* = 1), easy to learn how to use (*Median* = 5, *IQR* = 1), and they would like to use StreamWiki in the future (*Median* = 4, *IQR* = 1). They also felt that they participated more in the discussions using StreamWiki than without it (*Median* = 5, *IQR* = 1).

When asked how they would like to use the document of StreamWiki and how the document helped them during the task of writing an overview about the stream, they highlighted some benefits, including: "*The outcome of StreamWiki can be used as an outline which helps me review the knowledge*" (P1), "*I would like to share it with my friends, and choose keywords in it to delve deeper*" (P14), "*It helps me construct a knowledge web from scattered memories*" (P23), and "*It enables me to navigate the archive video based on my interest*" (P20).

We now report on viewer feedback on three main features, using both their ratings and quotes.

7.2.1 Writing and Reading Summaries on Cards. Most viewers did not find writing summaries while watching the stream time consuming (*Median* = 2, *IQR* = 0), hard (*Median* = 2, *IQR* = 2), or distracting (*Median* = 2, *IQR* = 2; Fig. 4). Although asking the viewers to write summaries when watching the live streams put an extra burden on them, they did not find it unpleasant to use, but instead agreed that writing summaries had several benefits, including helping them understand the content (*Median* = 5, *IQR* = 1), making them feel more engaged in the stream (*Median* = 4, *IQR* = 1), increasing their interest in the topic (*Median* = 4, *IQR* = 1), helping them answer questions raised in the stream (*Median* = 5, *IQR* = 1), making them feel a stronger sense of social presence in the stream (*Median* = 4, *IQR* = 1), and giving them a good overview of the information in the stream (*Median* = 5, *IQR* = 1). From their responses to open-ended questions, we further found several potential benefits of writing summaries and reading summaries written by others.

Writing summaries facilitates in-stream active learning. Viewers noted that writing summaries made them more actively engaged in learning, which helped them clarify their

thought process, deepen their impressions of key concepts, and improve their memory about the content, e.g., “I felt that I was more focused in learning when I was writing summaries. It deepened my impression of the content and made my understanding of the content more structured” (P22) and “when I was learning new content, writing summaries explicitly helped me recall the previous content, and such repetition made me memorize it better” (P3). They also noted the benefits of collaboration, i.e., “I felt that since we were collaborating, it saved time for everyone, so that I could focus on watching the part I was most interested in” (P16).

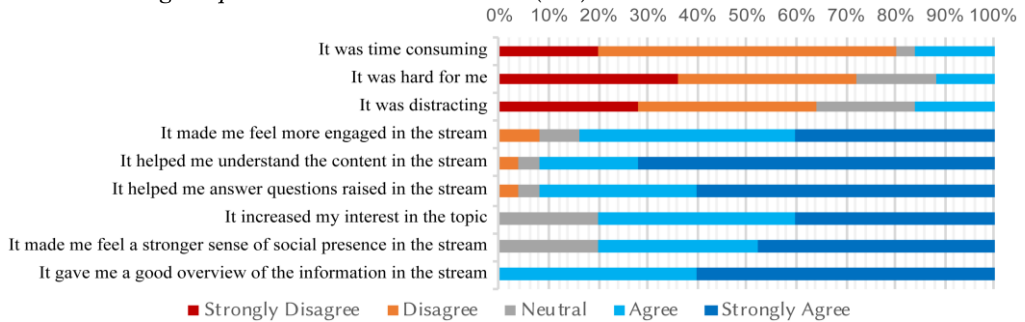


Fig. 4. Survey responses about the experience of writing summaries using StreamWiki.

Reading summaries by others improves understanding. Ten viewers mentioned that the summaries helped them organize their thoughts and find important points when watching KSLs, e.g., “I felt that writing summaries or reading the summaries written by others made me understand the structure of knowledge better, and made it easier to find key points in the stream” (P9). Viewers noted that the cards could serve as captions or tips for live videos, which could complement the video and help them recall important content, e.g., “Some people may find it hard to learn since live streams often don’t have captions. The cards can serve as a form of captions to help these learners.” (P5). Five viewers also mentioned benefits when one is distracted during the stream or watching the video archive of the stream for post-hoc learning, e.g., “For live streams it is common to encounter unstable connections and missed out important parts. The summaries on cards can help me quickly recover from it” (P11) and “When I watch the archive video, I think the summaries can help me find the content I am interested in quickly and accurately” (P14).

Summaries encourage peer learning. Participants also emphasized the benefits of being able to see other viewer’s summaries in real time, including encouraging peer learning, and getting inspiration, e.g., “I personally don’t like taking notes and I am not good at it, but using StreamWiki I could make use of the notes of other good note-takers, and I learned a lot from them” (P2), “looking at other viewers’ summaries helped me find what I had not learned well” (P21), and “since every viewer has different ideas, I felt inspired by reading summaries written by different viewers and got some new understanding about the content” (P20).

Concerns about efficiency and quality. Three viewers expressed some concerns they had about summaries on cards, including the time limit for typing and the quality of the summaries, e.g., “Sometimes the talking pace of the streamer is too fast for us to type, and if someone is not typing fast enough, she may miss some of the stream” (P10), “Some summaries were repetitive or missed out important points, and some were inaccurate or even misleading. Maybe the streamer or the moderator can check and revise some summaries after the stream” (P8), and “I am more interested in notes [summaries] written by those who have at least the same level of understanding with me, but I cannot check this” (P17). However, their ratings were still positive.

7.2.2 Upvoting Comments and Danmaku. Upvoting comments and promoting comments to be Danmaku were liked by the viewers. They agreed that upvoting comments (*Median* = 5, *IQR* = 1) and promoting comments to be Danmaku (*Median* = 4, *IQR* = 1) were helpful for the communication during the stream. They also agreed that when their comments were promoted as Danmaku, they felt a stronger sense of social presence in the stream (*Median* = 5, *IQR* = 0). The responses to open-ended questions provided more details about their perception of the feature. In general, viewers enjoyed this feature and found it useful.

Danmaku as a highlight and filter. Viewers stated that only showing the promoted comments as Danmaku reduced its potential negative influence on the watching experience while still engaged viewers, e.g., *“On commercial live streaming platforms, Danmaku is overwhelming and distracting. Only showing the promoted comments as Danmaku emphasized the comments that represent most viewers’ confusion or interest”* (P5). Nine viewers noted that Danmaku also serves as a filter for comments, e.g., *“A lot of comments don’t make sense or are noisy. By upvoting we can filter out some noise and make comments less distracting for the streamer”* (P10). Viewers also noted that it can make some valuable comments reappear for further discussion. *“With Danmaku, everyone can have a chance to make what s/he thinks valuable but buried in the comments to catch the attention of everyone, since the streamer cannot respond to every comment”* (P9).

Danmaku may improve quality of comments and attention. Five viewers mentioned that the design of promoting comments to become Danmaku also serves as an incentive for improving quality of comments. *“Since Danmaku can easily catch other viewers’ attention, I felt that I would like to send better comments so that they can become Danmaku. And if my comment becomes upvoted as Danmaku, I felt a greater sense of participation and belonging to the community”* (P12). One viewer mentioned its impact on attention, highlighting that *“it made me refocus on the stream when I was zoning out, since it stood out on the screen”* (P24).

Concerns about potential distractions and timeliness. Two viewers noted that they may not have enough time or energy to upvote comments if they are focused on learning (P6, P20). Two were concerned that some Danmaku were not meaningful, but just for fun (P7, P23). P22 mentioned that waiting for her comments to be upvoted and promoted as Danmaku sometimes distracted her from learning. P15 noted that *“it is valuable to make the selected thoughtful comments to appear on the video so that more people can see them in time. However, it is challenging to make viewers vote in time and show the Danmaku in time, since the context may pass when it gets enough votes”*.

7.2.3 Visualizations of Content and Context. The viewers agreed that the visualizations of comment volume and keywords were helpful for understanding the context (*Median* = 4, *IQR* = 1) and gave them a good overview of the information in the stream (*Median* = 5, *IQR* = 2). There was some variance in their perception of the usefulness of this feature. During the streams, fifteen viewers hovered over at least three keywords to see their timestamps. After the streams, nineteen viewers used the visualizations to navigate the archive video, using the comment volume visualization, the cards, and the keywords visualizations together. However, in general, viewers interacted with the keywords visualization more than the comment volume visualization.

Visualizations provide high-level information. The visualization of comment volume helped viewers *“identify important moments when there were hot debates or key concepts”* (P21) and gather ideas about all the viewers’ interest (P17, P23). The keywords visualizations helped viewers find key concepts in the stream efficiently (P4, P6, P7), remind them to *“relate concepts*

throughout the stream” (P5), allow them to “compare to other viewers’ understanding of the stream” (P21), and helped them “quickly get context information when distracted” (P11). Although the keyword visualization was not designed to function as a mind map or concept map, P10 and P12 noted that it seemed like a different representation of mind map or concept map for them, since “it visualized relationships between different keywords” (P12).

Visualizations may be more useful for post-hoc reflection. All viewers noted that when asked to write an overview of the stream they had watched in the survey, they used the visualization to recall the content and thought it was helpful, e.g., “The visualization lays out the structure of the whole stream. I used it for finding important cards which contain key concepts, and connected these thoughts to write my overview of the stream” (P14). Two viewers (P1, P2) noted that they had hidden the visualizations during the stream, so did not think it useful, but mentioned that “it would be helpful for someone who joined mid-stream” (P1). The perception of the usefulness may also be influenced by the scale of the study, as P25 noted, “if used at a larger scale with more comments and more summaries, I think it would be more useful”. Viewers also noted its usefulness for streamers, i.e., “It could be useful for the streamer to decide the future topics of the streams” (P14).

7.3 Feedback from Streamers and Moderators

The moderators’ responses generally aligned with the viewers’. They felt that the information provided by StreamWiki could be very useful for post-processing the archive video, since the comment volume visualization and the keywords visualization could be used to easily obtain ideas about what most viewers were interested in (M1, M2). M1 stated that he would like to have a tool to help him process the video using the data in the future. They also expressed concerns about more workload for moderation, because, if deployed in the wild, some viewers might abuse writing summaries and upvoting comments for Danmaku, which would make moderation harder (M1, M2). They also expressed that it was sometimes a little cumbersome to initiate cards manually and suggested to introduce tools to initiate cards automatically.

The streamers also gave positive feedback to StreamWiki and its outcome. S1 and S2 mentioned that the collaborations between viewers was efficient, and the summaries they wrote during the stream could not be written by a single person. They also noted that there was far less noise in summaries than in comments, and most of the comments that were upvoted and promoted as Danmaku were meaningful (S2, S7), “During the stream, I mainly looked at the upvoted comments and Danmaku, and responded to them. It saved me time and made me focused on streaming” (S2).

As for how the information provided by StreamWiki could help them *after* the stream, they stated that the summaries provided insights about what part of the stream viewers found useful, and how well they understood the content (S2, S8). All the streamers said that when looking into the summaries, they could find something new or unexpected. For example, S1 mentioned that she found that viewers wrote few summaries about active learning using clustering techniques, and thought that maybe she did not explain the concepts well in the stream, i.e., “by comparing my outline with summaries written by viewers, I can get a sense of what viewers have understood and what they have not, and I can adjust the content of future streams accordingly, for example, repeat some content that were missed out in summaries” (S1). They noted that they would also like to edit the outcome of StreamWiki, since the summaries might have some errors or repetition, e.g., “I would like to delete some summaries, for example, some repetitions. I would add some content to the cards to make it clearer, and also adjust the positions or order of some summaries” (S7). They

would also like to share the archived information of video, summaries, Danmaku, and visualizations to all their fans on social media (e.g., Weibo or WeChat), e.g., *“It can help those who missed the live stream quickly get an overview of what it was about, and they can see how others understood the topic by reading the summaries and the archived comments.”*(S8).

8 DISCUSSION AND FUTURE WORK

Our studies revealed several potential future directions to further improve the experience of using live streaming for knowledge sharing.

8.1 Reducing Information Overload

Although most viewers rated the features of StreamWiki positively, there were concerns about potential information overloads caused by the StreamWiki interface or the information contributed by many concurrent viewers. Some viewers were concerned about the quality of summaries and the difficulty of finding helpful summaries if there were too many. In future iterations, instead of showing all summaries, the interface could allow users to select a subset of viewers who they trust, and thus only show summaries contributed by these viewers. Danmaku can either catch a viewer’s attention or distract them. In future iterations, StreamWiki could enable users to set a ‘mute’ period or utilize algorithms to mute Danmaku automatically when users do not want to be distracted by Danmaku. As the visualizations may cause visual clutter during a stream, they seem to be more useful post-hoc. StreamWiki could allow viewers to choose a time window for recent activities they are interested in, e.g., within the last 5 minutes, and only show recent visualizations that occurred within this window. To maintain context, however, StreamWiki should show the whole visualization to those who have joined mid-stream and missed most parts of the stream.

8.2 Motivating Viewers to Contribute

Our natural deployments with unpaid viewers resulted in few contributed summaries, though we observed some unpaid viewers in the paid deployments contributing summaries in support of the streamers. Although the low participation rate might be the result of the ‘cold start’ problem or the small scale of the streams, motivating more viewers to contribute remains as an important question to address. To address the ‘cold start’ problem, one possible solution is to solicit streamers, moderators or super fans to seed summaries and votes on StreamWiki. Another possible way to motivate viewers might be to make the perceived benefits of using StreamWiki clearer. For example, the interface could have a personal notes section or personalized collections and allow for the social sharing of such elements in StreamWiki. Some viewers also mentioned distractions as a reason for their limited interaction with StreamWiki. Future work could adopt methods used in real-time crowdsourcing, for example, automatically dividing up the work so that everyone is not overwhelmed by tasks [28], to make contributing summaries less distracting. As gamification has been shown to be effective in increasing crowdsourcing motivation and participation [41], and some live streaming platforms already have used some elements of gamification (e.g., virtual gifts and leaderboards [34]), StreamWiki could embed more meaning in gift sending or display special badges to encourage participation. However, care must be taken to ensure that the gamification elements do not influence the learning experience.

8.3 Supporting Post-hoc Learning

As noted by viewers in our study, StreamWiki could support post-hoc learning by highlighting the key points and the structure of the knowledge and enabling easy navigation of archived video. However, more studies are needed in the future to evaluate how well StreamWiki supports viewers in post-hoc learning. To support post-hoc learning, future work should explore how to enable streamers to efficiently polish their archived video and how to synchronize the document generated by StreamWiki with the archived video to provide useful materials for post-hoc learning. Since viewers noted that they would like to share the information in StreamWiki with friends, this information should be easy for them to refer and link to from social media sites, note-taking applications, forums, or group chat to enable collaborative learning. Further, the interaction data in StreamWiki could also be used to enable data-driven interfaces using the post-hoc document, similar to those developed for MOOCs, e.g., in-video prompting [47] and personalized content recommendations [25], to further enhance learning. We leave such explorations for future work.

8.4 Trust and Authenticity

A few viewers and moderators in the study mentioned trust as an important factor while using summaries written by viewers for learning. Some even suggested that the summaries should all come from streamers and their moderators, but not every viewer, to make sure the information is accurate. However, it is infeasible for the streamers and moderators to do extra work to create these summaries, given their already overwhelming workload before and during the stream. To make the documentation of live streams more scalable, future work can explore how to encourage viewers to write summaries with responsibility, and how to improve trustworthiness of the peer-written summaries of live streams, e.g. how design can impact trustworthiness in real-time social interactions, similar to the study on perceived trustworthiness of wikis [27].

8.5 Virtual Team Formation in KSLS

From our study, we found that viewers have different patterns of contributing summaries, and prefer to take on different roles. For example, a few viewers only proposed improvements to existing summaries but did not write their own. We could optimize the formation of a virtual team for the microtasks to ensure that all the viewers in a team are compatible and their skills complement each other, so that they can finish the tasks more efficiently. Previous research in MOOCs has also shown many positive effects of team-based learning, including improved attendance, better performance, and the development of interpersonal and team skills [54]. Research has also explored different technologies to support team formation, such as self-selection based [52] and algorithm-based team formation [2]. However, as the motivations, expectations, norms, and data available about team members differ between KSLS community and MOOCs, it is challenging to directly apply technologies in MOOCs to KSLS. Future work should explore how to support better team formation in KSLS community, to combine the benefits of social interactions in the whole community and teams.

8.6 Integration with other Tools and Systems

From our interviews, we found that streamers used a variety of different hardware and software to prepare, conduct, and post process live streams. StreamWiki should be a part of this ecosystem of tools. For example, since some streamers edit the archived videos after the live streams to post them on social media, we could integrate StreamWiki with video editing functionality, further

enabling the viewers to collaboratively edit a video archival while watching the stream. Future work could also explore how to import streamer's data into the system, such as the streamer's outlines or slides, and leverage this information to reduce the workload of viewers. Since several streamers also expressed their willingness to edit the archival documents after the live stream, future iterations will also consider how to support them edit the archival more efficiently.

To enable knowledge sharing live streaming to be used as a formal educational approach, we envision that we could introduce more concepts from learning analytics, which has been shown to provide many advantages for MOOCs and online education [10]. For example, we can leverage the viewers' interaction data of both in-stream and post-hoc watching, to better inform streamers about viewers' interest and confusion, and viewers about their own learning. Further, as pointed out by two streamers we interviewed, KSLs, traditional education, online education, and MOOCs should work together to support everyone who desires access to knowledge, so they are not in conflict. Future research could also explore how to bridge these different systems to combine the benefits of them and optimize the outcomes of learning.

9 CONCLUSION

In this work, we interviewed knowledge sharing streamers, their moderators, and viewers to better understand live streaming knowledge sharing. We found that viewers desire better tools to archive the interactive learning experience during live streams for effective in-stream and post-hoc learning and streamers desire tools to get better feedback and reflect on the streams. Based on the findings, we designed, developed, and evaluated StreamWiki, a tool which leverages the viewers available during live streams to produce useful archives of the content and context in the stream, and provide visualizations for quicker post-live stream browsing. With StreamWiki, moderators initiate tasks that viewers complete by completing microtasks, such as writing a summary, commenting, or voting for informative comments. In this way, an archival document is built in real time, during the stream. Through the evaluation of our prototype with streamers and viewers, we found that the microtasks were not perceived hard or distracting by the viewers, and the results generated by StreamWiki were satisfying and useful, which effectively helped the viewers to get an overview and understand the content that was presented, and let the streamers understand more about their viewers' understanding of the content and improve their future streams accordingly.

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REFERENCES

- [1] Gregory Abowd, Maria da Graça Pimentel, Bolot Kerimbaev, Yoshihide Ishiguro, and Mark Guzdial. 1999. Anchoring Discussions in Lecture: An Approach to Collaboratively Extending Classroom Digital Media. In *Proceedings of the 1999 Conference on Computer Support for Collaborative Learning (CSCL '99)*. Retrieved from <http://dl.acm.org/citation.cfm?id=1150240.1150241>
- [2] Antonio R. Anaya and Jesus G. Boticario. 2009. Clustering learners according to their collaboration. In *2009 13th International Conference on Computer Supported Cooperative Work in Design*, 540–545. DOI:<https://doi.org/10.1109/CSCWD.2009.4968115>
- [3] David Baron, Andrew Bestbier, Jennifer M Case, and Brandon I Collier-Reed. 2016. Investigating the effects of a backchannel on university classroom interactions: A mixed-method case study. *Comput. Educ.* 94, (2016), 61–76.

DOI:<https://doi.org/https://doi.org/10.1016/j.compedu.2015.11.007>

- [4] Debbie Chen. A Comprehensive Overview: Yizhibo - ChoZan - Chinese Social Media Made Easy. Retrieved April 11, 2018 from <https://chozan.co/2017/03/10/comprehensive-overview-yizhibo/>
- [5] China Internet Network Information Center (CNNIC). 2017. *2016 Chinese social application user behavior research report*. Retrieved from <http://www.cnnic.net.cn/hlwfzyj/hlwzxbg/sqbg/201712/P020180103485975797840.pdf>
- [6] Soon Hau Chua, Toni-Jan Keith Palma Monserrat, Dongwook Yoon, Juho Kim, and Shengdong Zhao. 2017. Korero: Facilitating Complex Referencing of Visual Materials in Asynchronous Discussion Interface. *Proc. ACM Hum.-Comput. Interact.* 1, CSCW (December 2017), 34:1--34:19. DOI:<https://doi.org/10.1145/3134669>
- [7] Nicholas Diakopoulos, Mor Naaman, and Funda Kivran-Swaine. 2010. Diamonds in the rough: Social media visual analytics for journalistic inquiry. In *Visual Analytics Science and Technology (VAST), 2010 IEEE Symposium on*, 115–122.
- [8] Brian Dorn, Larissa B Schroeder, and Adam Stankiewicz. 2015. Piloting TrACE: Exploring Spatiotemporal Anchored Collaboration in Asynchronous Learning. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '15)*, 393–403. DOI:<https://doi.org/10.1145/2675133.2675178>
- [9] Audubon Dougherty. 2011. Live-streaming mobile video: production as civic engagement. In *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '11)*, 425. DOI:<https://doi.org/10.1145/2037373.2037437>
- [10] Rebecca Ferguson. 2012. Learning analytics: drivers, developments and challenges. *Int. J. Technol. Enhanc. Learn.* 4, 5–6 (2012), 304–317.
- [11] Colin Ford, Dan Gardner, Leah Elaine Horgan, Calvin Liu, a. m. tsaasan, Bonnie Nardi, and Jordan Rickman. 2017. Chat Speed OP PogChamp: Practices of Coherence in Massive Twitch Chat. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '17)*, 858–871. DOI:<https://doi.org/10.1145/3027063.3052765>
- [12] D Randy Garrison and Martha Cleveland-Innes. 2005. Facilitating cognitive presence in online learning: Interaction is not enough. *Am. J. Distance Educ.* 19, 3 (2005), 133–148.
- [13] Elena L Glassman, Juho Kim, Andrés Monroy-Hernández, and Meredith Ringel Morris. 2015. Mudslide: A Spatially Anchored Census of Student Confusion for Online Lecture Videos. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*, 1555–1564. DOI:<https://doi.org/10.1145/2702123.2702304>
- [14] Lassi Haaranen. 2017. Programming As a Performance: Live-streaming and Its Implications for Computer Science Education. In *Proceedings of the 2017 ACM Conference on Innovation and Technology in Computer Science Education (ITiCSE '17)*, 353–358. DOI:<https://doi.org/10.1145/3059009.3059035>
- [15] Oliver L. Haimson and John C. Tang. 2017. What Makes Live Events Engaging on Facebook Live, Periscope, and Snapchat. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*, 48–60. DOI:<https://doi.org/10.1145/3025453.3025642>
- [16] William A. Hamilton, Oliver Garretson, and Andruid Kerne. 2014. Streaming on twitch: fostering participatory communities of play within live mixed media. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems (CHI '14)*, 1315–1324. DOI:<https://doi.org/10.1145/2556288.2557048>
- [17] William A Hamilton, Nic Lupfer, Nicolas Botello, Tyler Tesch, Alex Stacy, J Bryce Merrill, Blake Williford, Frank R Bentley, and Andruid Kerne. 2018. Collaborative Live Media Curation: Shared Context for Participation in Online Learning. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*, Paper 555, 14 pages. DOI:<https://doi.org/https://doi.org/10.1145/3173574.3174129>
- [18] Anna Hansch, Lisa Hillers, Katherine McConachie, Christopher Newman, Thomas Schildhauer, and Philipp Schmidt. 2015. Video and Online Learning: Critical Reflections and Findings from the Field. *SSRN Electron. J.* (March 2015). DOI:<https://doi.org/10.2139/ssrn.2577882>
- [19] Stefan Hrastinski. 2008. Asynchronous and synchronous e-learning. *Educ. Q.* 31, 4 (2008), 51–55.
- [20] Stefan Hrastinski. 2009. A theory of online learning as online participation. *Comput. Educ.* 52, 1 (2009), 78–82.
- [21] Yen-Chia Hsu, Tay-Sheng Jeng, Yang-Ting Shen, and Po-Chun Chen. 2012. SynTag: A Web-based Platform for Labeling Real-time Video. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work (CSCW '12)*, 715–718. DOI:<https://doi.org/10.1145/2145204.2145312>
- [22] Ellen A Isaacs, Trevor Morris, and Thomas K Rodriguez. 1994. A Forum for Supporting Interactive Presentations to Distributed Audiences. In *Proceedings of the 1994 ACM Conference on Computer Supported Cooperative Work (CSCW '94)*, 405–416. DOI:<https://doi.org/10.1145/192844.193060>
- [23] Gavin Jancke, Jonathan Grudin, and Anoop Gupta. 2000. Presenting to Local and Remote Audiences: Design and Use of the TELEP System. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '00)*, 384–391. DOI:<https://doi.org/10.1145/332040.332461>
- [24] Sasa Junuzovic, Kori Inkpen, Rajesh Hegde, Zhengyou Zhang, John Tang, and Christopher Brooks. 2011. What Did I Miss?: In-meeting Review Using Multimodal Accelerated Instant Replay (Air) Conferencing. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*, 513–522. DOI:<https://doi.org/10.1145/1978942.1979014>
- [25] Mohamed Koutheaïr Khribi, Mohamed Jemni, and Olfa Nasraoui. 2015. Recommendation Systems for Personalized Technology-Enhanced Learning. Springer, Berlin, Heidelberg, 159–180. DOI:https://doi.org/10.1007/978-3-662-44659-1_9
- [26] Juho Kim, Philip J Guo, Carrie J Cai, Shang-Wen Daniel Li, Krzysztof Z Gajos, and Robert C Miller. 2014. Data-driven interaction techniques for improving navigation of educational videos. In *Proceedings of the 27th annual ACM symposium on User interface software and technology (UIST' 14)*, 563–572. DOI:<https://doi.org/10.1145/2642918.2647389>
- [27] Aniket Kittur, Bongwon Suh, and Ed H Chi. 2008. Can you ever trust a wiki?: impacting perceived trustworthiness in

- wikipedia. In *Proceedings of the 2008 ACM conference on Computer Supported Cooperative Work (CSCW' 08)*, 477–480. DOI:<https://doi.org/10.1145/1460563.1460639>
- [28] Walter S. Lasecki and Jeffrey P. Bigham. 2014. Real-time captioning with the crowd. *interactions* 21, 3 (May 2014), 50–55. DOI:<https://doi.org/10.1145/2594459>
- [29] Jean Lave and Etienne Wenger. 1991. *Situated learning: Legitimate peripheral participation*. Cambridge university press.
- [30] Yi-Chieh Lee, Wen-Chieh Lin, Fu-Yin Cherng, Hao-Chuan Wang, Ching-Ying Sung, and Jung-Tai King. 2015. Using time-anchored peer comments to enhance social interaction in online educational videos. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*, 689–698.
- [31] Jinglan Lin and Zhicong Lu. 2017. The Rise and Proliferation of Live-Streaming in China: Insights and Lessons. In *International Conference on Human-Computer Interaction*, 632–637.
- [32] Ching Liu, Juho Kim, and Hao-chuan Wang. 2018. ConceptScape: Collaborative Concept Mapping for Video Learning. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*, Paper 387, 12 pages. DOI:<https://doi.org/10.1145/3173574.3173961>
- [33] Jun Liu, Hao Chen, Mengting Zhan, Jianhong Mi, and Yanzhang Lv. MicroblogPCU Data Set. Retrieved January 11, 2018 from <https://archive.ics.uci.edu/ml/datasets/microblogPCU#>
- [34] Zhicong Lu, Haijun Xia, Seongkook Heo, and Daniel Wigdor. 2018. You Watch, You Give, and You Engage: A Study of Live Streaming Practices in China. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*, Paper 466, 13 pages. DOI:<https://doi.org/10.1145/3173574.3174040>
- [35] Xiaojuan Ma and Nan Cao. 2017. Video-based Evanescent, Anonymous, Asynchronous Social Interaction: Motivation and Adaptation to Medium. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '17)*, 770–782. DOI:<https://doi.org/10.1145/2998181.2998256>
- [36] Adam Marcus, Michael S Bernstein, Osama Badar, David R Karger, Samuel Madden, and Robert C Miller. 2011. Twitinfo: aggregating and visualizing microblogs for event exploration. In *Proceedings of the 2011 SIGCHI conference on Human factors in computing systems (CHI '11)*, 227–236.
- [37] Joseph F McCarthy and danah m. boyd. 2005. Digital Backchannels in Shared Physical Spaces: Experiences at an Academic Conference. In *CHI '05 Extended Abstracts on Human Factors in Computing Systems (CHI EA '05)*, 1641–1644. DOI:<https://doi.org/10.1145/1056808.1056986>
- [38] Matthew K Miller, John C Tang, Gina Venolia, Gerard Wilkinson, and Kori Inkpen. 2017. Conversational Chat Circles: Being All Here Without Having to Hear It All. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*, 2394–2404.
- [39] Toni-Jan Keith Palma Monserrat, Shengdong Zhao, Kevin McGee, and Anshul Vikram Pandey. 2013. NoteVideo: Facilitating Navigation of Blackboard-style Lecture Videos. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*, 1139–1148. DOI:<https://doi.org/10.1145/2470654.2466147>
- [40] Bill Moorier. Introducing Twitch Creative – Twitch Blog. Retrieved April 10, 2018 from <https://blog.twitch.tv/introducing-twitch-creative-fbfe23b4a114>
- [41] Benedikt Morschheuser, Juho Hamari, and Jonna Koivisto. 2016. Gamification in crowdsourcing: a review. In *System Sciences (HICSS), 2016 49th Hawaii International Conference on*, 4375–4384.
- [42] Ahmed E Mostafa, Kori Inkpen, John C Tang, Gina Venolia, and William A Hamilton. 2016. SocialStreamViewer: Guiding the Viewer Experience of Multiple Streams of an Event. In *Proceedings of the 19th International Conference on Supporting Group Work (GROUP '16)*, 287–291. DOI:<https://doi.org/10.1145/2957276.2957286>
- [43] Amy Pavel, Colorado Reed, Björn Hartmann, and Maneesh Agrawala. 2014. Video Digests: A Browsable, Skimmable Format for Informational Lecture Videos. In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology (UIST '14)*, 573–582. DOI:<https://doi.org/10.1145/2642918.2647400>
- [44] Anthony G Picciano. 2002. Beyond student perceptions: Issues of interaction, presence, and performance in an online course. *J. Asynchronous Learn. networks* 6, 1 (2002), 21–40.
- [45] José Miguel Santos-Espino, Maria Dolores Afonso-Suárez, and Cayetano Guerra-Artal. 2016. Speakers and Boards: A Survey of Instructional Video Styles in MOOCs. *Tech. Commun.* 63, 2 (2016), 101–115.
- [46] Beejoli Shah. Facebook Live Is the New QVC | WIRED. Retrieved April 11, 2018 from <https://www.wired.com/story/facebook-live-qvc-pearl-parties/>
- [47] Hyungyu Shin, Eun-Young Ko, Joseph Jay Williams, and Juho Kim. 2018. Understanding the Effect of In-Video Prompting on Learners and Instructors. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*, Paper 319, 12 pages. DOI:<https://doi.org/10.1145/3173574.3173893>
- [48] Anselm Strauss and Juliet Corbin. 1998. *Basics of qualitative research: Techniques and procedures for developing grounded theory, 2nd ed.* Sage Publications, Inc, Thousand Oaks, CA, US.
- [49] Karen Swan. 2002. Building learning communities in online courses: The importance of interaction. *Educ. Commun. Inf.* 2, 1 (2002), 23–49.
- [50] John C. Tang, Gina Venolia, and Kori M. Inkpen. 2016. Meerkat and Periscope. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*, 4770–4780. DOI:<https://doi.org/10.1145/2858036.2858374>
- [51] John Tang, Gina Venolia, Kori Inkpen, Charles Parker, Robert Gruen, and Alicia Pelton. 2017. Crowdcasting: Remotely Participating in Live Events Through Multiple Live Streams. *Proc. ACM Human-Computer Interact.* 1, November (December 2017), 1–18. DOI:<https://doi.org/10.1145/3134733>

- [52] Carine G. Webber and Maria de Fátima Webber do Prado Lima. 2012. Evaluating automatic group formation mechanisms to promote collaborative learning - a case study. *Int. J. Learn. Technol.* 7, 3 (2012), 261. DOI:<https://doi.org/10.1504/IJLT.2012.049193>
- [53] Sarah Weir, Juho Kim, Krzysztof Z. Gajos, and Robert C. Miller. 2015. Learnersourcing Subgoal Labels for How-to Videos. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW '15)*, 405–416. DOI:<https://doi.org/10.1145/2675133.2675219>
- [54] Miaomiao Wen. 2016. Investigating virtual teams in massive open online courses: deliberation-based virtual team formation, discussion mining and support. Carnegie Mellon University.
- [55] Qunfang Wu, Yisi Sang, Shan Zhang, and Yun Huang. 2018. Danmaku vs. Forum Comments: Understanding User Participation and Knowledge Sharing in Online Videos. In *Proceedings of the 2018 ACM Conference on Supporting Groupwork (GROUP '18)*, 209–218. DOI:<https://doi.org/10.1145/3148330.3148344>
- [56] Sarita Yardi. 2006. The Role of the Backchannel in Collaborative Learning Environments. In *Proceedings of the 7th International Conference on Learning Sciences (ICLS '06)*, 852–858. Retrieved from <http://dl.acm.org/citation.cfm?id=1150034.1150158>
- [57] Amy X Zhang, Lea Verou, and David Karger. 2017. Wikum: Bridging Discussion Forums and Wikis Using Recursive Summarization. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '17)*, 2082–2096. DOI:<https://doi.org/10.1145/2998181.2998235>
- [58] Saijing Zheng, Mary Beth Rosson, Patrick C Shih, and John M Carroll. 2015. Understanding Student Motivation, Behaviors and Perceptions in MOOCs. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW '15)*, 1882–1895. DOI:<https://doi.org/10.1145/2675133.2675217>
- [59] Saijing Zheng, Pamela Wisniewski, Mary Beth Rosson, and John M Carroll. 2016. Ask the Instructors: Motivations and Challenges of Teaching Massive Open Online Courses. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing (CSCW '16)*, 206–221. DOI:<https://doi.org/10.1145/2818048.2820082>
- [60] Sacha Zyto, David Karger, Mark Ackerman, and Sanjoy Mahajan. 2012. Successful Classroom Deployment of a Social Document Annotation System. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '12)*, 1883–1892. DOI:<https://doi.org/10.1145/2207676.2208326>
- [61] API Guide — Streamlink 0.11.0 documentation. Retrieved from https://streamlink.github.io/api_guide.html#api-guide
- [62] Douyu - Educational Live Streams. Retrieved March 11, 2018 from <https://www.douyu.com/directory/game/yj>
- [63] OpenVis Conf by Bocoup. Retrieved January 18, 2018 from <http://www.openvisconf.com/2016/#videos>
- [64] Video-React - React Video Component. Retrieved January 1, 2018 from <https://video-react.js.org/>
- [65] Douyu-danmu Github. Retrieved January 2, 2018 from <https://github.com/BacooTang/douyu-danmu>
- [66] Nodejieba - Github. Retrieved February 1, 2018 from <https://github.com/yanyiwu/nodejieba>

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