NarrationBot and InfoBot: A Hybrid System for Automated Video Description

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ABSTRACT
Video accessibility is crucial for blind and low vision users for equitable engagements in education, employment, and entertainment. Despite the availability of professional and amateur services and tools, most human-generated descriptions are expensive and time-consuming. Moreover, the rate of human-generated descriptions cannot match the speed of video production. To overcome the increasing gaps in video accessibility, we developed a hybrid system of two tools to 1) automatically generate descriptions for videos and 2) provide answers or additional descriptions in response to user queries on a video. Results from a mixed-methods study with 26 blind and low vision individuals show that our system significantly improved user comprehension and enjoyment of selected videos when both tools were used in tandem. In addition, participants reported no significant difference in their ability to understand videos when presented with autogenerated descriptions versus human-revised autogenerated descriptions. Our results demonstrate user enthusiasm about the developed system and its promise for providing customized access to videos. We discuss the limitations of the current work and provide recommendations for the future development of automated video description tools.

CCS CONCEPTS
• Human-centered computing → Accessibility technologies; Accessibility systems and tools.

KEYWORDS
Video Accessibility; Video Description; Blind and Low Vision Users; Artificial Intelligence

1 INTRODUCTION
Blind and low vision individuals face unique challenges in our modern environment, where much critical information related to education, employment, entertainment, and community is presented in the form of digital videos. The pace at which new video media are created is incredible, including 500+ hours of content uploaded to YouTube every minute as of March 2021 [13]. Inaccessible information can result in social exclusion at best, or impact one’s well-being if individuals require access to it in order to make decisions related to their health and safety. For example, in a personal or global health crisis, individuals may need to access the mass amounts of information conveyed via videos or dynamic infographics in order to make informed decisions [26]. Moreover, the digital accessibility gap exacerbates blind and low vision (BLV) people’s disproportionate exclusion from social media [49] and educational and employment opportunities [2, 11, 48]. Recognizing the impacts of the digital accessibility gap, the World Wide Web Consortium’s Web Content Accessibility Guidelines recommend that description be provided for all online videos [20]. Video description [54], also referred to as audio description (AD), facilitates non-visual access to visual components of a video by providing a narrative audio track that is synchronized with the video. Narrations relay information about settings, actions, on-screen text, and any other visual information that would otherwise be missed. However, descriptions for online videos remain the exception rather than the rule. A professional video description typically has a long turnaround time and can cost hundreds or thousands of dollars, depending on length [1]. Obtaining such descriptions for the explosion of videos appearing on the Internet is simply not an option.

Professional video descriptions in live and recorded formats have been promoted since the 1920s [27]; however, similar to the advent of novice-created videos for social media such as YouTube, description work has evolved to warrant contributions from nonprofessionals who can meet more immediate needs for video accessibility and bridge access to novice-created content. This shift from professional to amateur description became possible in 2013 when the Smith-Kettlewell Eye Research Institute (SKERI) launched a web-based tool called YouDescribe [78]. YouDescribe enables anyone to record and upload descriptions of YouTube videos. The platform has resulted in a community of more than 3000 volunteer describers and an active wish list where BLV users can request descriptions for any YouTube video. However, 92.5% of videos on the YouDescribe
user wish list remain undescribed despite the dedicated volunteer community. Previous works show that the time, training, and confidence needed to create high-quality descriptions might deter potential describers from completing more descriptions [52, 79]. For example, Be My Eyes [28] is an application that connects BLV people with two million sighted volunteers who provide visual assistance through live and generally short video calls. Informal feedback from Be My Eyes volunteers to the authors has revealed that the difficulty of video description and the skills required, such as language and writing skills, have deterred them from volunteering for this task. In our experience, video narrators are often limited by their own vocabulary and visual experiences and may have difficulty producing informative and thorough descriptions. Moreover, novice describers must view a video numerous times to identify the details of the visual content and determine their importance for the storyline. The YouDescribe waitlist for described YouTube videos is merely an initial peek at a greater problem of video accessibility; countless other videos are disseminated directly on websites, digital carousels, within learning management systems, and other outlets not related to YouTube. To keep up with the pace of information stored in online videos, artificial intelligence (AI)-driven tools are needed to automatically generate video descriptions and supply key information with decreasing needs for human input.

To begin, we define two types of video descriptions:

(1) **Baseline descriptions** narrate visual components of a video, such as the main objects, their spatial relations and interactions, on-screen text, the setting, costumes, and lightning. We allow inline baseline descriptions that play alongside video playback as well as extended baseline descriptions that play while a video is paused.

(2) **On-demand descriptions** provide answers or additional information in real time in response to user queries on a video. The video remains paused as the response is provided as an extended description.

As systems for automatically generating video descriptions continue to develop, the affordances and constraints of these tools warrant ongoing research to explore how they can be applied to video accessibility, and how they can enhance rather than constrain BLV users’ access to information. To this end, we set forth to answer the following research questions:

(1) **How do autogenerated versus human-revised autogenerated baseline descriptions impact BLV users’ enjoyment and comprehension of videos?** We hypothesize that autogenerated baseline descriptions will positively impact the video experience of BLV users. We investigate whether the state-of-the-art video understanding techniques will allow an accessibility system to automatically generate baseline descriptions and decrease reliance on human describers. We examine and compare the quality of the autogenerated descriptions versus human-revised descriptions.

(2) **How do autogenerated on-demand descriptions impact BLV users’ enjoyment and comprehension of videos?** We hypothesize that a functionality similar to conversational agents, such as Alexa or Siri, can be applied to enhance real-time video accessibility. Users can pause a video at any time and query for more information. However, it is unclear how the state-of-the-art video understanding techniques can support the quality of information that people seek while watching a video. Accuracy and usability measures as well as qualitative feedback from users are important to evaluate the current affordances of such functionality and identify directions for future development.

(3) **How might autogenerated baseline and on-demand descriptions work in tandem to benefit BLV users’ enjoyment and comprehension of videos?** We anticipate that with a hybrid of baseline and on-demand descriptions, we can take advantage of affordances for both types of descriptions while mitigating the limitations of each one. For example, baseline descriptions are most appreciated when they are concise and minimally intrusive to the video experience. However, detail is in order to accommodate a variety of users who may want more or less information at different points of a video. On-demand descriptions enable users to customize what and when additional information is provided. Given the promise of these two types of descriptions, we investigate how well the combination can work in practice.

To investigate the above questions, we built a hybrid system of two tools:

(1) **NarrationBot** that generates baseline descriptions automatically, which can be conveyed directly or further revised by a human in the loop (HITL) before reaching the user; and

(2) **InfoBot** that delivers on-demand descriptions by pausing the video and providing additional information in response to user queries on a video.

InfoBot enables users to ask for additional descriptions, pose natural language questions about visual elements of a video, and get natural language responses back in real-time (e.g., “What breed is the dog?”, “Cocker spaniel”). NarrationBot and InfoBot can work in tandem as an add-on or widget with any platform that hosts videos. The developed system gives BLV individuals considerable control over their ability to navigate the virtual world of online videos. NarrationBot fully automates the process of video description generation providing timely access to online videos. Its companion, InfoBot, empowers users to decide what information is obtained about a video—and when.

We took a mixed methods approach to determining how individual tools of the system, as well as selected variations and combinations of tools, impact users’ experiences while watching videos. A randomized, multivariate repeated-measures design with six conditions was used along with written qualitative responses to assess the impact of the system on BLV users’ comprehension and enjoyment of selected videos. Data from 26 BLV users suggest that the system improves certain aspects of users’ experiences, and results highlight potential next steps for improvement. Results show that our system significantly improved user comprehension and enjoyment of selected videos. In addition, participants reported no significant difference in their ability to understand videos with autogenerated descriptions versus human-revised autogenerated descriptions.

We anticipate that tools such as NarrationBot and InfoBot will promote broader equity in video and information accessibility by
reducing the dependence of BLV users on human describers and empower them to decide what information is provided at any given time. On the other hand, all contributions from this work must be regarded with extreme caution. The usability of automated tools for generating video descriptions require continued refinement to ensure that meaningful information is delivered to BLV users. Without proper foresight regarding how automated accessibility tools are brought to end users, these systems can be wielded as weapons for compliance rather than for the purpose of meeting user needs and ensuring universal accessibility [65].

2 BACKGROUND AND STATE OF THE ART

We review the relevant body of literature in human-computer interaction, accessibility, computer vision, and natural language processing that has developed methods, tools, and datasets to improve access of online media, with a focus on videos, for BLV users.

2.1 Accessibility for Visual Media

There have been a wide range of works performed for BLV users. Advances have occurred in visual graphics [43], data visualizations [73], maps [51, 55], programming [60], and video games [10, 33, 66]. Despite the tools available for BLV users [28, 76], visual media accessibility remains dependent on how content creators choose to author and disseminate their media.

Recent studies conducted by Romero-Fresco et al. [64] and Perego et al. [59] with BLV users showed that the use of audio descriptions with movies improved the overall watching experience. For static media webpages and documents, heading styles can be formatted to ensure accessible navigation of text elements [20]. Alternative text or alt text is commonly used to add captions to images; however, a study conducted by Bigham et al. [12] of browsing patterns of sighted and BLV candidates for a week showed that only half of all website media contained alt text inserted by the original source. Just as sighted web surfers are more likely to engage with web content that contain images, Bigham et al. [12] also concluded that BLV users were more likely to view images containing alt text. To further explore this phenomena, several other studies analyzed images in social media and developed a variety of tools for bridging accessibility. Guinness et al. built Caption Crawler [34], a browser plugin that uses reverse image search to find similar web images with alt text and dynamically updates images as they are encountered with a screen reader. Gleason et al. [31] built a tool for automated alt text extraction from memes and built an interface for creating accessible memes with support for both alt text and audio clips. Gleason et al. also built the Twitter A11y [32] browser extension to generate or fetch an existing alt text for a given image. Although automated tools can expand the availability of alt text, the generated information is solely objective without inferential intelligence regarding the context of the image. Consequently, the result may not meet BLV users’ needs as it does not maintain the integrity of the information being conveyed about the image [24].

2.2 Toward Automated Video Description

Early efforts to automate generating descriptions for video accessibility were generally focused on facilitating sighted describers’ authoring of descriptions. LiveDescribe [15] was the first known computer-assisted video description technology, followed by various prototype softwares that used computer vision techniques, such as face and text recognition, to extract visual content from videos [29, 30] and support describers’ ability to create and refine descriptions [57]. In addition to Pavel et al.’s work on defining when and how to insert a description [58], these tools have become the foundation for systems that can automatically detect silent periods within a video in which descriptions can be inserted, pause a video when extended descriptions are warranted, and decrease the human labor needed to produce descriptions. However, none of these tools can generate partial or full descriptions automatically.

A standard benchmark in video understanding involves action recognition from videos, and numerous datasets [17, 44, 53, 62] have been created for this task. Specifically, ActivityNet [17] consists of nearly 10K videos with 200 different activity class annotations. Alongside action recognition, a more challenging task of dense video captioning [22, 42] was also introduced which involves generating multiple natural language sentences for all and potentially overlapping events in a video [3]. The ActivityNet Captions dataset [42] introduced for the task contains nearly 20K video clips with each video annotated with 3.65 sentences on average. Rohrbach et al. also created a movie description dataset [63] of 128K video clips with audio descriptions and also benchmarked and evaluated various video description approaches.

Automated approaches to video description, currently dominated by deep learning, are usually divided into two stages: 1) visual content extraction or the encoding stage and 2) text generation or the decoding stage. For encoding, convolutional neural networks (CNNs) [71] are used to learn visual features, and for decoding, different variations of recurrent neural networks (RNNs), such as long short-term memory (LSTM) [37] and gated recurrent unit (GRU) [19] networks are used for language modeling and text generation [14, 40]. Recent state-of-the-art methods [47, 69] have replaced RNNs with BERT [25] due to the success of Transformers [72]. Additionally, using self-supervised objectives such as the masked token prediction or cloze task for pre-training have shown to greatly improve performance, such as in VideoBERT [70]. The resulting description can be a single sentence or multiple sentences. Our work uses CNNs and RNNs and focuses on generating descriptions from representative keyframes of the input video. In a recent work, Yuksel et al. [79, 80] investigated a human-in-the-loop machine learning approach to facilitate novice describers’ ease of authoring video descriptions. The developed system automatically generates initial baseline descriptions and then sighted humans revise them. This human-AI collaboration produces high-quality video descriptions while requiring reduced effort from volunteer describers. In contrast, the current work takes a step toward removing humans from the loop.

2.3 Toward Automated Question Answering

While video description generation models have shown promise, they quite frequently abstract, summarize and omit over the granularity of the visual scene in order to frame a coherent and succinct description. This might be detrimental to the experience of a BLV user who wishes to understand certain details better (e.g., reading text shown on a billboard) or better understand the context of a
scene. To mitigate this issue, we leveraged the recent advances in vision and language research on image captioning [67] and visual question answering [5, 21] to develop a tool to answer questions asked by BLV users at any given time of the video. Alamri et al. also introduced the Audio Visual Scene-Aware Dialog task [7]. The task is to answer natural language questions about a short video. The developed model combines information from different modalities (i.e., video, audio track, video caption, dialog history, and the question to be answered) and then predicts an answer. Practical applications of these concepts currently exist in popular visual interpreter apps that provide answers to blind users’ queries about static or dynamic visual information, either in real time (e.g., Aira [6]) or within a window of time (e.g., Be My Eyes [28]).

The VizWiz dataset [35] was curated from pictures taken by blind users of objects from their daily lives, questions they have about the pictures’ content, and answers to those questions provided by sighted users. Questions from the VizWiz dataset differ from questions in datasets sourced from sighted users [5]; as blind users are more likely to query text in images (e.g., “What is the expiry date of this medicine?”) and ask about objects, instead of asking “where” and “why” questions. While answering questions about text in images is currently an open research problem known as TextVQA [38, 41, 68, 77], inspired by this statistic, we augment our descriptions with text extracted from video frames.

Home digital voice assistants (HDVAs), such as Siri, Alexa, Google Assistant, and Cortana are popular on-demand softwares providing answers or additional information in response to user queries over phone or dedicated devices. A recent study conducted by Abdolrahmani et al. [4] with 14 BLV users concluded that HDVAs were prone to making input errors when used by blind users and that it is important for them to recover from these errors in a timely manner. The study also pointed out that HDVAs often do not function at the right amount of details and do not have alternate audio routines to replace the visual cues (e.g., colored lights of Alexa).

3 SYSTEM

To offer blind video users more immediate, relevant, and self-directed information, we built a system that consists of two tools for automatically generating baseline and on-demand descriptions for online videos. There are several unique features to each and common features for both. Figure 1 shows the overall architecture of the developed system.

3.1 Baseline Description (NarrationBot)

Baseline descriptions inform blind and low vision users about the visual components of a video, such as the main objects; actors, the spatial relations and interactions between them, and their actions; on-screen text; and the setting, costumes, and lighting. We developed a tool, called NarrationBot, consisting of various modules to automatically generate baseline descriptions. Figure 2 shows sample baseline descriptions generated by NarrationBot. A benefit of our modular approach is that as technology matures in the future, modules can be replaced by their improved counterparts. Below we explain different modules of the developed tool.

3.1.1 Keyframe Selection. YouTube videos normally play at 30 or 60 frames per second; this rate presents too many frames to efficiently work with, without much visually changing between them. Many of these frames capture a blurry, unclear snapshot of objects in the scene. Hence, this module selects a subset of frames, or keyframes, which represent the main events in the video clearly. To select the keyframes, we sample ten frames per second of video and run a pre-trained YOLOv3 [61] object detection model on each of the extracted frames. Each frame is given a score based on the

Figure 1: The system architecture for generating baseline (NarrationBot) and on-demand (InfoBot) descriptions for videos.
confidences of the detected objects. Since the object detection model often returns many overlapping detections of the same object, we choose only the highest confidence detection of each distinct object in the frame. If we let $c_{o,i,f}$ denote the confidence of the $i$th instance of the detection of object $o$ in the frame at timestamp $f$, the frame score is given by

$$score(f) = \sum_{o} \max_{i} c_{o,i,f}^2.$$  

After manual tuning the granularity of our keyframe selection algorithm, we found that extracting one keyframe every six seconds on average led to best results while also keeping the computing costs manageable. Concretely, given the previous keyframe timestamp $F_n$ and a target interval $T = 6$ between keyframes, we choose the next keyframe timestamp $F_{n+1}$ to be

$$F_{n+1} = \argmax_f score(f)(f - F_n)(F_n + 2T - f).$$

3.1.2 **Image Caption Generation.** This module uses the Pythia [40] caption generation model to create a description for every selected keyframe. The Pythia model uses a Bottom-up-Top-Down (BuTD) [8] attention network for visually grounded language modeling. The bottom-up part is composed of two CNNs to identify objects and annotate bounding boxes in the images. The top-down part, composed of two LSTM networks, conditions on these detected objects through soft attention to generate text. Object detections from the bottom-up network are passed to the top-down language model for next word prediction. The bottom-up network was trained on ImageNet [23], and the top-down network was trained on the COCO dataset [46].

3.1.3 **Scene Detection.** This module partitions the video into a sequence of scenes of varying time spans using Microsoft Azure Video Indexer [39]. Scenes are defined as a set of consecutive frames that are semantically related and temporally adjacent, depicting a high-level concept or story. The scene is our base unit for generating and embedding baseline descriptions within a video. We use the information from the dialog timestamps, extracted by ListenByCode API [16], to merge the scenes having a continuous dialog element.

3.1.4 **On-Screen Text Extraction.** Text is a rich source of information in videos. This module extracts captions and scene text (e.g., license plates, building and street signs, handwritten documents) that convey information that may not be present in the audio. Using the selected keyframes to extract the on-screen text proved to be less than ideal because the text would occasionally be in the process of fading in or out since it is not of interest to the object detection model we use for selecting keyframes. Thus, we run an optical character recognition (OCR) API [9] on every extracted frame to ensure we do not miss any text. This produces a large collection of texts often repeated from frame to frame, from which we must then filter and select the best representatives. We split the detected texts into clusters based on similarity across consecutive frames using a Levenshtein distance metric [45]. After choosing one text from each cluster in which the text remains very similar for at least five frames, we do a further pass in which we remove non-ASCII characters and remove any text that has appeared at least three times previously in the chosen texts. This is to prevent watermark logos from being read every time the text on screen is read.

3.1.5 **Text Summarization.** This module generates a baseline description for each scene by summarizing the captions generated
for the selected keyframes. We pick the three most distinct but also most repeated captions in the scene by calculating their pairwise similarity scores and concatenate them. We use the BLEU score [56] to obtain the similarity between two captions. The captions with a BLEU score of above 40% are put in the same cluster. The clusters are then sorted by the number of captions with the sum of BLEU scores of all individual captions in each cluster breaking ties. After sorting, one caption with the highest BLEU score is chosen from each of the top three clusters. The selected three captions are summarized into a baseline description for the scene.

3.1.6 Text to Speech and Audio Insertion. As the final part of the process, this module converts descriptions from text to speech and finds appropriate positions in the video to play them. A scene’s description is played between the scene’s start and end times. The system finds empty gaps for each scene in the video, which are sections with no background music, speech, or dialog. The audio description is played inline if the length of an empty gap is sufficient to insert it. Otherwise, the video is paused and an extended description is played.

3.2 On-Demand Description (InfoBot) On-demand descriptions, generated by InfoBot, provide more information in real time when requested or asked by a user. InfoBot works by first identifying a frame from the video at the point where the viewer decides to pause it. Occasionally, the point where the viewer pauses contains blurred objects (due to motion, for example) or lacks vital visual information, in which case InfoBot automatically refines the choice of keyframe to be close to but not exactly.
3.2.1 Requesting a Description. Users can request a description at any instant of the video. The selected keyframe will have the description as a caption, and this description is obtained and read to the user. This kind of functionality will give the user the option to learn information about the current instant of the video. Users can use this functionality by pressing the ‘D’ key on the keyboard. The video will be auto-paused while the additional description is being read out. The video will be auto-played once the complete description is read out.

3.2.2 Asking a Question. Users can pose natural language questions about visual elements of a video and get natural language responses back in real time. For automatically answering queries without humans in the loop, we make use of the visual dialog model [21]. This model is trained on 120k examples of question-answer dialogs paired with images from the COCO dataset [46] collected via a 2-person chat interface where one side cannot see the image and is tasked with asking questions to understand the image better. Specifically, given an image, dialog history consisting of a sequence of question-answer pairs (Q: ”How many people are in wheelchairs?”; A: ”Two,” Q: ”What are their genders?”; A: ”One male and one female”), and a follow-up question about the image (Q: ”Which one is holding a racket?”), this model predicts a free-form natural language answer to the question (A: ”The woman”). This model extracts attention-based [8] object detection features based on Mask-RCNN [36] for each image and combines these features with the dialog history in an LSTM network to predict the answer. Users can press the ‘Q’ key to ask a question on the video, which is recorded via a microphone. A pause at the end of the user’s speech terminates the recording. We convert the question to the corresponding text. Next, we feed the relevant keyframe, the user’s question, and the previous dialog history (if available) as inputs to the visual dialog model to generate an answer. The answer received from the visual dialog model is converted back to audio via a text-to-speech API and read aloud to the user. The visual dialog model is capable of handling multiple questions allowing the user to clarify their questions. Hence, users can ask as many questions as they wish at any particular instance of the video. Figure 3 shows sample questions and answers from our BLV participants’ interactions with InfoBot.

4 EVALUATION
4.1 Experimental Design
We used a mixed-methods design to evaluate self-reported enjoyment and comprehension for BLV users who watched videos using various conditions of the system. For the qualitative component, we solicited written feedback to open-ended questions regarding participants’ opinions about the system and its functionalities. For the quantitative assessment, we used a randomized, multivariate repeated-measures design. In order to understand the unique contributions of each of the tools to BLV users’ experience, as well as the impact of the tools used in combination with each other, we included six system conditions as outlined below. Six videos1 with similar content and length were chosen from the YouDescribe wish list to be used in combination with the system. Each participant was administered all six conditions across all six videos in random order and with random assignment of system conditions to videos. The videos used in the experiment were related to dog rescues. All videos were approximately five minutes long and shared the same narrative components to maintain consistency between videos: background information, specific setting of the rescue, treatments for injuries, and an adoption.

Before beginning the study, each participant also completed a interactive tutorial session to learn how to use NarrationBot and InfoBot while watching a video. All videos and the tutorial were presented in English and all InfoBot and NarrationBot support was provided in English as well. After successfully completing the tutorial, each participant was administered videos under each of the following six conditions:

- **Condition 1 – No support.** This condition does not allow access to any tools of the system or provide any extra support.
- **Condition 2 – InfoBot only.** This condition does not allow access to NarrationBot descriptions, but users can request descriptions or ask questions on the videos through the interactive InfoBot.
- **Condition 3 – NarrationBot only.** This condition does not allow access to InfoBot but provides baseline descriptions via NarrationBot.
- **Condition 4 – HITL-NarrationBot only.** This condition is similar to the third condition. In condition 4, however, baseline descriptions are provided by NarrationBot and then revised by an experienced human describer (HITL-NarrationBot) for use with our videos. The revised descriptions are converted to audio and played inline or extended. The audio voice is identical to that of NarrationBot. Users are not informed whether it is condition 3 or 4.
- **Condition 5 – NarrationBot + InfoBot.** This condition allows users access to both tools of the system: NarrationBot and InfoBot. The baseline descriptions are generated by NarrationBot while watching a video. All videos and the tutorial were provided in English and all InfoBot and NarrationBot support was provided in English as well. After successfully completing the tutorial, each participant was administered videos under each of the following six conditions:

1Note that this research was carried out at San Francisco State University, and consent with academic standards, these six YouTube videos were used only for the purpose of validating the idea(s) proposed in the paper. Figures 2, 3, and 6 were reproduced with permission from the video authors.
Participants were recruited from community listservs, rehabilitation and service organizations, and social media groups that are dedicated to serving BLV adults. Recruitment criteria included self-identification as being blind or low vision and access to a computer with an internet browser. Due to inherent differences in how individuals with and without visual impairments process sensory information (including video descriptions) and the pervasive nature of visual input on an individual’s contextual and experiential knowledge [75], we deliberately did not recruit sighted participants to test tools meant for blind users. Thirty nine blind and low vision individuals successfully completed the tutorial, 32 of these individuals began the user study, and 26 participants completed the entire user study. Only individuals who completed the entire study were included as participants for the purposes of this analysis. Participants ranged in age from 22 to 53 years old, with a mean age of 37 (SD = 9.01). Detailed demographic information for participants is available in Figure 4.

4.2 Results

4.2.1 Preliminary Analyses. Preliminary analyses were conducted to determine whether the data met the assumptions of MANOVA. Analysis of Mahalanobis distances indicated no multivariate outliers were present in the dataset, with probabilities associated with a chi squared analysis of the distances all greater than 0.038. Following Warner’s [74] recommendation that sample sizes over 20 are robust to violations of normality, our sample size of 26 allows the assumption of normality to be met. Further, both variables had skew and kurtosis values well within the limits considered indicative of normality. Visual inspection of the scatterplot matrix indicated that the dependent variables (comprehension and enjoyment) appear to be linearly related for each of the groups of the independent variable (condition). A Pearson correlation was conducted between the two dependent variables to assess for multicollinearity; the correlation between users’ self-reported comprehension and enjoyment was 0.847; a relatively high correlation, but still below the threshold for concern (0.9) about multicollinearity [50].

4.2.2 Repeated-Measures MANOVA. A repeated-measures MANOVA was conducted to determine whether significant differences exist between blind and low vision users’ perceptions of their own comprehension and enjoyment for videos watched under the six conditions outlined above. A statistically significant effect was found, with Pillai’s trace = 0.415, \( F(10, 250) = 6.54, p < 0.000 \). Partial \( \eta^2 \) for this analysis was 0.207, meaning that 20.7% of the variance in the users self-reported scores can be attributed to the condition under which a given video was watched.

Follow up ANOVAs were conducted to determine whether significant differences exist between conditions on each of the two dependent variables (comprehension and enjoyment). Mauchly’s Test of Sphericity indicated that the assumption of sphericity had been violated for these follow-up ANOVAs, with \( \chi^2(14) = 25.90, p = 0.027 \) for comprehension and \( \chi^2(14) = 28.19, p = 0.014 \) for enjoyment; thus, a Greenhouse-Geisser correction was used to limit the type 1 error rate. Using a Greenhouse-Geisser correction, both of these ANOVAs were significant; for comprehension, \( F(3.71, 92.70) = 16.56, p < 0.000 \), and for enjoyment, \( F(3.33, 83.14) = 12.31, p < 0.000 \). Partial \( \eta^2 \) for comprehension was 0.399, meaning that 39.9% of the variance in the users’ comprehension scores can be attributed to the condition under which a given video was watched. Partial \( \eta^2 \) for enjoyment was 0.330, meaning that 33.0% of the variance in the users’ enjoyment scores can be attributed to the condition under which a given video was watched.
Table 1: User comprehension and enjoyment for videos under six different system conditions. Means and standard deviations on a 6-point Likert-type scale.

| Condition | Ability to understand video | Enjoyability of video |
|-----------|-----------------------------|-----------------------|
| 1 - No support | 2.27 [1.25] | 2.81 [1.47] |
| 2 - InfoBot | 2.65 [1.62] | 3.00 [1.55] |
| 3 - NarrationBot only | 3.73 [1.54] | 3.92 [1.41] |
| 4 - HITL-NarrationBot only | 4.58 [1.03] | 4.81 [1.06] |
| 5 - NarrationBot + InfoBot | 4.15 [1.38] | 4.27 [1.25] |
| 6 - HITL-NarrationBot + InfoBot | 4.54 [1.45] | 4.58 [0.99] |

Table 2: InfoBot usage statistics. Means and standard deviations for number of uses.

| Condition | Number of questions asked | Number of descriptions requested | Total number of InfoBot uses |
|-----------|---------------------------|----------------------------------|-----------------------------|
| InfoBot only | 10.19 [11.75] | 12.92 [12.06] | 23.12 [21.38] |
| HITL-NarrationBot + InfoBot | 6.08 [7.21] | 7.62 [5.88] | 13.69 [10.41] |
| NarrationBot + InfoBot | 8.00 [8.18] | 15.15 [14.28] | 23.15 [20.41] |
| HITL-NarrationBot only | 3.00 [1.55] | 11.89 [11.60] | 19.98 [18.41] |

Finally, planned post-hoc pairwise comparisons were conducted to examine individual differences between selected combinations of the six conditions on both of the outcome variables. A Bonferroni correction was used to limit the type I error rate for these comparisons. The mean scores and standard deviations for all conditions are presented in Table 1. Boxplots from the pairwise analyses can be seen in Figure 5.

4.2.3 Baseline Description (NarrationBot). Results from the planned pairwise analyses indicated that BLV users found videos watched under conditions with a baseline description (i.e., NarrationBot only or HITL-NarrationBot only) significantly easier to understand than videos watched with no available supports [NarrationBot only: \( t(25) = 3.42, p = 0.032 \); HITL-NarrationBot only: \( t(25) = 7.49, p < 0.000 \)]. Results also showed that videos watched in the HITL-NarrationBot only condition were significantly more enjoyable for users than videos watched with no support [\( t(25) = 6.01, p < 0.000 \)]. In contrast, users reported no significant difference between their enjoyment of videos watched under the NarrationBot only and no support conditions [\( t(25) = 2.53, p = 0.273 \)]. Thus, use of HITL-NarrationBot baseline description improved both users’ comprehension and enjoyment of videos, and use of NarrationBot improved their comprehension but not their enjoyment of videos.

Further, pairwise analyses showed no significant difference between the two baseline description conditions (NarrationBot only and HITL-NarrationBot only) for comprehension [\( t(25) = 3.065, p = 0.077 \)], indicating that BLV users felt that both these tools had a similar impact on their ability to understand what happened in a video. However, users also indicated that videos watched under the HITL-NarrationBot only condition were significantly more enjoyable than videos watched under the NarrationBot only condition [\( t(25) = 3.065, p = 0.077 \)].

4.2.4 On-Demand Description (InfoBot). InfoBot was used by each participant an average of 19.99 times per 5-minute video, with 8.09 of those uses in the service of asking a question (‘Q’ key), and 11.90 to request a description (‘D’ key). Table 2 shows the means and standard deviations for the number of times InfoBot description (‘D’ key) and question-answering (‘Q’ key) functions were used by participants in each of the conditions.

Overall, participants tended to use the description function more frequently than the question-answering function across all conditions, but there was a great deal of variation in how often different participants used InfoBot. InfoBot usage results also show that participants used InfoBot more frequently when the description received via NarrationBot was less accurate. In the InfoBot-only condition (which had no other description provided) and the NarrationBot + InfoBot condition (which had some other description provided by NarrationBot, but this description was not always accurate), they used InfoBot much more often than they did in the HITL-NarrationBot + InfoBot condition (which had some other description provided by NarrationBot, but this description was revised by a human in the loop, and thus had verified information provided). InfoBot’s responses to users’ questions were reviewed for accuracy after the study was completed. A total of 625 questions were asked by users in this study and InfoBot demonstrated a 48.2% accuracy rate, providing the correct response to the question 301 times and an incorrect response 324 times.

Planned pairwise comparisons for InfoBot showed no significant difference in either enjoyment or comprehension for videos watched under the InfoBot only condition when compared with the no tools condition [enjoyment: \( t(25) = 0.43, p = 1.000 \); comprehension: \( t(25) = 0.93, p = 1.000 \)]. Thus, use of InfoBot alone did not improve BLV users’ self-reported comprehension or enjoyment of videos.

4.2.5 Baseline Description (NarrationBot) and On-Demand Description (InfoBot) in Combination. Planned comparisons were also used to examine the impact of the baseline description (NarrationBot) and on-demand description (InfoBot) tools used in combination. The HITL-NarrationBot + InfoBot condition was rated significantly higher for both enjoyment or comprehension than...
Using a hybrid system comprised of two tools, NarrationBot and InfoBot, we set forth to explore three general questions regarding the fit of such a system to meet blind and low vision users’ needs for video accessibility: 1) How do autogenerated versus human-revised autogenerated baseline description impact BLV users’ enjoyment and comprehension of videos? 2) How do autogenerated on-demand descriptions impact BLV users’ enjoyment and comprehension of videos? and 3) How might autogenerated baseline and on-demand descriptions work in tandem to benefit BLV users’ enjoyment and comprehension of videos?

5 DISCUSSION

After participants had viewed all of the videos, they took a final survey to provide qualitative feedback about their overall impressions of the system. These responses provide context and insight that would be difficult to assess via quantitative methods, and selected quotes are used to illustrate the conclusions we draw in the following sections.
5.2 On-Demand Description (InfoBot)

InfoBot presents a novel approach for offering on-demand descriptions to BLV users in two ways: (1) it skirts the timing issue of when descriptions should be inserted by enabling the user to determine when more description is warranted, and (2) the tandem use of NarrationBot and InfoBot balances when the system versus a human user dictates a need for description. While NarrationBot was conceived to deliver only minimal information via baseline description as authored by a human, InfoBot was conceived to empower BLV users to decide what and when more information is desired. InfoBot is activated when a user pauses the video and offers two functions for obtaining on-demand information: a description function (describes the paused scene) and a question-answering function (ask a question about the paused scene). We believe that the relative ease of requesting a description over needing to construct a question led participants to use the description function more often than the question function. Overall, InfoBot’s question-answering function achieved a 48.2% accuracy rate across. When used alone, InfoBot was not rated significantly better than having no description support at all. Despite InfoBot’s lack of impact on users’ comprehension and enjoyment of a video, participant feedback about InfoBot was positive and emphasized the potential of such a tool for gaining additional description information as desired. Several participants spoke to this potential, noting “The InfoBot was useful for getting a bit of extra information, some people want ALL the details they can get.” and “If the baseline description and video content misses something, I can use the InfoBot to try to fill in those gaps.” Despite commenting on the low accuracy of information from InfoBot, participants appreciated the power of having a tool that “…doesn’t give me the info I am looking for [but allows me to] choose what descriptions to hear.” The anecdotal feedback is critical in supporting our efforts to continue developing a tool such as InfoBot; while InfoBot is well suited to provide what BLV users tell us they want, it is presently limited by what the current state of the art can deliver. We believe that InfoBot can continue to improve with time, as video understanding models develop more inferential reasoning capabilities and are trained on diverse datasets that match the variety of vocabulary, scenes, and contexts in videos.

5.3 Baseline Description (NarrationBot) and On-Demand Description (InfoBot) in Combination

As mentioned earlier, the tandem use of NarrationBot and InfoBot is meant to allow for flexibility that addresses differences in when an automated system versus a human user dictates a need for description. We conceptualized this hybrid system for automating video descriptions in order to adapt to different users’ preferences for description and verbosity. While NarrationBot automatically generates a baseline description whenever there is text on screen or a scene change, the BLV user can activate InfoBot at any given time to access more description of the current scene. The balance...
between offering description at generic times versus additional descriptions whenever curiosity strikes allows our hybrid system to enhance the self-determination of BLV users within the accessible video experience. In other words, having tools for deciding when and to what extent more information is desired can better empower BLV users to customize their needs for accessibility.

We found that the tandem use of NarrationBot and InfoBot significantly improved both user enjoyment and comprehension, while when either tool was used alone it did not. When asked if NarrationBot or InfoBot was preferred in singularity or in tandem, participants noted: “I would use both, as the videos I tend to watch the most would possibly be better if I had access to both of these tools at the same time. Not every video needs the baseline description, and not every video needs the InfoBot” and “If the baseline description and video content misses something, I can use the InfoBot to try to fill in those gaps.” These observations indicate that by having both tools available throughout a video, participants could leverage the affordances of each tool at will or jigsaw when each tool was needed to deliver different types of information. Although it is possible that in some instances the baseline descriptions provided enough information that InfoBot was not called upon, simply having an option to fetch more information anytime enhanced the accessibility experience. Ultimately, our participants at large recognized the broad applicability of this hybrid system for improving video accessibility, particularly for “videos that contain text . . . and videos that do not currently have audio description or [lack] adequate audio cues or dialog that explains the content.”

5.4 Limitations

While developing the system and designing the user study, we unintentionally operated with several assumptions that became apparent during the recruitment and active testing phases of the project. We learned to cherish input from BLV users beginning with the initial phases of system development, throughout the user study, and especially participants’ feedback at the conclusion of each user study.

5.4.1 Access to Technology: We designed a system that required testing on a computer with the internet. During recruitment, several individuals were unable to participate due to not having a computer or reliable internet; instead, smartphones seemed more readily available across all participants. We recognize that inequities in the digital divide continue to separate those who have access to computers and internet from those who do not.

5.4.2 Screen Reader Proficiency: We solicited input from particularly tech-savvy BLV individuals during the initial design phases of the system. These individuals were extremely proficient screen reader users, whereas the expanded participant group included individuals with varying degrees of screen reader proficiency. It became clear that BLV participants had varying experiences with, and access to assistive technology training. This learning experience highlights the need for assistive technology developers to be more conscious of the social responsibilities related to allying with individuals in the disability community. Participant differences in screen reader proficiency were made more apparent due to the demands of our testing interface. We expected users to type ‘D’ or ‘Q’ keys while watching video within the Google Chrome browser and did not anticipate that these key commands would conflict with screen readers (text-to-speech technology that reads information on a screen, e.g., JAWS, NVDA, Navigator). Participants needed to know that the virtual PC cursor had to be turned off. This created confusion with several pilot testers because screen readers on Windows or Mac computers are configured differently. In addition, access to the microphone (to capture user’s questions) was not easily granted.

5.4.3 Running a Study Remotely: Unlike typical user studies where participants are physically invited to meet in person and use a preset system, we instead emailed a user study link to each participant in order to comply with shelter-in-place directives due to the COVID-19 pandemic. Expecting each participant to navigate a list of 13 hyperlinks resulted in missed testing conditions that required 1:1 participant follow-up to complete the full study and evaluate each testing condition. The remote format made it difficult for us to provide technical support in real time, instead relying on participants to reach out for help or provide feedback after evaluation activities.

5.4.4 Video Understanding Models and Datasets: Video understanding models are still in their infancy, and these models are notoriously data hungry. The datasets we need to train our system on must be significantly larger and more diverse than what was used in this work to match the variety of vocabulary, scenes, and contexts in videos. Moreover, datasets such as COCO [46] or ImageNet [23] that our system was trained on were not developed for nonvisual accessibility. Additional labor is necessary to customize information from these datasets. In terms of our system functionality, we use the Pythia [40] caption generation model to create a description for every selected keyframe. This approach ignores the temporal information in a video. Tasks such as state transitions (e.g., facial expression from happy to sad, action from running to standing) require temporal reasoning in video understanding. To improve our system’s accuracy, we need to extend the image captioning model and investigate the temporal aspect of videos by employing 3D convolutional neural networks (3D CNNs) [18] and Transformers [72] to analyze a sequence of frames at one time.

6 CONCLUSION AND FUTURE DIRECTIONS

Ultimately, greater effectiveness and usability of the developed system will promote broader equity in video and information accessibility. By maintaining how and what information is generated depending on human factors, automated tools can potentially overcome gaps in video accessibility that human-driven tools could not accomplish alone. Efforts at automating description labor can help to alleviate the burden on media creators while meeting expectations for information accessibility; however, in order for automated systems to truly be of service, tools and datasets must be developed in partnership with end users to ensure that they serve the intended purpose.

We also look to our BLV participants to identify future directions for development. For example, although our initial pilot was focused on improving access to YouTube videos, a participant identified a future implication to “see [how] these tools [could be] implemented
as a browser extension or be built directly into the YouTube experience, but also be available for other video services on the web and in apps.” Broader applications of our system will support more universal and multimodal information as well, just as closed captioning has benefited individuals without a hearing impairment, described videos can potentially benefit individuals without a visual impairment by embellishing communication experiences (for English Learners) or allowing any individual to multi-task their vision (e.g., cooking with one’s back to the television). As one participant wrote, “All forms of audio description should be welcomed, not just for us visually impaired people, but sighted people who don’t want to look at a screen after a long day of work.”

Finally, our shift away from dependency on sighted human assistance better empowers BLV individuals to dictate their own points of access. Our hybrid system experiments with the interdependent nature between humans and machines and potentially gives rise for the end user to decide who yields the information. As one of our participants noted, “I believe these tools, with a little tweaking, can go really far to enhance the lives of us who are blind/visually impaired.”

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