Received: 1 December 2022 | Revised: 5 April 2023 | Accepted: 22 April 2023

DOI: 10.1002/cae.22641

RESEARCH ARTICLE

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Visualizing timeline-anchored comments enhanced social presence and information searching in video-based learning

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Funding information
National Natural Science Foundation of China, Grant/Award Number: T2192932; Shanghai Summit Discipline in Design

Abstract

Numerous learners watch knowledgeable videos with comments or annotations anchored to the video timeline. These comments are learners' discussions with abundant informational and social content along with video timelines, but the content is usually fragmented and scattered. To extract, organize, and highlight useful information from the discussion, we adopted text mining approaches and designed an interactive visualization tool in the lecture interface for learners, including the following components along with the video timeline: (1) the relevance of comments to the lecture, (2) the comment topics throughout the lecture, and (3) the difficulty level perceived by learners. We conducted a lab experiment with 24 students to examine the effects of the visualization tool on the learning process and outcomes. We found that learners perceived a significantly higher social presence and performed better in open-book quizzes, searching tasks, and summarizing lectures using the visualization tool. This suggests that the visualization of timeline-anchored commenting potentially facilitates learners' participation in discussions and contributions to the learning community.

KEYWORDS

data visualization, text mining, timeline-anchored commenting, video-based learning

1 | INTRODUCTION

Many people learn from online recorded or live-streaming videos formally (e.g., from schools or massive open online courses [MOOCs]) or informally (e.g., from YouTube). This has become more prevalent during the COVID-19 pandemic [41]. In China, over 113 million users learn informally through videos on Bilibili, a video-sharing platform with timeline-anchored commenting [18]. Such comments from previous viewers are anchored to the playback time of the video to promote social interaction and annotation sharing. This anchored-commenting function is also afforded by educational platforms, such as commercial platforms (e.g., echo360) or studies of innovative interface design [13, 15, 43, 84, 86].

Timeline-anchored comments provide qualitative and rich information about the complicated feelings and opinions of previous learners. On the one hand, this information benefits learning [11, 13, 38, 84]. These comments provide a way for information seeking, make the discussion more visually salient, promote discussion, and enhance cognitive learning. The comments also involve learners in more discussion specific to video timepoints, mimic a feeling of coviewing with others synchronously, and promote social interaction and social presence. On the other hand, timeline-anchored comments are usually fragmented, scattered, and on a large scale, thus bringing visual clutters, distraction, and decreased satisfaction [11, 13, 84].

Researchers have attempted to reduce complexity and highlight valuable parts of forum discussions by identifying patterns and extracting knowledge from the discussion. They applied approaches such as learning analytics, such as text mining, and social network analysis [26, 42, 48, 49, 88]. These analyses and visualizations were then used to design tools to support learners' learning [9, 21, 45, 55]. With respect to timeline-anchored commenting, researchers also analyzed and visualized various factors such as the number of comments, keywords, and topics, to improve the learning experience for both learners and instructors [8, 43, 47, 57, 75].

However, previous studies have been insufficient in both the design and evaluation of the visualization of timeline-anchored comments. Regarding design, there is a lack of visualization tools that are connected or interactive with lecture videos [8, 57], making it difficult for learners to navigate or interact with the videos via the tools. In addition, previous designs [8, 47] visualized the numbers of comments or annotations, which were difficult for learners to interpret. Regarding evaluation, some research has suggested improved usability and increased engagement [43, 47], but it lacks an examination of how visualization tools affect cognitive learning and experience, such as social presence, an essential element for successful learning [4, 25]. Previous research suggests that visualization of these comments can potentially support the activities of searching, memorizing, and comprehending [40, 43], and can engage learners in more discussions [9, 55]. It may further establish the social context of collaborative learning, which requires further investigation.

Therefore, this study aimed to (1) design a learner-oriented tool that analyzes and visualizes timeline-anchored comments to support video-based learning and (2) examine its effect on learning. Using text mining approaches, we evaluated the relevance of comments to lecture videos, clustered comments into several topics, and identified how difficult other learners experienced along a video timeline. Then, we visualized this information on the lecture-video interface along the video timeline. Finally, we conducted a lab experiment that compared the interfaces with and without visualization to examine the effects on cognitive and social aspects of learning.

2 | LITERATURE REVIEW

2.1 | Learning analytics and data visualization for learners

In video-based learning, learners usually require interaction and knowledge of the states of other learners for better learning and knowledge building in the community [1, 20, 31]. To facilitate interaction and the awareness of the community, researchers have integrated platforms with learning analytics and visualizations of extensive learning data [80]. These tools analyze learners' data at both the course and video levels.

Numerous studies have designed course-level tools to support learners to, for example, compare a learner's performance with the community average level [65] or predict performance [56] throughout the course. A common approach is to conduct social network analysis and text mining on learner-generated content from course forums [9, 21, 45, 55] and course reviews by learners [52, 53]. The accuracy of text mining, such as the sentiment analysis and keyword extraction, has significantly improved with the rapid development of deep learning technologies in natural language processing [51, 54]. The majority of these studies aimed to study the relationships between learning processes or outcomes and the features of discussions [26, 42, 48, 49, 70, 88] rather than to design tools to support learning.

Other studies have visualized video-level interaction data. Video-level visualization could be more beneficial for casual learners who only watched individual videos without browsing forums. It helps learners know what others are thinking and how others' mental states, such as cognitive load and engagement, change throughout the video. Common approaches include analyzing behavioral data, such as learners' clickstream [33, 50, 68, 71], and analyzing physiological signals such as facial expressions and eye movement [58, 59, 73]. However, these data involve privacy issues and lack qualitative insights, including learners' subjective feedback. Thus, it is difficult to interpret learners' feelings and understanding of knowledge. This gap can be filled by text mining of timeline-anchored comments, which potentially reflect learners' thoughts along the video timeline.

2.2 | Analyzing and visualizing timeline-anchored comments

A few studies have visualized timeline-anchored comments or annotations to support learning or teaching. For example, Chatti et al. [8] designed CourseMapper, with which the lecture video timeline was colored to represent the number of timeline-anchored annotations and views. Similarly, Mitrovic et al. [47] visualized the number of personal annotations along a video timeline. They found that learners left more comments with the tool. Sung et al. [74, 75] designed tools named ThemeRiver and ToPIN for instructors. They visualized how the valence of learners' emotions, the relevance of discussions, and the topics changed along the video timeline using line charts and topic blocks. Peng et al. [57] collected both facial expressions and timeline-anchored discussions, calculated learners' perceived difficulty and interest, and presented them as line charts along a lecture video timeline. Lu et al. [43] designed StreamWiki for live-streaming learning. It shows the number of keywords extracted from real-time comments. These keywords are linked to related timestamps in the video.

These studies showed that the visualization of timeline-anchored comments could benefit learners and instructors, but certain issues need further investigation. First, many tools (except StreamWiki) did not interact with the lecture videos. For example, ThemeRiver and ToPIN [74, 75] were designed to help instructors and were independent of the video interface. Although Peng et al. [57] and Chatti et al. [8] visualized above or on the video timeline, viewers could not directly control or interact with the video or discussions using the tools.

Second, the presented raw number of comments [8, 43] is difficult to interpret. A larger number at a time point could result from many possible reasons, such as previous learners' interests, difficulties, or simply irrelevant social interactions. Similar problems have also been reported in studies of clickstreams [33]. Thus, rather than the raw number, learners require higher-level and interpretable information about their learning status.

Third, some studies have suggested improved usability and increased engagement in commenting or annotating [43, 47], but it remains uncertain how the visualization of timeline-anchored discussions affects cognitive learning and social presence, which are widely concerned variables during learning. Therefore, in the next section, we review the potential effects of the visualization.

2.3 | Potential effects of visualization on learning

2.3.1 | Cognitive effects

The analysis and visualization of comments can provide learners with additional knowledge and experience from other learners, potentially affecting the learning process and outcomes both cognitively and socioculturally [35]. From a cognitive perspective, learning is the increased comprehension and retention of knowledge and the development of intellectual abilities and skills [7, 34], also termed cognitive learning. From this perspective, basic activities or tasks of online video-based learning include memorizing [5, 62, 78] and information searching/seeking [85, 87].

Memorizing and searching can be facilitated through highlighting and organizing important content, also known as the signaling principle or cueing principle [66, 79]. Common approaches for signaling include (1) organizing the information (e.g., previews and headings) and (2) visually emphasizing the information (e.g., by light coloring).

To better organize learning materials, widely adopted strategies include chunking and outlining. Chunking refers to grouping coherent information into chunks and building an interconnected structure [17]. The sophisticated organization of chunks can support the process of memory knowledge and thus facilitate learning [3, 17]. Outlining can provide a hierarchical structure and an overview of this information [22, 23]. In video-based learning, researchers have labeled the table of contents and headings on the video timeline and verified that such hierarchically organized visualization could support navigation and provide an overview of the content [40].

These outlines, such as the table of contents, are typically pre-defined by instructors. Timeline-anchored comments can serve as a data source for automatically generating outlines. Previous studies have found that video learners often navigate through a video by referring to individual timeline-anchored comments or annotations [13, 27, 43, 44, 86]. Further extraction and highlighting of keywords [43, 74] can be used as outlines and may potentially enhance cognitive learning.

2.3.2 | Social effects

From a sociocultural perspective, learning also refers to adaptation to the environment. Based on a community of inquiry (CoI) framework [19], learning requires interaction among content, learners, instructors, and other contextual elements. During these interactions, learners develop a social presence that is essential to successful learning [1, 20, 31].

Social presence has been defined differently in the literature. Generally, social presence is the extent to which users perceive others' and others' activities as real, presented, and intimate in the community [24, 69, 82]. In the learning context, in addition to the awareness or closeness of others, social presence is also the perception that the community is friendly and comfortable for communication. Based on this definition, researchers identified three dimensions of social presence [77]: (1) social context (e.g., task orientation, topics, and social relationships), (2) online communication (i.e., the attributes and applications of online language), and (3) interactivity (i.e., the activities in which learners engage).

Visualization of forum discussions encouraged learners to participate more [9, 55], indicating that it may also enhance social presence. In the video interface, visualization of comments, such as keywords, may also highlight other learners' existence and contributions, amplify their feelings and emotions, and potentially create a collaborative social atmosphere. Thus, visualization may enhance social presence. However, there are not many studies conducted on the effects of discussion visualization on social presence.

3 | DESIGN OF THE VISUALIZATION TOOL

3.1 | Design goals

Based on previous research, we established the following design goals for the visualization tool: First, the tool needs to organize or outline timeline-anchored comments clearly and easily. Previous research has shown that well-organized learning materials support memorizing, searching, and overviewing information, thus promoting learning [16, 22, 40, 66]. Learners use timeline-anchored comments to search for information [85, 87] or navigate a video [13, 86]. As the number of comments increases, learners may find it difficult to navigate a video with a single comment. These navigation and search needs may be satisfied by an overview or organization of comment keywords implemented by text mining.

Second, the tool needs to be integrated with the video timeline to facilitate information search and navigation. As mentioned above, learners need effective ways to search for information in videos [85, 87]. Therefore, interactive tools that allow users to control the video should be provided. However, such features have rarely been afforded by previous designs of visualizing timeline-anchored comments [8, 57].

Third, the tool needs to reduce distractions from timeline-anchored discussions. Comments inevitably introduce visual clutters and irrelevant information, which can distract viewers and hinder their comprehension [10, 11]. Although irrelevant information may not affect learning performance when the material is easy [64], learners may gradually ignore all of the discussions and miss valuable parts [12, 13]. Therefore, the tool needs to highlight relevant information and help screen discussions.

Finally, the tool needs to help viewers share feelings and promote social presence. The visualization tool requires summarizing individual comments and revealing others' feelings to create a friendlier and more shared social context for discussion. Besides specific topics, learners are also interested in community members' feelings, such as the perceived difficulty in understanding the lecture [12, 13]. Sharing perceived difficulty can promote emotional resonance and social presence. Thus, the tool needs to provide ways for learners to share their feelings, thereby fostering a sense of social presence and promoting collaborative learning.

3.2 | Text mining of timeline-anchored comments and initial evaluation

To achieve these goals, this study designed a tool with three main features along the video timeline: (1) relevance, (2) topics, and (3) difficulty level. The relevance of the comments refers to how comments are related to the subtitle scripts of the video. The extracted topics are comment clusters, which include the keywords of each cluster and the cluster to which a comment belongs. The difficulty level refers to how difficult previous learners perceived the content at different time points in the video. We adapted typical text mining procedures [2] with Python 3.6, as shown in Figure 1 and the following subsections.

3.2.1 | Relevance

Relevance was estimated in two steps: (1) representing comments as vectors and (2) calculating the cosine similarity between two vectors. To represent a comment (C_j), first, C_j was segmented, and stop words were removed using the Jieba package. Then, a comment was encoded by averaging the Word2Vec embeddings [46] of all the words, which were weighted by their term frequency-inverse document frequency (tf-idf) values. The word embeddings were pre-trained on about 60 million posts in Chinese on Weibo by a previous study [61]. The vocabulary size was 40 thousand, and the dimension was set to 100. Suppose a comment (C_j) is segmented into N_j words. For word i ($w_{j,i}$), the vector from the word embeddings is $v_{j,i} = (v_{j,i,1}, v_{j,i,2}, \ldots, v_{j,i,100})$. Additionally, we considered all the comments and the video subtitles as the document set and calculated the

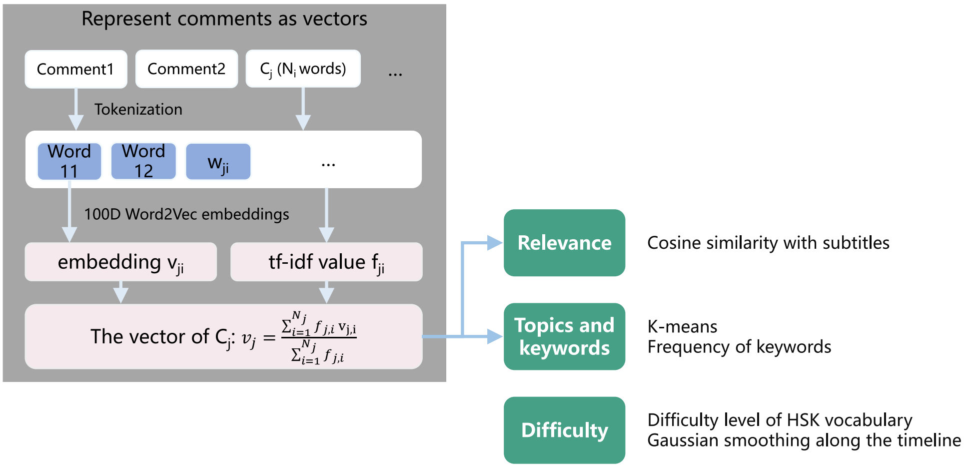

FIGURE 1 Text mining of timeline-anchored comments.

tf-idf values of each document (i.e., a comment or the subtitles). Suppose that the tf-idf of a word $w_{j,i}$ is $f_{j,i}$. The vector of comment C_j (i.e., v_j) was calculated using the below equation.

$$v_j = \frac{\sum_{i=1}^{N_j} f_{j,i} v_{j,i}}{\sum_{i=1}^{N_j} f_{j,i}}. \quad (1)$$

To indicate how relevant a comment was to the lecture, we computed a relevance index of each comment using the cosine similarity between the comment and the entire lecture video subtitles. To initially evaluate the validity of this relevance index, two researchers manually labeled the 256 comments of a lecture video used in this study. Each comment was labeled at three interval levels: irrelevant, neutral, or relevant. Pearson's correlation between the manual labels by the researchers and the calculated relevance indices was 0.44. The visualization tool illustrated the sum of the relevance indices of all the comments per minute to indicate the overall relevance of the timeline-anchored comments to the lecture along the timeline.

3.2.2 | Topics and keywords

Based on the encoded comments, we clustered all the comments of a video using the k-means method. In this study, we tested k values from three to six for the comments of each video used in the experiment. We found that when k was 6 for both videos, the clusters were the most meaningful, and the number of comments in each cluster was the most balanced. Thus, we clustered six topics for each video. Then, the topics were sorted by the mean time points to which all the comments in a topic were anchored. The frequency of each word was also counted for visualization purposes.

3.2.3 | Difficulty perceived by previous learners

Most available sentiment analysis algorithms focus on emotion, but not on the difficulty or cognitive load perceived by the authors of the texts. We assumed that more complex discussions involved more difficult words. Thus, we attempted a method based on the vocabulary lists of the Chinese Proficiency Test (HSK), a standardized test of Chinese language proficiency for nonnative speakers. It provided six vocabulary lists ranking from level 1 to 6 (from the easiest to the most difficult). The difficulty level per second was calculated in two steps: (1) calculating the difficulty score of each comment and (2) smoothing the difficulty along the timeline.

First, we calculated the difficulty of comment C_j, denoted as D_j. Suppose that C_j consists of N_j words. The difficulty of the word $w_{j,i}$, denoted as $d_{j,i}$, was defined as its rank (1–6) in the vocabulary lists. If $w_{j,i}$ did not appear in any of the lists, the difficulty was defined as 0. The difficulty of C_j (i.e., D_j) is the sum of the difficulty values of all the words in C_j, as shown in the below equation.

$$D_j = \sum_{i=1}^{N_j} d_{j,i}. \quad (2)$$

Then, we smoothed the difficulty along the timeline. For comment C_j, we averaged the difficulty of C_j and the nearest eight comments (from $C_{j\text{-}4}$ to C_{j+4}), denoted as $\overline{D_j}$. The difficulty values of the comments were Gaussian smoothed and sampled at each second to obtain the estimated difficulty of each second for further visualization.

To initially verify this method, we compared the calculated difficulty values with ratings provided by students. Four participants, who were students majoring in STEM, were invited to rate the difficulty of each minute of several lecture videos (101 min in total) from the machine learning course adopted in this experiment. Each participant independently rated each minute from 1 to 5, where 1 represented the easiest and 5 represented the most difficult. The ratings were standardized into a range of 0 to 1 and Gaussian smoothed, resulting in ratings for 92 min. The internal reliability of the four participants' ratings (Cronbach's α) was 0.73. We further removed the minutes in which the standard deviations of the ratings were larger than 0.15 among the four participants. Scores of 68 min remained, and Cronbach's α increased to 0.84, indicating acceptable internal reliability. The rated difficulty at each time point was defined as the mean value of their ratings. We also sampled each minute and used Gaussian methods to smooth the difficulty values of comments calculated by the above method. Pearson's correlation between the method and human ratings was 0.40 ($p < .001$).

3.3 | Interface design

Figure 2 demonstrates the interface of the lecture video visualization tool, which includes three main features: (1) relevance, (2) topics and keywords, and (3) difficulty along the video timeline. The relevance of comments is presented as a curve graph on the video timeline and is folded and hidden by default (Figure 2a,c). The difficulty level is indicated by the color of the video timeline, with red representing difficult parts and blue representing easy parts (see Figure 2a,b). The topics extracted from the comments are represented as word clouds of keywords underneath the timeline. The size of each word represents its frequency. The topics are aligned in the order of the mean anchored timepoints. When a learner clicks on a topic, the tool highlights the timepoints of the relevant comments on the video timeline, as well as the associated word cloud (see Figure 2b).

4 | EXPERIMENT

4.1 | Hypotheses

To examine the effect of visualization on learning, we conducted a laboratory experiment comparing two interfaces with or without the visualization tool. At both interfaces, the video was incorporated with timeline-anchored commenting.

The features of the visualization tool may support cognitive learning for the following reasons. First, the relevance and difficulty charts could help learners save cognitive resources and assign attention to more relevant or cognitively challenging comments. Thus, it could further support memory and the construction of knowledge according to the signaling principle [66, 79]. Second, the topic word clouds organized comments in several chunks and were aligned chronologically. They provided an overview of discussions, which could enhance the memory of the relevant knowledge [16, 22, 72], the navigation of the video, and the understanding [23, 40]. Third, the highlighting function of word clouds and timepoints also provided an interactive way to search for information from abundant comments. This may support the integration of information from both videos and timeline-anchored comments. Therefore, we have:

Hypothesis 1. *Learners have better cognitive learning with the visualization tool than without the tool.*

The colors of the timeline show how difficult the previous learners have perceived during learning. When a learner resonates with others, it can increase the immediacy between the learner and the previous learners, further increasing social presence [24, 82]. The summarized topics and keywords implied that learners' discussions contributed to community learning, providing a collaborative, open, and reliable social context. This context could facilitate learners to engage in more communication and lead to a higher social presence [63, 77]. Therefore, we have:

Hypothesis 2. *Learners perceive a higher level of social presence with the visualization tool than without it.*

Previous research has shown that interaction and presence are associated with higher satisfaction with the course [32, 36]. Thus, the visualization tool may increase satisfaction with the course. In addition, the tool may help learners notice and search for useful information, and thus learners would be more satisfied with the comments and platform. We have:

Hypothesis 3. *Learners are more satisfied with the use of visualization tools than without the use of them.*

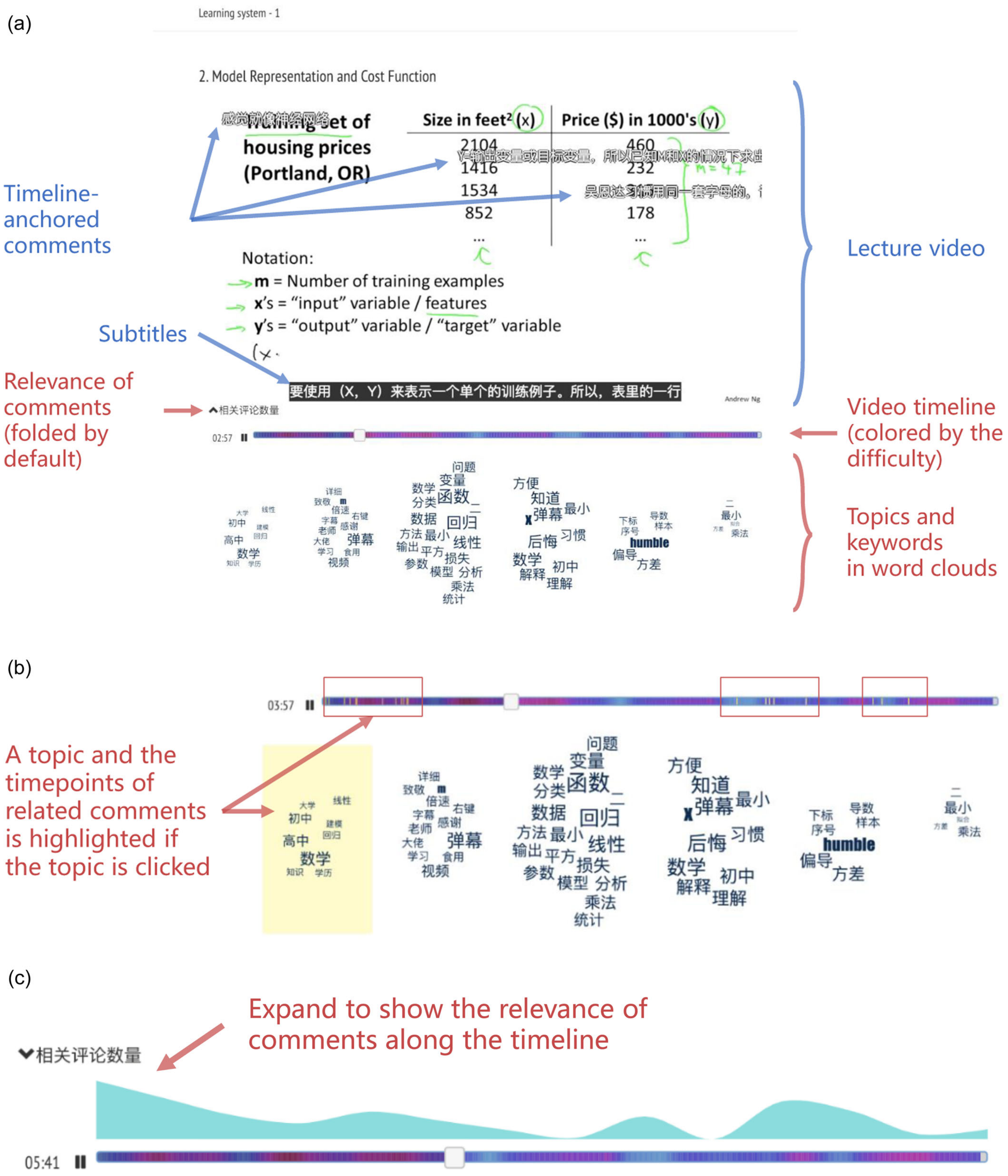

FIGURE 2 Screenshots of the interface with the visualization tool. (a) The lecture video and the visualization tool below the video. (b) The clicked topic and time points were highlighted. (c) Expand to show the relevance of comments along the timeline.

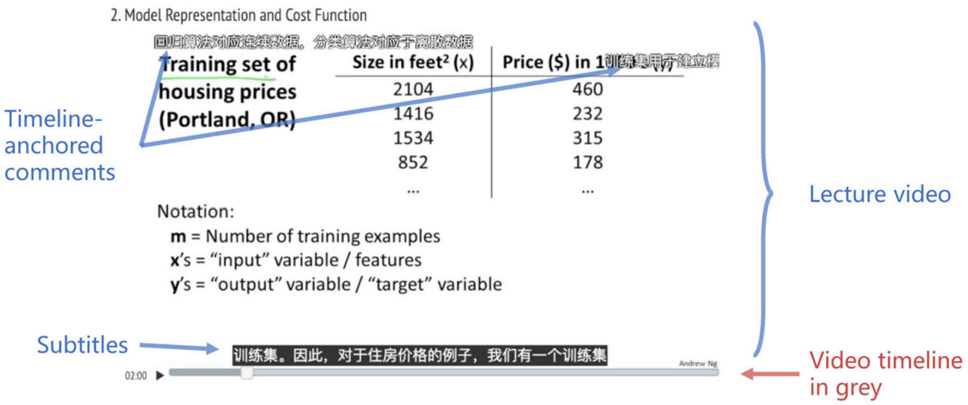

FIGURE 3 The interface when visualization tool is not used.

4.2 | Materials and methods

4.2.1 | Experimental platform

The experiment compared lecture interfaces with and without the visualization tool. The platform was developed using the Django 2.1.1 framework and Python 3.6. In the experiment, the web pages were displayed on a 23.8-inch screen with a resolution of 1920 × 1080. The interface without the tool is shown in Figure 3. The webpage consists of a video player with timeline-anchored comments. The shape of the video timeline was the same as that in the visualization condition, but the color was gray.

4.2.2 | Learning materials

We selected two lectures with comments in a video series on Bilibili reposted from a machine learning[1] course on Coursera. The course was popular and viewed millions of times on both Bilibili and Coursera. It provided sufficient comments for analysis and visualization. Video 1 was about unsupervised learning, which lasted for 14 min and 14 s, and involved 256 comments. Video 2 was about model representation and cost functions, which lasted for 14 min and 8 s, and involved 245 comments. Both videos were conveyed by the same instructor, lasted for similar periods, and involved similar numbers of comments. The four-student evaluation of the difficulty suggested that the two videos had similar difficulty levels. The content of the two videos was relatively independent, and thus, it was convenient to counterbalance the conditions.

[1]https://www.bilibili.com/video/av9912938/

4.2.3 | Measurement

Cognitive learning was measured by both self-report and objective performance. Self-reported learning was measured by a 7-point Likert scale with one item, "I learned a lot of meaningful things from this lecture." Objective performance was measured by the scores and completion time of four quizzes, referring to a previous study [33].

Quiz 1 was closed-book and involved two short answer questions for each lecture. An example question was "What are the differences between supervised and unsupervised learning?" Participants were asked to answer each question within three minutes. Quiz 2 involved the same questions in Quiz 1, but learners could review the lecture video with comments and modify their previous answers in Quiz 1. Each question had to be answered within three minutes. Quiz 3 consisted of six search-tasks for each lecture in a random order. Participants were asked to identify the video timepoints at which the six concepts occurred. An example is "the timepoint where cost functions occur for the first time." Among the six concepts, three appeared in the word clouds of the visualization tool. Participants were asked to complete a searching task within 1 min. Quiz 4 was to summarize the content of the lecture within five minutes, possibly including concepts, examples, and applications. When answering Quiz 4, participants were able to review the videos and comments.

For Quizzes 1, 2, and 4, each question was scored based on the number of correct points mentioned by the participant. Each question in Quizzes 1 and 2 was worth four points, and Quiz 4 was worth 8 points in total. For each task in Quiz 3, participants were asked to provide a timepoint. If the answer was within 20 s before or after the correct timepoint, the score was two points. If this answer was within 1 min before or after the correct timepoint, the score was one point. Otherwise, the score was 0. The full score for the searching tasks where the concepts appeared in the word cloud was 6, and the score for all searching tasks was 12.

Social presence was measured using a nine-item, 7-point Likert scale from an adapted version [39] of the Social Presence and Privacy Questionnaire [76, 77]. It consists of three dimensions: social context, online communication, and interactivity. Each dimension consists of three items. The Cronbach's α coefficients of these dimensions were 0.83, 0.69, and 0.71, respectively. Cronbach's α for the overall social presence was 0.86. The scores of each dimension and the overall social presence were the mean values of the included items.

Satisfaction with the course and **satisfaction with the comments** were measured using a four-item 7-point Likert scales. **Satisfaction with the platform** was measured using a two-item 7-point Likert scale. Cronbach's α coefficients were 0.85, 0.94, and 0.82, respectively. Course satisfaction was measured immediately after the learning session. During quizzes, participants also reviewed videos and discussions; therefore, comment and platform satisfaction were measured after quizzes.

In addition, after quizzes in the visualization condition, participants were also asked about their perceived validity of the methods to calculate relevance, difficulty, and topics. They were asked how the values of these functions matched their feelings. The validity of each method was measured using a one-item, 7-point Likert scale.

4.2.4 | Participants

The participants were 24 students (11 females and 13 males) in a university aged from 17 to 27 years (M = 21.42, SD = 2.69). They majored in science and engineering subjects, except math, statistics, and information science. They had not learned previously about machine learning or the topics of the materials. All participants had experience of learning through lecture videos and watching videos with timeline-anchored commenting.

4.2.5 | Procedure

Each student participated in the experiment individually in a quiet room. First, the researcher introduced the aims and procedures of the experiment. Then, the participants went through two trials under two conditions in a counterbalanced order. In each trial, the participant first learned a video within 19 min (14 min of a lecture video plus an additional 5 min for pauses or review). After this learning session, the participant completed the first questionnaire about perceived cognitive learning, presence, and course satisfaction. The participant then took four quizzes. After completing the quizzes, the participant completed the second questionnaire about the satisfaction with comments and platform and perceived validity of the tool (if it was the visualization condition). The participant was then rested and went through the second trial. After finishing the two trials, the participants were interviewed about their preferences between the two conditions and any design suggestions in a structured manner. The entire experiment took approximately 90 min to complete, and the participant was compensated 100 Yuan.

4.2.6 | Data analysis

The experiment employed a within-group design. The two lecture videos may have introduced variance. To control the influence of videos, instead of *t*-tests, this study examined the effect of the tool by comparing two linear mixed-effects models [37]. One model included an intercept and a random variable for video (Supporting Information: Videos S1 or S2). The other included an intercept, a random variable for video, and a variable for interface (with or without the visualization tool). The two models were compared using the likelihood ratio tests.

4.3 | Results

4.3.1 | Cognitive learning, social presence, and satisfaction

Table 1 presents the results of the likelihood ratio tests evaluating the effects of the visualization tool on cognitive learning, social presence, and satisfaction. First, the visualization tool had a significant effect on objective performance of cognitive learning. Participants answered more completely and correctly in the open-book quizzes with the visualization tool (M = 3.36, SD = 0.94) than those without the tool (M = 2.84, SD = 1.00, $p = .02$). They performed better in searching for terms appearing in the word clouds with the tool (M = 4.80, SD = 1.08) compared to those without the tool (M = 4.16, SD = 1.28, $p = .02$). They summarized lectures more completely with the tool (M = 5.96, SD = 1.02) compared to those without the tool (M = 5.24, SD = 1.39, $p = .005$). However, no significant effect was found on self-reported perceived learning or closed-book quizzes.

Second, social presence with the visualization tool (M = 5.31, SD = 0.85) was significantly higher than that

TABLE 1 The effect of the visualization tool on cognitive learning, social presence, and satisfaction.

Item	Visualization tool M (SD)	Baseline M (SD)	Likelihood ratio	*p*-value
Objective performance				
Quiz 1 closed-book	2.29 (1.02)	2.23 (1.11)	0.07	.80
Quiz 2 open-book	3.42 (0.92)	2.88 (1.00)	5.86	.02*
Quiz 3 search the items appearing in word clouds	4.92 (0.93)	4.25 (1.22)	5.28	.02*
Quiz 3 search: total	8.83 (1.69)	8.75 (1.94)	0.03	.87
Quiz 4 summary	5.92 (1.02)	5.29 (1.40)	6.60	.01*
Self-reported learning	5.17 (1.20)	5.00 (1.25)	0.37	.55
Social presence	5.31 (0.85)	5.03 (0.87)	4.32	.04*
Social context	5.33 (1.19)	4.94 (1.06)	3.39	.07.
Online communication	5.43 (0.78)	5.26 (0.82)	1.55	.21
Interactivity	5.15 (0.91)	4.88 (1.04)	3.19	.07.
Satisfaction				
Course satisfaction	5.69 (0.76)	5.58 (0.91)	0.34	.56
Comment satisfaction	4.92 (1.38)	4.72 (1.21)	0.45	.50
Platform satisfaction	5.50 (0.87)	5.17 (0.88)	2.16	.14

*$p < .05$.

without the tool (M = 5.03, SD = 0.87, $p = .04$). Regarding the three dimensions, marginal significance was found in the social context and interactivity.

Third, there was no significant difference in satisfaction though the mean values under the visualization condition were generally higher. Regarding the perceived validity of the tool, the values of relevance and topics were 4.83 (SD = 1.17) and 4.67 (SD = 1.27), respectively. The value of difficulty was 3.71 (SD = 1.43), which was slightly less than the neutral value 4.

4.4 | Post-task interview

Among the 24 participants, 22 preferred the interface with the visualization tool, whereas two did not prefer either condition. Consistent with the performance results, 12 participants mentioned that the word clouds of topics could support the search for certain knowledge. In addition, 10 participants also mentioned that the word clouds helped learners quickly get an overall impression of the lecture. These word clouds provided a thumbnail of the video content, which would be useful for retrieval among several videos.

Some participants suggested an improvement in word clouds. Four mentioned that certain topics extracted from the discussion were relevant but not mentioned in the lecture video. For example, in the video on unsupervised learning, the instructor used MATLAB, but several comments by previous learners discussed the difference between MATLAB and Python. Though these comments probably extended learners' knowledge, they confused some participants. Three participants said there were too many keywords and suggested a multilevel organization, for example, by extracting topics by hierarchical clustering. One participant suggested providing a function for screening comments in the video by topics.

Regarding the difficulty function, three participants said that the red parts (more difficult) attracted their attention. They paid more attention to these parts during the search quizzes. Two participants said that the red color made them more vigilant and focused. Five participants said this function was more helpful when reviewing the video than when watching the video for the first time.

5 | DISCUSSION

5.1 | Findings

Many people learn from online videos with timeline-anchored comments or annotations, which provide rich content generated by learners. This study applied text mining and visualized timeline-anchored comments on a video timeline. The visualization tool showed the extent to which the comments were relevant to the lecture in a foldable line chart, the topics of comments in several interactive keyword clouds under the timeline, and the difficulty level perceived by other learners in the colors of the video timeline.

Compared with the previous visualization of timeline-anchored comments [8, 43, 47, 57, 74, 75], this design has distinguishing features. First, instead of raw numbers of comments, this study attempted to present interpretable information, such as the relevance and difficulty perceived by previous learners. Although the algorithms needed further improvement, the experiment initially suggested that these variables supported retrieval and understanding. Second, this design linked keyword clouds of topic clusters to the video timeline and thus supported interaction with the video, including searching for knowledge and relevant comments.

We also experimented to compare interfaces with or without a visualization tool to investigate the effects on learning. Some studies [33, 55] investigated how the visualization of discussions or behavioral data affected learning, with most focusing on the cognitive aspects or learners' participation. However, the experiment in this study found that visualization could improve both cognitive learning and social presence.

In terms of cognitive learning, **the visualization tool significantly supported information searching and summarization**. The reason was the organized word clouds. On the one hand, consistent with the previous studies that found that outlines can facilitate learning [23, 40], word clouds supported searching tasks and further facilitated open-book quizzes (Pearson's r between the performance of the two tasks was 0.27, $p = .07$). On the other hand, word clouds helped learners quickly grasp an overview of a lecture video before or after watching it. Before learners watch the video, the word clouds may serve as advance organizers [6, 30], facilitating better understanding during video learning [14, 67]. The facilitated search and overview further increased the performance of summarizing the video content. In addition, these results provide evidence supporting the signaling principle [66, 79].

However, the experiment did not show a significant enhancement in closed-book quizzes and selfreported learning, indicating that the tool did not affect learners' memory of knowledge and their perception of outcomes. A possible reason is that the visualization tool affects learning less than other variables, such as learning materials and individual differences, such as working memory capacity [29]. Therefore, further verification is required.

We also found that **the visualization of timeline-anchored comments significantly enhanced learners' social presence**. Although social presence is crucial to meaningful learning, little research has been conducted on how the visualization of discussion affects learners' social presence. Therefore, we attempted to explore this area and found that even in short-term learning, visualization strengthened the effects of timeline-anchored comments on social presence [13, 38]. The possible reason is that visualization highlighted useful discussions and contributions from other learners. Thus, learners perceived a more positive social context of the learning community. Similarly, previous research suggested that visualizing forum discussions also increased engagement in discussions [9, 55].

Although satisfaction was not significant, 22 of the 24 participants preferred the interface with the visualization tool. Hypothesis 3 was not supported by the questionnaire data for the following possible reasons. First, the participants hardly changed their attitudes toward a course through a 15-minute video learning session. Our data suggested that satisfaction with the comments and the course was associated with social presence (Pearson's $r = .725$ and 0.515, $p < .001$), whereas social presence was significantly increased by the visualization tool. Therefore, the difference could potentially become significant in a long-term study. Second, the impact of the visualization tool was probably smaller than that of other aspects, such as individual differences. As a result, the questionnaires suggested no significant difference, but most participants preferred the visualization tool when interviewed to compare the two conditions. Third, the algorithms required improvements. In the post-task interviews, some participants suggested that although they liked the idea of visualization, the values calculated from the algorithms were different from their feelings, which could decrease their satisfaction.

5.2 | Implications for future research

First, visualizing timeline-anchored comments can facilitate cognitive learning by providing a summary and supporting navigation and information searching. Future studies may expand the design in terms of interactivity and cross-video integration. In terms of interactivity, the relevance graph and word clouds can be improved in several ways. For instance, a horizontal control line could be added to the relevance graph, allowing learners to click and drag to screen the comments above the relevance level set by the learner. The word clouds could also be adapted to extract only relevant keywords. Regarding the cross-video integration, the visualization tool can integrate data from other videos and content of the course, enabling better performance in determining relevance and difficulty. Additionally, the word clouds could serve as an outline or thumbnail for the video and be presented on the lecture video list page, allowing learners to search for information across different lecture videos.

Second, the visualization of comments can be combined with the analysis of other data sources, such as video content and behavioral data like clickstream data. For instance, previous studies have analyzed the text in lecture videos and displayed keywords to aid video learning [28, 60]. More recently, researchers have used a combination of commenting and clicking behavior data to create visual summaries of video highlights [83]. By integrating multiple sources of interaction data, the visualization tool can provide more precise and comprehensive summaries.

Third, visualizing timeline-anchored comments can be used to increase social presence and further engage learners in more discussions. As discussed above, visualization can strengthen the positive effects of timeline-anchored comments on social presence [13, 38]. Learners perceiving a higher social presence have been found more motivated and engaged in discussions [81]. In a long term, it may promote learners' contributions, knowledge accumulation, and collaborative social climate in the community. It would promote learning of all the learners in the community from a sociocultural perspective [1, 20, 31].

5.3 | Limitations

This study has several limitations and can be improved in future works. From the perspective of text mining, the algorithms used in this study can be improved, especially for perceived difficulty. This study adopted a relatively traditional method for text mining. Future research may increase the accuracy by using recent large language models so that the relevance and difficulty will be more in line with the learner's perception. In addition, the experiment suggests large individual differences in perceived difficulty, and thus future studies may adopt personalized approaches that quantify difficulty based on the learner's previous learning data.

From the perspective of the experiment, the participants only engaged in short-term learning in a laboratory setting which did not reveal the long-term impacts and effects of contextual variables. In a long-term and real-world scenario, learners could engage in discussions and would be more likely to develop a higher social presence and sense of community. Cognitive learning may also be strongly affected by individual differences, such as motivation and cognitive abilities. Therefore, long-term verification is required.

6 | CONCLUSION

This study applied text mining and visualized timeline-anchored comments on the video timeline to facilitate video-based learning. A laboratory experiment suggested that visualization supported information searching, summarizing, and increased social presence. It suggests that the visualization of timeline-anchored commenting potentially facilitates learners' participation in discussions and contributions to the learning community as well as cognitive learning.

ACKNOWLEDGMENTS

This study was supported by Shanghai Summit Discipline in Design (“上海市设计学IV 类高峰学科资助“) and the National Natural Science Foundation of China (Project no. 71942005).

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author, Qin Gao, upon reasonable request.

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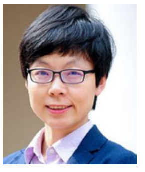

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Y. Chen and Q. Gao, *Visualizing timeline-anchored comments enhanced social presence and information searching in video-based learning*, Comput. Appl. Eng. Educ. (2023), 1–15. https://doi.org/10.1002/cae.22641