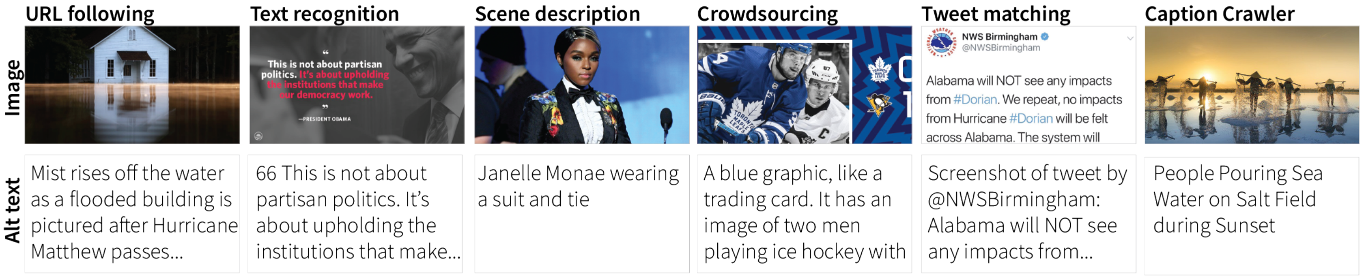
Twitter A11y: A Browser Extension to Make Twitter Images Accessible

Cole Gleason[1], **Amy Pavel**[1], **Emma McCamey**[2], **Christina Low**[3],
Patrick Carrington[1], **Kris M. Kitani**[1], **Jeffrey P. Bigham**[1]

[1]Carnegie Mellon University
Pittsburgh, USA
{cgleason,apavel,pcarrington,
kkitani,jbigham}@cs.cmu.edu

[2]Virginia Commonwealth University
Richmond, USA
mccameyec@vcu.edu

[3]Stony Brook University
Stony Brook, USA
chlow@cs.stonybrook.edu



This is not about partisan politics. It's about upholding the institutions that make our democracy work.
—PRESIDENT OBAMA

NWS Birmingham
@NWSBirmingham
Alabama will NOT see any impacts from #Dorian. We repeat, no impacts from Hurricane #Dorian will be felt across Alabama. The system will

URL following	Text recognition	Scene description	Crowdsourcing	Tweet matching	Caption Crawler
Mist rises off the water as a flooded building is pictured after Hurricane Matthew passes...	66 This is not about partisan politics. It's about upholding the institutions that make...	Janelle Monae wearing a suit and tie	A blue graphic, like a trading card. It has an image of two men playing ice hockey with	Screenshot of tweet by @NWSBirmingham: Alabama will NOT see any impacts from...	People Pouring Sea Water on Salt Field during Sunset

Figure 1. Twitter A11y describes images posted to Twitter depending on the image type including user-posted images, external link previews, and text-based screenshots. For each method, we include a sample tweet image (top) and sample alt text produced by the method (bottom).

ABSTRACT

Social media platforms are integral to public and private discourse, but are becoming less accessible to people with vision impairments due to an increase in user-posted images. Some platforms (*i.e.* Twitter) let users add image descriptions (alternative text), but only 0.1% of images include these. To address this accessibility barrier, we created Twitter A11y, a browser extension to add alternative text on Twitter using six methods. For example, screenshots of text are common, so we detect textual images, and create alternative text using optical character recognition. Twitter A11y also leverages services to automatically generate alternative text or reuse them from across the web. We compare the coverage and quality of Twitter A11y's six alt-text strategies by evaluating the timelines of 50 self-identified blind Twitter users. We find that Twitter A11y increases alt-text coverage from 7.6% to 78.5%, before crowdsourcing descriptions for the remaining images. We estimate that 57.5% of returned descriptions are high-quality. We then report on the experiences of 10 participants with visual impairments using the tool during a week-long deployment. Twitter A11y increases access to social media platforms for people with visual impairments by providing high-quality automatic descriptions for user-posted images.

CHI'20, April 25–30, 2020, Honolulu, HI, USA

ISBN 978-1-4503-6708-0/20/04...$15.00
DOI: https://doi.org/10.1145/3313831.3376728

Author Keywords

Screen reader; Twitter; social media; accessibility.

CCS Concepts

•**Human-centered computing** → **Accessibility systems and tools;** *Empirical studies in accessibility; Accessibility technologies;*

INTRODUCTION

Social media platforms provide a medium for online discussion and information dissemination, but accessibility barriers on these sites can prevent users from accessing them with a screen reader. People who are blind or low-vision use screen reader software to read the text on a webpage or application aloud, but social networks lack the necessary descriptions for visual content, like images or videos. For example, Twitter was originally a very popular social network for people with vision impairments, as the text-based posts were accessible via screen readers [25]. However, the steady increase in the number of images posted by users has lead to these platforms becoming less accessible because they do not include image descriptions (alternative text). Around 12% of content on a random sample of Twitter consists of images, and while Twitter allows users to add alternative text descriptions to images, only 0.1% of the images on Twitter include them [8].

Access to social media platforms is critical for people with vision impairments to both communicate with friends and colleagues, and to participate in public discourse. People with vision impairments interact with social media features to the same extent as sighted users, but prior work notes a decrease in interaction with visual content and features on Facebook [26]. In addition, people with disabilities often use social media to share information about their disabilities or organize around disability activism. For example, the #HandsOffMyADA and #CripTheVote campaigns on Twitter were organized by disability activists around pending legislation in the US [1,7]. Auxier et al. found that even in the #HandsOffMyADA campaign, only 7% of images contained alternative text, leaving most of the images inaccessible to people with vision impairments.

To provide high-quality descriptions for images on social media platforms, we designed an end-to-end system, Twitter A11y, to generate or retrieve alt text for images on Twitter (Figure 1). Prior research has developed several automatic and human-in-the-loop methods to generate image descriptions, and these methods are now robust enough to deploy at scale to address the growing lack of image accessibility on social media. Twitter A11y includes three methods that automatically add alt text for user-posted images: text recognition (optical character recognition), scene description, and the Caption Crawler method [11] (reverse image search). Two additional methods seek to address Twitter-specific images categories: screenshots of tweets and preview images for external links. Finally, if none of the prior methods produce a satisfactory alt text description for the image, Twitter A11y asks a crowd worker to describe the image on Amazon Mechanical Turk using a set of provided guidelines. Twitter A11y's browser extension dynamically requests alt text in the background for images as a user uses the Twitter website, and adds it to the image as if it had been there originally.

To evaluate the coverage and quality of alt text from the six methods, we performed a static analysis of images from 50 blind Twitter users' timelines. We randomly sampled tweets they may have read over the course of a day, creating a sample of 1,198 images. Through a combination of automatic methods, Twitter A11y increased the alt text coverage from 7.6% to 78.5%. We then rated a subset of these images to compare the quality of the descriptions returned from each method on a four-point scale. We consider the alt text that achieves either the highest rating ("Great") or second-highest rating ("Good") to be high-quality alt text. The highest percentage of quality alt text was from the text recognition (32.7% "Good", 44.9% "Great") and scene description (53.1% "Good", 14.3% "Great") methods. We also evaluated crowdsourcing as an additional method, finding that 62.5% of the resulting descriptions were rated "Great" (and 18.8% "Good").

We recruited 10 participants who access Twitter via a screen reader, to evaluate the perception of Twitter A11y and the six methods. Twitter A11y was able to add automatic descriptions to 82.4% of the content they accessed, crowdsourcing the remaining 17.6%. On average, participants' perceptions were that 12.1% of images were accessible in their timelines before the study, and 72.3% of images were accessible when using Twitter A11y.

In this work, we make social media content accessible by asking people with vision impairments to install a browser extension, but the technological and financial costs of making social media accessible should not be borne solely by people with disabilities in the long term. Rather, the platforms should bear the responsibility to ensure their hosted content is accessible through more accessibility features, user education, and employing the methods used by Twitter A11y. Therefore, the Twitter A11y approach and user evaluation results should be informative for application developers, not used as a justification for user-installed solutions.

This work represents a combination and comparison of known methods that are now robust enough to address the accessibility issues plaguing social media platforms. We show the potential for dramatic improvement in accessibility, the differences between coverage and quality of different methods, and the impact of this tool on the social media experiences of our participants. This work opens future directions for researchers to improve and combine the methods used by Twitter A11y and provides guidance for social media designers on integrating methods to make their platforms accessible at scale.

RELATED WORK

This research is related to prior work on (1) automatically generating alternative text for people with vision impairments, (2) crowdsourcing image descriptions, and (3) accessibility on social media platforms.

Automatically Generating Alternative Text

Alternative text is a property in the HTML specification [2] to include a textual description of visual content in an image. It is primarily used by people with vision impairments who browse the web with screen readers or braille displays, but can also be used by search engines [14] and other machine learning applications [13]. While alt text is currently just textual, researchers have proposed updating the standard to include richer representations of images, such as background audio or sound effects [9,19]. The lack of alternative text is a perennial problem on the web [3,12], and various methods can be used to describe visual aspects of the image.

Optical character recognition attempts to extract text characters captured in images and correct errors to make coherent words or sentences [3]. Object recognition algorithms can locate and identify entities in the image that the model has been trained to recognize, such people or animals [27]. Instead of a list of objects, scene description methods generate a caption for the image, attempting to describe aspects of the image in a grammatically-correct sentence structure. This approach is available in commercial applications like Microsoft Seeing AI [17]. MacLeod *et al.* explored the impact of these captions when viewed by people with vision impairments, finding that they are not sufficiently accurate [15]. They also evaluated ways of expressing the uncertainty in the caption model to engender skepticism when viewed as alt text. Automated approaches are popular because they are fast and cheap, allowing platforms to deploy them at scale to make large swathes of the web accessible for screen readers. However, they are often less descriptive compared to human-written alternative text on websites that prioritize accessibility and we consider how to combine strengths of both types of methods.

Crowdsourcing and Reusing Alternative Text

Human-in-the-loop systems can generate accurate alt text of images by soliciting descriptions from sighted crowd workers [3] or friends online [5]. Salisbury *et al.* explored employing crowd workers to correct for errors in automatic captions [25]. The authors allowed people with vision impairments to ask clarifying questions from crowd workers, but users were unable to recover from inaccurate captions.

Human-in-the-loop methods are often framed as solely using workers on crowd platforms to label images on the fly, but alt-text can also reuse human-written text from around the web. ALT-Server was an architecture proposed in 1997 that stored image descriptions written by sighted people in a central database for future use [6]. When a user accessed an image without alt text, they could check ALT-Server to see if any description existed for that URL. Instead of looking for alt text written for the image at a specific URL, the Caption Crawler project retrieves existing alt text by searching for the same image posted elsewhere [11]. As this method utilizes reverse image search to find the image on other websites, the image must appear elsewhere and be indexed by a search engine for this to be successful. Similarly, WebInSight [3] retrieves alt text using OCR and crowdsourcing, but also looks for images with links and retrieves alt text from the linked webpages' title and headings. Twitter A11y utilizes the Caption Crawler method of reusing alt-text from other websites, a variation of WebInSight to collect alt text from image links, and stores alt text for later use similar to ALT-Server. However, these projects all focused on images on the web in general, and the images on social media may differ enough to thwart these methods, which we discuss next.

Social Media Accessibility

The content posted on social media platforms has become more visual over time as they have prioritized images, videos, and animations (GIFs). Morris *et al.* estimated that 28.4% of tweets on Twitter contained some multimedia in 2015 [20]. While Twitter does allow users to add alt text to their images, Gleason *et al.* has found that only 0.1% of images contained alt text, as the feature is not on by default [8]. Tweets do contain additional post text, but this is not the same as describing the contents of an image, and Morris *et al.* found that only 11.2% of post text would also be a good image description. Facebook has addressed the issue of alt text at social media scale by deploying object recognition software to efficiently create a large quantity of images descriptions [27], but they often do not contian enough detail to fully meet the needs of people with vision impairments. For example, Facebook describes the third picture in Figure 1 (Scene Description) as "1 person".

Because social media is uploaded by end-users and not website developers, the images are unlikely to be shared elsewhere on the web, and if so, may not be indexed quick enough for Caption Crawler to find. Additionally, few images on platforms like Twitter are links to external websites, except for image previews of external links (which the user cannot choose). Specialized types of images, such as screenshots or memes, are more common on social media [20]. Gleason *et al.* designed a method for creating accessible memes by matching images to crowdsourced descriptions and extracting unique text from the image using OCR [9]. Another method recognizes the facial expression in memes to convey its emotional tone [23].

Method	Cost	Agg. Cost	Agg. Time
URL Following	0.00¢	0.00¢	3.0s
Text Recognition	0.15¢	0.15¢	2.5s
Tweet Matching	0.00¢	0.15¢	2.3s
Scene Description	0.25¢	0.40¢	2.4s
Caption Crawler	0.40¢	0.80¢	14.8s
Crowdsourcing	36.00¢	36.80¢	126.7s

Table 1. The time and per-request costs incurred with Twitter A11y's methods. Because it tries methods in a specific order, the aggregate costs and time are presented to respond with a result from that method.

When describing end-user uploaded images, existing methods have trade-offs between description quality and frequency of applicability across a wide range of content. We build on prior work by integrating a broad set of automatic, retrieval, and crowdsourcing-based methods tailored to make a high percentage of Twitter images accessible.

TWITTER A11Y

Twitter A11y combines a browser extension (Figure 2, square corners) with a backend server (rounded corners) to make image tweets accessible through one of six methods.

Requesting Alternative Text

When the user loads the Twitter.com web interface, the browser extension observes new images loaded on the page. When an image associated with a tweet is loaded on the user's timeline, the extension extracts the image URL, any existing alt text, and context of the tweet (*e.g.*, tweet ID, user ID, tweet text). If the tweet contains a preview image and link to an external website, the extension also records the linked URL. The extension automatically requests alt text from the server using this data, without user input.

Obtaining Alternative Text

The Twitter A11y server receives requests for alt text that include the image URL and tweet context and attempts to use up to six methods as applicable to fetch or generate the image descriptions. The methods are ordered to prioritize a quick response, with methods that take less time returning early if they result in alt text for the image. The monetary costs (*i.e.*, API request or crowd payment) and total time taken to return a response if a method is successful is present in Table 1. These are the costs incurred per Twitter A11y response in our study, but we expect social media platforms or third-party application developers could implement these methods cheaper and faster. If an image has already been requested by another user and alt text exists in the database, that alt text is returned to the user immediately. Because of this, requests for tweets from popular Twitter accounts will have a very quick response time. If a tweet image contains existing alternative text written by the poster, it will not be replaced by Twitter A11y, as the original alt text is likely the most suited for the image.

If no alt text is present for the image, then Twitter A11y tries the following methods in order: URL Following, Text Recognition, Tweet Matching, Scene Description, Caption Crawler, Crowdsourcing (Figure 2). When a method returns alt text and the alt text satisfies the threshold conditions, the progression

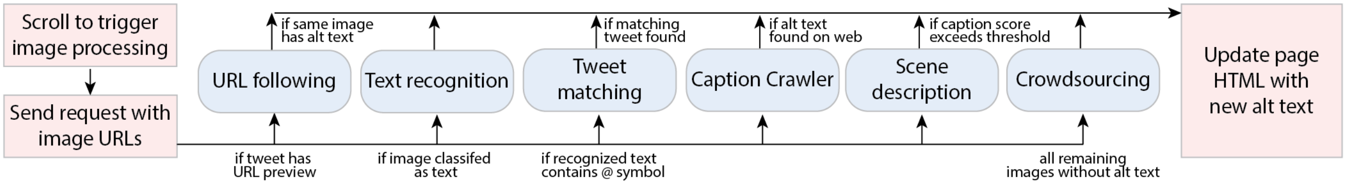

Scroll to trigger image processing
Send request with image URLs
if same image has alt text
if matching tweet found
if alt text found on web
if caption score exceeds threshold
URL following
Text recognition
Tweet matching
Caption Crawler
Scene description
Crowdsourcing
Update page HTML with new alt text
if tweet has URL preview
if image classifed as text
if recognized text contains @ symbol
all remaining images without alt text

Figure 2. Flowchart of Twitter A11y process. Square rectangles depict steps that happen in the browser extension, and rectangles with rounded corners depict steps on the server. When the user scolls on the Twitter webpage, the extension will send all tweets with images to the server. The server progressively attempts up to six different methods to generate alt text for the image, returning a result early if one is successful.

breaks early. Otherwise, a crowd worker writes alt text to ensure all images receive a description.

External link previews. Websites such as news organizations share external articles on Twitter that contain described images on the external website but do not include alt text for the link previews that appear in such tweets (Figure 1, URL Following). If this is included in the tweet context data, the system crawls the page at the given external URL to extract all images. We compare the color histogram of the image to be described with the color histograms for all images in the external page (~3-10 images total for news articles). If a matching image is found and contains alt text, this is returned to the requester.

Text-based images. Many tweets feature images of text (*e.g.*, text that exceeds the Twitter character limit, text messages, screenshots of tweets). We determine if an image tweet depicts primarily text (Figure 1, Text Recognition) using whole-image labeling via the Google Cloud Vision API [10]. If the confidence of the "text" label exceeds 0.8, we record the resulting Optical Character Recognition result (also via Google Cloud Vision API) as the alt text. We selected this threshold empirically to achieve high-precision (lower recall) such that users are unlikely to receive inaccurate alt text.

Screenshots of tweets. Twitter provides a way for users to share other tweets by using the retweet feature, but users often share screenshots of tweets instead. This could be to preserve a tweet in case the author later deletes it or prevent harassment by sharing a tweet without notifying the original author. If the text recognition results from the previous step include a Twitter username beginning with the "@" symbol, we use the Twitter API to search for tweets by that user containing the first 10 words in the text recognition results. If a matching tweet is found, we describe that it is a screenshot of a tweet and return the tweet text directly, which can be more accurate than text recognition results.

Reverse image search. Some images shared on social media are copied from elsewhere on the web, where alt text might be present. We re-implemented the Caption Crawler [11] project to source alt text from other websites with the same image. This method utilizes the Bing Image Search API [18] to perform a reverse image search. Once we have a list of locations where the same image appears around the web, we crawl up to 25 webpages to find the image and any alt text it contains. If multiple webpages have alt text, we return the longest one, as evaluation of the Caption Crawler project found length to be a good heuristic for image caption quality.

Automatic image captioning. Other social media platforms, such as Facebook, have experimented with providing image captions automatically generated by object recognition or scene description algorithms [27]. These are useful because they can be easily scaled to many images, but can lead blind users astray if the generated caption does not accurately or fully describe the image [15]. Twitter A11y will attempt to use this method if the previous ones were not applicable or did not result in alt text. It uses the Microsoft Cognitive Services Vision API to generate an image caption, and chooses the resulting caption with the highest score. If no caption exceeds a threshold of 0.7, determined empirically, then it is ignored.

Crowdsource all remaining images. For remaining images not handled by the prior, rather quick methods, we post a crowd task on Amazon Mechanical Turk. This ensures that all requested images will receive some alt text from Twitter A11y. The task asks workers to generate image descriptions using the guidelines informed by Salisbury *et al.* [25]. The task time was originally estimated by the authors to take ~60 seconds and crowd workers were paid $0.17 per image ($10 per hour). After evaluation with some crowd workers, we found the median task to take 108 seconds (mean = 122s), so the task reward was increased to $0.30 per image. As the worker may take some time to write the description (~2-5 minutes), the browser extension displays "Waiting for crowd worker" until the written description is ready. Crowdsourcing carries the benefit that humans may be able to best describe characteristics such as humor that automatic methods miss.

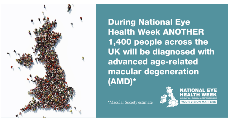
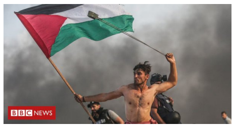
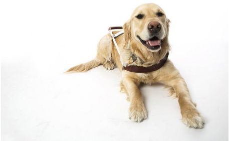
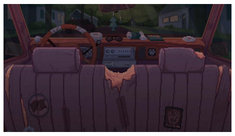
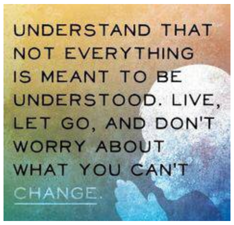
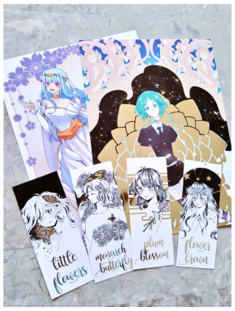
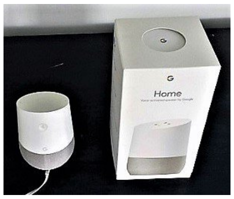
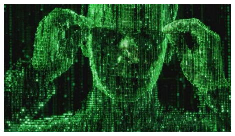
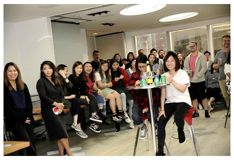
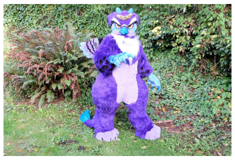
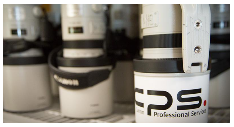
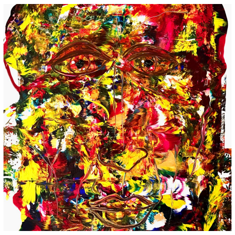
Displaying Alternative Text

From the server, the extension receives either the existing alt text in the database, newly generated alt text from one of the above methods, or the status of an uncompleted crowdsourced description. The browser extension then dynamically inserts it into the alt text tag for the image. The user's preferred screen reader can then read the newly generated alt text for an image when it focuses on the tweet, just as it would if the alt text had been there by default. While automatically-generated alt text appears soon after viewing (~2-10 seconds), crowd-generated alt text takes longer (on the scale of minutes) such that the user could view the text upon re-visiting the tweet (*e.g.*, by scrolling back in their timeline, or revisiting a user's page where the tweet appeared).

STATIC ANALYSIS OF BLIND USERS' TIMELINES

To gather a large number of users who may use a screen reader to access Twitter, we examined the Twitter accounts following the National Federation for the Blind (@NFB_Voice) and the American Federation for the Blind (@AFB1921). We selected 50 users from this list who self-described themselves as blind or visually impaired in the profile description. It's possible that these users do not use a screen reader to access Twitter,

Table 2. A high-quality and low-quality alt text example for different images made accessible by each method utilized in Twitter A11y.

	High-Quality Alt Text Rating		Low-Quality Alt Text Rating	
Strategy	**Image**	**Alt Text**	**Image**	**Alt Text**
Original	 During National Eye Health Week ANOTHER 1,400 people across the UK will be diagnosed with advanced age-related macular degeneration (AMD)* *Macular Society estimate NATIONAL EYE HEALTH WEEK YOUR VISION MATTERS	Overhead map of the UK made up of people standing and the words During NEHW another 1,400 people across the UK will be diagnosed with advanced age-related macular degeneration	 	Palestinian protester
URL Following		A guide dog with a harness sits on the ground.		A point & click adventure game about the fun, alienation, stupidity and agony of being a teen.
Text Recognition	 UNDERSTAND THAT NOT EVERYTHING IS MEANT TO BE UNDERSTOOD. LIVE, LET GO, AND DON'T WORRY ABOUT WHAT YOU CAN'T CHANGE.	UNDERSTAND THAT NOT EVERYTHNG IS MEANT TO BE UNDERSTOOD. LIVE, LET GO, AND DON'T WORRY ABOUT WHAT YOU CAN'T CHANGE	 little flowers monarch butterfly plum blossom flower crown	Cittle oullorly Blesseng l (lowerserarch c Croaon
Caption Crawler	 	Google home device pictured next to packaging box for size perspective		How to Make Special Video Effects
Scene Description		a group of people posing for a photo		a teddy bear sitting on top of a grass covered field
Crowdsourcing	 	A row of large, white Cannon professional video camera lenses are sitting on a perforated surface like a vent panel or an appliance.		Two faces hidden in the beautiful painting

Alt Text Method	Covered		Unique		Selected	
	N	%	N	%	N	%
Original Alt	91	N/A	12	N/A	91	N/A
Scene Description	746	67.3	465	42.0	547	49.4
Text Recognition	216	19.5	60	5.4	199	18.0
Caption Crawler	213	19.2	70	6.3	70	6.3
URL Following	57	5.2	8	0.7	33	3.0
Tweet Matching	0	0.0	0	0.0	0	0.0
Crowdsourcing	1107	100	258	23.3	258	23.3

Table 3. Evaluation of alt text methods in a sample of 1,198 images from blind users' timelines. Covered indicates how many images in the sample the strategy could provide alt text for, and Selected indicates if that method was chosen according to Twitter A11y's method priority order. Because different methods can provide alt text for the same image, the Covered column does not sum to 100%.

and therefore they may not notice the presence or absence of alternative text. However, we are making the assumption that a large majority of these accounts that self-identify as blind or visually impaired do care about the presence of alt text on Tweets. The "Home Timeline" is the feed of tweets that a user reads when they log in to Twitter. We simulated a version of this timeline by collecting all of the tweets posted or retweeted by accounts each user followed over a 24 hour period. We then placed them in chronological order. All 50 users had at least 1,000 tweets in this simulated timeline.

These simulated timelines have some differences from those that would be experienced by users. First, Twitter does not always include all tweets in chronological order, choosing to place popular tweets first in the timeline. The Twitter algorithm may also hide replies to tweets that are not relevant, or include tweets liked by accounts the user follows. The actual timeline may also include ads. Finally, we were unable to collect tweets that had been deleted or were posted by protected (non-public) accounts, which the user may be able to see.

Accessibility of Timelines

Accounts followed by blind users tend to include more alternative text in their tweets than Twitter as a whole [8]. For the 50 accounts, we randomly sampled 50 tweets from each user that either contained images or links to external website. From this 2,500 tweet sample, after examining the links, 1,041 tweets remained with either an image or valid link preview for a total of 1,198 images (a tweet can contain up to 4 images).

Of these 1,198 images, 62 contained alternative text from the tweet poster, and 29 link previews had alternative text from the linked website, meaning 7.6% was already accessible. We then evaluated each method except crowdsourcing on all of the images, and calculated the ability of each to add alt text to the images (Table 3). The automatic methods increased the presence of alt text from 7.6% to 78.5% before applying crowdsourcing to the remaining 21.5%.

When evaluating methods we considered three metrics in addition to quality:

- **Image Coverage**: How many images did this method produce alt text for in the sample?
- **Method Uniqueness**: For how many images in the sample was this the only method that produced alt text?
- **Selected**: Using the Twitter A11y method priority as defined in Figure 2, how often was this method's alt text chosen?

Using these metrics, we can change Twitter A11y's method priorities to optimize for different aspects of the user experience. We can see that in all metrics, Scene Description is providing a bulk of the alt text, meaning that if optimizing for speed then it should be first in the method priority. Twitter A11y only used 70 of the images provided by Caption Crawler (because it was last in the order before crowdsourcing), while it was able to source alt text for up to 216. As automatic descriptions may have lower quality than human-written descriptions from Caption Crawler, perhaps it should be the "last resort" automatic method instead of Caption Crawler. We examine the quality of captions returned by each method next.

Description Quality

Two members of the research team independently rated a random subset of the data collected, consisting of 50 images and alt text for each method (except URL Following and tweet matching as they did not have enough examples). We include sample descriptions for each method in Table 2. As in Gleason *et al.* [8], we utilized a four-point rating scale based on prior work [20, 25]. The scale ranged from "Irrelevant to image (0)" to "Great: almost everything described (3)" (available in Supplemental Material). To estimate agreement, we computed Cohen's Kappa = 0.61, indicating substantial agreement [16]. The two raters then met and discussed each instance where their ratings differed until they reached agreement.

In Table 4 and Figure 3 these ratings are broken down by method. Crowdsourcing provided the highest "Great" quality descriptions as they were human-written with specific instructions for writing high-quality alt text. Text recognition has the highest "Great" percentage for an automatic method, comparable to alt text provided by the original poster and the only "Good" quality automatic captions from scene description. Surprisingly, Caption Crawler and URL following provided mostly "Irrelevant" or "Somewhat Relevant" alt text, even though they should source human written descriptions. Upon examination of the low quality descriptions, we found that this was typically because website authors were using an image filename or article title as the alt text for the image, instead of properly describing the visuals in the image itself (Table 2).

Method (N)	Irrelevant	Relevant	Good	Great
Original Alt (48)	4.2%	20.8%	25.0%	50.0%
Scene Description (49)	8.2%	24.5%	53.1%	14.3%
Text Recognition (49)	6.1%	16.3%	32.7%	44.9%
Caption Crawler (38)	26.3%	42.1%	23.7%	7.9%
URL Following (26)	26.9%	46.2%	7.7%	19.2%
Crowdsourcing (48)	10.4%	8.3%	18.8%	62.5%

Table 4. Two members of the research team rated a subset of the entire sample to estimate the quality of captions returned by each method.

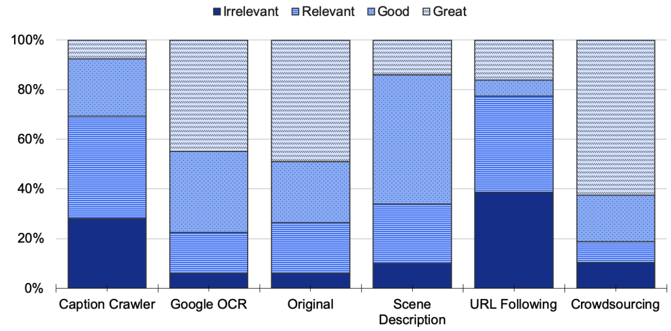


Figure 3. A breakdown of the distribution for level of quality for alt text descriptions generated by each strategy from Great at the top to Irrelevant at the bottom. The columns are normalized by the number of example images in our sample.

This measure of quality by method allows us to measure the value for each method used by Twitter A11y that has external costs (*e.g.,* API fees or crowd payments). We define value as the number of "Good" or "Great" image descriptions a method can produce per $1 spent. This results in a value ranking of text recognition (571), scene description (269), Caption Crawler (79), and crowdsourcing (3). While money may not be a limiting factor for social media platforms, if third-party client developers wished to pass these external method costs along to blind users, crowdsourcing may not offer enough value to warrant using on every remaining image as in Twitter A11y. However, we do not advocate for passing these costs along to blind social media users as a long-term solution, and instead believe that social media platforms need to invest in accessibility solutions rather than relying on third-party application developers to create additional tooling.

EVALUATION WITH BLIND TWITTER USERS

The examination of Twitter A11y's performance on this static sample of images from blind users' timelines helped us get a sense of the ability of different methods to add alt text to images and at what quality level. Next, we wished to evaluate the usability of Twitter A11y and the perception of its ability to make Twitter content more accessible. We recruited 13 participants who use a screen reader to access Twitter to install and use the browser extension. The participants each completed a 30-minute semi-structured interview about their experiences with Twitter accessibility in the past. Then they installed and used the browser extension for one week. We followed up after that week for another 30-minute interview about their experience using Twitter A11y. Three participants (P3, P9, P13) did not complete the data collection or final interview due to technical difficulties or lack of access to a computer. Their responses are included in the first interview, but not in the post interview results.

Participant Demographics

We recruited people with vision impairments who had participated in previous studies, as well as sending out a call for recruitment on Twitter. Participant ages ranged from 19 to 54, with an average age of 33.5. Six participants were female and seven were male. All participants accessed Twitter using a screen reader, although many said they used additional applications to access Twitter either on their computers or on their smartphones. These are detailed in Table 5.

Participants were compensated $10 for each interview, and $6 per 10 minutes of using the system, up to a maximum amount of $62 for the entire study.

Pre-study Interview

Before using Twitter A11y, we asked participants about their impressions of accessibility on Twitter, and what problems they saw with the social media platform and content on that platform. The specific questions can be found in the Appendix.

Regarding Twitter's accessibility as a whole, ten participants said they found the platform itself mostly accessible. A few participants (3) complained about using a screen reader on the Twitter website, but stated the mobile applications were satisfactory. However, most participants (10) still choose to use third-party clients (e.g., Twitterific, TWBlue) either because they supported screen readers more effectively or because they did not change layouts often. TWBlue was especially popular, as it is an open source application designed with screen reader accessibility in mind. Participants lauded its support of global keyboard commands, meaning they did not have to switch applications to use it. They also liked that it included a function to request the text in an image using OCR.

The most common accessibility issue mentioned by every participant was media accessibility. They noted that most images did not include alt text, even though they likely followed accounts that added alt text more often compared to the sighted population. Twelve participants said they could sometimes guess at the content of some images depending on the text content of the tweet, but they commonly said this worked for less than half of images.

To understand how participants perceived the scope of the lack of alt text on image, we asked them to estimate what percent of their feed contained images and what percent of those images were accessible. On average, they estimated 50.5% of their feed contained images (max = 70%, min = 10%) and believed 12.1% of the images they encountered contained alt text (max = 30%, min = 1%). Eight of the participants mentioned that the percentage of images that people post affect their decision to follow an account, with some stating they would not follow an inaccessible account, some stating they would unfollow someone who did not add alt text after they requested it, and one stating they blocked those accounts to keep inaccessible images out of their feed.

Participants also complained that there was no mechanism to make GIFs (short animations), which are common on Twitter, accessible by adding alt text. When asked about video accessibility, responses were mixed, and many said they found videos consisting of mostly dialogue already reasonably accessible. Three participants suggested that videos on Twitter should support the addition of audio descriptions as a secondary audio track or as timestamped text content.

Some users circumvented the issues with image accessibility by utilizing other applications. Participants stated they used Microsoft Seeing AI on their iPhones to receive a textual description of an image (similar to Twitter A11y's scene descriptions) or to read text in an image, if it was present. P12 noted that he could tell if an image contained text using his

ID	Age	Gender	Years on Twitter	Level of vision	Screen reader	Twitter Applications	Other Social Media
P1	19	M	6	Blind since birth	NVDA	TWBlue	Facebook
P2	39	F	11	Blind since birth	Voiceover	Twitterific	Facebook
P3	25	F	5	Blind since birth	NVDA, JAWS	TWBlue, Twitter (mobile site), Twitter for iOS	Facebook
P4	19	M	7	Blind since birth	NVDA, Voiceover, Talkback	TWBlue, Twitterific, Twitter for iOS, Twitter for Android	LinkedIn
P5	32	M	12	Blind since birth	NVDA, JAWS	TWBlue	None
P6	41	M	12	Blind since age 21	VoiceOver, JAWS, NVDA, Narrator	twitter.com, Twitterific, Tween	LinkedIn, Facebook, Instagram
P7	47	M	12	Blind since birth	JAWS, NVDA, VoiceOver	TWBlue, Twitterific, Twitter for iOS	LinkedIn, Facebook
P8	44	F	8	Blind since age 28	JAWS, NVDA, VoiceOver, Talkback	TWBlue, twitter.com, Twitter for iOS	Facebook, Instagram
P9	41	F	8	Blind since birth	VoiceOver	Twitter for iOS	None
P10	29	F	7	Blind since age 1	VoiceOver, JAWS	twitter.com, Twiter for iOS	Facebook
P11	22	F	8	Blind since birth	NVDA, VoiceOver	TWBlue, Twitter for iOS	Facebook
P12	23	M	2	Peripheral vision, no central vision since age 13	VoiceOver	Twitterific	Reddit, Youtube
P13	54	M	11	Totally blind since age 1.5	VoiceOver, NVDA	Twitterific	Facebook

Table 5. Demographics of participants who participated in the online study including age, gender, years on Twitter, level of vision, screen reader, methods of accessing Twitter, and other social networks used. Note that P3, P9, and P13 did not complete the data collection and post-study interview.

peripheral vision, but people who were totally blind would not be sure if an image contained text.

Participants who used other social networks stated that the lack of image accessibility was common to Facebook, LinkedIn, Reddit, and Instagram. Most participants who used Facebook mentioned their automatic image alt text, stating that they wished they were more descriptive, but it was better than no alt text at all. P10 stated that she liked Facebook's automatic captions simply because it stated "This image may contain: text", so she knew to send the image to an OCR application.

Finally, we asked participants what they would do to make Twitter more accessible. Eight participants wished Twitter would make the alt text feature more prominent, ensuring all users are aware of the feature and how to use it. Three even suggested the feature should be mandatory, while 4 others wanted Twitter to fill in empty alt text with automatic descriptions similar to Facebook. Users who utilized third party applications stated Twitter should better support them, especially by ensuring all features (especially muting, blocking, and other reporting tools) were available via the API.

Twitter A11y Usage

After the interview, participants were directed to install Twitter A11y on their computers, and asked to use it for about 10 minutes a day over 7 days. Whenever they accessed Twitter, the browser extension logged every tweet containing images in their feed, and logged the alt text response added.

Session Length and Content

Participants used Twitter A11y for a total of 2,198 minutes over 145 sessions (mean = 15.2 minutes per session). During this time, they saw a total of 3,615 unique images (mean = 301.3). Of these, 86 already contained alternative text, and Twitter A11y provided descriptions for an additional 3,505 images. The breakdown of this by method and participant can be seen in Figure 4. The only time Twitter A11y did not provide any alternative text for an image was due to a technical error interrupting the request.

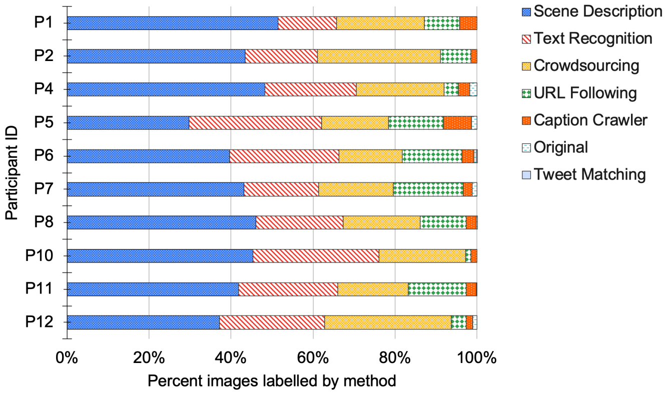


Figure 4. A breakdown of which method provided alt text for the images requested by a participant in our user evaluation. The bars are normalized to the number of requests for each user.

Post-study Interview

After 7-9 days had concluded, we asked the participants about their experiences with Twitter A11y. Overall, almost every participant stated that they enjoyed using the system and found that many images were more accessible with the alt text provided. P7 was the exception, as he stated he did not see much additional alt text on the images he viewed.

We asked each participant to rate the six methods used by Twitter A11y to generate alt text on a Likert item scale from Not useful at all (1) to Extremely useful (5) (see Table 6). When using Twitter A11y, the participants could tell which method generated a result, as each alt text was preceded by "From [method name]:". Some participants stated they did not see any examples of a particular method, in which case they were unable to give an answer. We also asked participants to order the methods they preferred from best to worst. Because the majority of participants only felt comfortable ranking scene description, text recognition, and crowdsourcing, we only show the mean ranks for those. We do not report statistical testing for these responses, as not all participants were able to rate or rank every method, resulting in a small sample size.

Method	Mean Usefulness	Mean Rank
Caption Crawler	4.8	N/A
Tweet Matching	4.5	N/A
URL Following	4.3	N/A
Text Recognition	4.3	1.3
Automatic	3.7	3.1
Crowdsourcing	3.6	3.4

Table 6. Participant ratings of methods on a scale from Not at all useful (1) to Extremely useful (5). Participant mean rankings for the three most common methods (with 1 being their first choice).

Note that this self-reported metric of "usefulness" does not distinguish between the quality of the alt-text received and the participants' perceived value of the method itself. Future work could attempt to separate these two factors. For example, when assessing the usefulness of a description method for a particular tweet image, some participants reported the value depended on both the content of a description along with the context of the surrounding tweet. As P1 describes:

> *[Scene description] is useful when the tweet itself gives some context so if a tweet talks about a protest, and [scene description] says "a person holding a sign", then that makes sense because I understand that they're protesting but it doesn't give a ton of detail.– P1*

When assessing the usefulness of a description method as a whole, participants also considered the usefulness of the method for their particular timeline. As P4 reports:

> *[Text recognition] is one of the most useful because a lot of my timeline is tech and geek stuff which often has screenshots. Text recognition is key to understanding what's going on. – P4*

Inaccurate descriptions could lead people with vision impairments to believe a tweet image contained something that was not actually present. We asked participants if they ever felt like they did not trust a caption because it seemed inaccurate. Several participants stated they read 1-2 captions from scene description method that did not make sense with the context of the rest of the tweet, but otherwise everyone said they assumed the tweets were accurate. This implies that future versions of Twitter A11y should integrate cautionary text explored by MacLeod *et al.* [15] to encourage distrust in automatic captions when uncertainty is high.

In general, participants felt Twitter A11y could be most improved by speeding up the responses from crowdsourcing, as they did not want to wait minutes for a worker to describe the image. Participants also wanted flexibility to choose the method by which an alt text is generated, possibly through keyboard commands or a menu. Additionally, they wanted to be able to use multiple methods together, specifically scene description and text recognition, to get a sense of the image and recognize any specific text. Finally, participants were eager to see Twitter A11y integrated into their preferred clients, as they find them more usable than the Twitter web interface.

DISCUSSION

The participants in our user study expressed that Twitter A11y offered an impressive level of accessibility compared to what they typically find on social media platforms. This mirrors our findings from the analysis of static sample of tweets in blind users' timelines, which increased the presence of alt text from 7.6% to 78.5%, with an estimated 57.5% of descriptions being rated "Good" or "Great". We integrate our findings from these analysis to discuss the alt text generation methods holistically.

Participants preferred the text recognition and automatic captioning methods because they were quick (~2.5s) and often descriptive (~67-77% "Good" to "Great"). While most participants were familiar with these methods from other applications, they expressed that having the alt text automatically attached to images made their experience much more accessible. In our static analysis, we see the crowdsourcing provides the highest percentage of "Great" alt text (62.5%), but offers the lowest value (only 2-3 "Good" or "Great" captions per dollar) due to the expense of paying human annotators. Participants also perceived crowdsourced descriptions as accurate, but too slow (~2 minutes) to wait for when browsing social media sites. The tweet matching, URL Following, and Caption Crawler methods were highly rated by the participants who encountered them, but results with the methods were too rare for all participants to form an opinion. However, we only used Caption Crawler when no other automatic methods produced a result (6.3% of sample), and the coverage results in the static analysis indicate it had results for many more images (19.2% of sample) that Twitter A11y did not use, suggesting that the priority of methods could be re-examined.

For social media platform designers and application developers seeking to add automatically generated alt text, we would recommend using methods that produce cheap, high-quality results first. This would include text recognition, followed by scene description methods. Caution should be used when integrating the latter, as prior research has shown that inaccuracies are not easily noticed by people with vision impairments [15, 25]. Other methods do produce additional alt text, including URL following and Caption Crawler, but the low-quality results indicate they should be a low priority. Crowdsourcing is clearly the solution that produces the highest-quality alt text, but asking crowd workers to label images is likely prohibitively expensive at scale. Instead, designers and developers should explore if they can design features to support friends and other volunteer in adding alt text [4, 5].

Several participants indicated that other social media platforms include a higher frequency of inaccessible images, including Facebook and Instagram. We designed Twitter A11y specifically for evaluation on the Twitter website, but there is strong indication that this tool would be useful on other websites. Participants were unanimous in their belief that Twitter A11y would work equally well if deployed on other social media platforms they used, and the methods that provided high coverage of images and high-quality captions are readily applicable to other platforms. The only method that could not be easily re-engineered for other platforms is tweet matching, which was not used in the static evaluation as screenshots of tweets are a rare image category.

Two participants in our user study raised the importance of distinguishing accessibility and accommodation. They viewed

Twitter A11y's efforts as important to provide reasonable accommodations for images that were not made accessible from the start. However, they were not willing to use this tool unless it also made an effort to increase alt text provided by end-users who uploaded photos. The image posters have important contextual knowledge, and even the best crowd worker will not fully understand their intent when posting the image or all important details (*i.e.,* names). The participants suggested that Twitter A11y automatically notify the image poster that a blind user found their post inaccessible, and provide instructions on how to add image descriptions on Twitter. We agree with the participants that social media platforms should consider additional accessibility features and user education that could improve accessibility, not just rely on accommodations such as scene description methods. Some recommendations specific to Twitter are to increase enable image descriptions by default, train users on what comprises good alternative text, and give users feedback on the alternative text they write [8].

As members of the research team (all sighted) tested Twitter A11y, we were surprised at how useful alt text could be even in conjunction with seeing the image, indicating the tool could provide value for sighted users. The image captions served as quick summaries of a scene, and provided additional context. Specifically URL following, scene description, and Caption Crawler often added the names of people and places or described events that were not easily discernible from the images (see Figure 1). Additionally, when an image contained alt text written by the original image poster, it served as an indication that they valued accessibility for people with vision impairments. In contrast, the constant lack of original alt text served as a reminder that the majority of images are inaccessible and why image descriptions are valuable.

Limitations & Future Work

The major limitation with our evaluation of Twitter A11y is the rather short week-long evaluation with small number of participants (10) completing the study. A longitudinal study with more participants would be necessary to understand any behavior change of Twitter users due to increased accessibility of images. Additionally, we asked participants to use the Twitter web interface, which was typically not their preferred client, so an evaluation of Twitter A11y that was more tightly integrated with their Twitter client of choice would likely yield results more representative of typical use. Finally, a major area for future work is validating that our rubric of alt text quality aligns with the expectations of blind users. While the rubric was constructed based on prior work with blind social media users, it has not been validated to ensure that the 4-point rating scale accurately captures different levels of "usefulness" that people with vision impairments might desire.

Our interviews with participants and evaluation of a tweet sample indicate other avenues for future work. First, participants raised the desire for an integration of multiple methods, such as scene description and text recognition. Additionally, Twitter A11y currently tries each method in a sequential order until an alt text result is found, but our static evaluation revealed overlap between some methods. If there was a clear approach to score the quality of image descriptions from multiple methods, Twitter A11y could ensure the best alt text is always returned. Gleason *et al.* [8] briefly suggested generating automatic feedback for users while they write image descriptions based on the post text and the image description. The inclusion of these language features and features from the image itself could be adapted to develop a ranking algorithm.

We only address image accessibility in Twitter A11y, but other forms of visual media, such as GIFs and videos, were reported by participants to be inaccessible on social media platforms. As GIFs are short looping animations, they straddle the line between a static image and a longer video. An exploration of the best way for Twitter A11y to make these accessible might explore the use of an alt text description versus an audio description that describes the action in the GIF.

It is unlikely that the methods we tested will be directly applicable to creating audio descriptions, so new avenues will need to be explored to address video inaccessibility. There is not yet a robust method for automatic description of actions in videos [21], but there is a dataset of audio descriptions for movies to encourage future research on generating video descriptions [24]. Additionally, the YouDescribe project [22] has demonstrated how dedicated volunteers can describe videos and share audio descriptions through browser extensions, meaning Twitter A11y could explore a crowd workflow for generating audio descriptions on social media networks.

CONCLUSION

The lack of accessible content on social media platforms is a major barrier for participation by people with disabilities. Our participants echoed this in their interviews, stating that it was their primary concern and they often had to find workarounds for images without alt text. Making the deluge of user-generated content accessible, at scale, seems challenging, but platforms such as Facebook are attempting this.

Twitter A11y represents an attempt to merge promising methods for finding or generating new alternative text into one tool that users can use on Twitter. We demonstrated Twitter A11y's ability to take the content followed by a blind user from 7.6% to 78.5% with accessible images. Of these images, 57.5% of descriptions recieve a "Good" or "Great" quality rating.

This tool represents a large leap in making content on these major platforms accessible, and we believe it could be easily modified, refined, and deployed on other social media platforms that include images with limited alternative text (Instagram, Reddit). We also encourage social media platforms to take note of the success of some of these methods, especially text recognition and automatic captioning, and integrate them into their platforms to improve accessibility for people with vision impairments.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship under Grant No. (#DGE-1745016). Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors(s) and do not necessarily reflect the views of the National Science Foundation.

REFERENCES

[1] Brooke E. Auxier, Cody L. Buntain, Paul Jaeger, Jennifer Golbeck, and Hernisa Kacorri. 2019. #HandsOffMyADA: A Twitter Response to the ADA Education and Reform Act. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, Article 527, 12 pages. DOI: http://dx.doi.org/10.1145/3290605.3300757

[2] Tim Berners-Lee and Dan Connolly. 1995. HTML 2.0 Specification. *W3C: http://www. w3. org/MarkUp/html-spec* 34 (1995).

[3] Jeffrey P Bigham, Ryan S Kaminsky, Richard E Ladner, Oscar M Danielsson, and Gordon L Hempton. 2006. WebInSight: Making Web Images Accessible. In *Proceedings of the 8th international ACM SIGACCESS conference on Computers and accessibility - Assets '06*. 181. DOI:http://dx.doi.org/10.1145/1168987.1169018

[4] Erin Brady, Meredith Ringel Morris, and Jeffrey P. Bigham. 2015. Gauging Receptiveness to Social Microvolunteering. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. ACM, New York, NY, USA, 1055–1064. DOI: http://dx.doi.org/10.1145/2702123.2702329

[5] Erin L. Brady, Yu Zhong, Meredith Ringel Morris, and Jeffrey P. Bigham. 2013. Investigating the appropriateness of social network question asking as a resource for blind users. In *Proceedings of the 2013 conference on Computer supported cooperative work - CSCW '13*. ACM Press, New York, New York, USA, 1225. DOI:http://dx.doi.org/10.1145/2441776.2441915

[6] Daniel Dardailler. 1997. *The ALT-server ("An eye for an alt")*.

[7] Amber Ferguson. 2016. The #CripTheVote Movement Is Bringing Disability Rights To The 2016 Election. (2016). Retrieved August 20, 2018 from https://www.huffingtonpost.com/entry/cripthevote-movement-2016-election_us_57279637e4b0f309baf177bd.

[8] Cole Gleason, Patrick Carrington, Cameron Cassidy, Meredith Ringel Morris, Kris M Kitani, and Jeffrey P. Bigham. 2019a. "It's almost like they're trying to hide it": How User-Provided Image Descriptions Have Failed to Make Twitter Accessible. In *The World Wide Web Conference*. ACM, 549–559.

[9] Cole Gleason, Amy Pavel, Xingyu Liu, Patrick Carrington, Lydia B. Chilton, and Jeffrey P. Bigham. 2019b. Making Memes Accessible. In *The 21st International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '19)*. ACM, New York, NY, USA. DOI: http://dx.doi.org/10.1145/3308561.3353792

[10] Google. 2016. Cloud Vision API. https://cloud.google.com/vision/docs/. (2016). Accessed 2019-07-10.

[11] Darren Guinness, Edward Cutrell, and Meredith Ringel Morris. 2018. Caption crawler: Enabling reusable alternative text descriptions using reverse image search. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, 518.

[12] Stephanie Hackett, Bambang Parmanto, and Xiaoming Zeng. 2004. Accessibility of Internet Websites Through Time. In *Proceedings of the 6th International ACM SIGACCESS Conference on Computers and Accessibility (Assets '04)*. ACM, New York, NY, USA, 32–39. DOI: http://dx.doi.org/10.1145/1028630.1028638

[13] Xiaodong He and Li Deng. 2017. Deep Learning for Image-to-Text Generation: A Technical Overview. *IEEE Signal Processing Magazine* 34, 6 (nov 2017), 109–116. DOI:http://dx.doi.org/10.1109/MSP.2017.2741510

[14] @JohnMu. 2018. Alt text is extremely helpful for Google Images – if you want your images to rank there. Even if you use lazy-loading, you know which image will be loaded, so get that information in there as early as possible & test what it renders as. (4 September 2018). https://twitter.com/JohnMu/status/1036901608880254976

[15] Haley MacLeod, Cynthia L. Bennett, Meredith Ringel Morris, and Edward Cutrell. 2017. Understanding Blind People's Experiences with Computer-Generated Captions of Social Media Images. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 5988–5999. DOI: http://dx.doi.org/10.1145/3025453.3025814

[16] Mary L McHugh. 2012. Interrater reliability: the kappa statistic. *Biochemia medica: Biochemia medica* 22, 3 (2012), 276–282.

[17] Microsoft. 2017. Seeing AI | Talking camera app for those with a visual impairment. (2017). https://www.microsoft.com/en-us/seeing-ai/

[18] Microsoft. 2019. Bing Web Search. https://azure.microsoft.com/en-us/services/cognitive-services/bing-web-search-api/. (2019). Accessed 2019-09-20.

[19] Meredith Ringel Morris, Jazette Johnson, Cynthia L. Bennett, and Edward Cutrell. 2018. Rich Representations of Visual Content for Screen Reader Users. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Article 59, 11 pages. DOI: http://dx.doi.org/10.1145/3173574.3173633

[20] Meredith Ringel Morris, Annuska Zolyomi, Catherine Yao, Sina Bahram, Jeffrey P. Bigham, and Shaun K. Kane. 2016. "With most of it being pictures now, I rarely use it". In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems - CHI '16*. 5506–5516. DOI: http://dx.doi.org/10.1145/2858036.2858116

[21] Jaclyn Packer, Katie Vizenor, and Joshua A. Miele. 2015. An Overview of Video Description: History,

Benefits, and Guidelines. *Journal of Visual Impairment & Blindness* 109, 2 (2015), 83–93. DOI: http://dx.doi.org/10.1177/0145482X1510900204

[22] Charity Pitcher-Cooper. 2017. YouDescribe. (2017). https://www.ski.org/project/youdescribe

[23] KR Prajwal, CV Jawahar, and Ponnurangam Kumaraguru. 2019. Towards Increased Accessibility of Meme Images with the Help of Rich Face Emotion Captions. (2019).

[24] Anna Rohrbach, Marcus Rohrbach, Niket Tandon, and Bernt Schiele. 2015. A Dataset for Movie Description. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[25] Elliot Salisbury, Ece Kamar, and Meredith Ringel Morris. 2017. Toward scalable social alt text: Conversational crowdsourcing as a tool for refining vision-to-language technology for the blind. In *Fifth AAAI Conference on Human Computation and Crowdsourcing*.

[26] Shaomei Wu and Lada A. Adamic. 2014. Visually impaired users on an online social network. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems - CHI '14*. ACM Press, New York, New York, USA, 3133–3142. DOI: http://dx.doi.org/10.1145/2556288.2557415

[27] Shaomei Wu, Jeffrey Wieland, Omid Farivar, and Julie Schiller. 2017. Automatic Alt-text: Computer-generated Image Descriptions for Blind Users on a Social Network Service. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW '17)*. ACM, New York, NY, USA, 1180–1192. DOI: http://dx.doi.org/10.1145/2998181.2998364

APPENDIX

PRE-STUDY INTERVIEW QUESTIONS

1. Demographics information:
   (a) Age
   (b) Gender
   (c) Years using Twitter
   (d) Visual ability
   (e) Any other disabilities?
   (f) Years of vision disability
   (g) What screen readers do you use?
   (h) What other social networks do you use?
2. How accessible do you find Twitter?
3. What are major barriers for using the site?
4. What percent of images that you encounter on Twitter do you think have an image description?
5. Do you find it easy to understand tweets that include an image with no description?
6. Does accessibility of images affect which accounts you follow?
7. What about other forms of media, such as videos and GIFs; how accessible are those?
8. What changes would you make to Twitter to make it more accessible for people with vision impairments?
9. Do you use any other tools to make Twitter more accessible?

POST-STUDY INTERVIEW QUESTIONS

1. What was your experience using the tool? Did you enjoy it?
2. What percent of image do you think were accessible when you used the tool and browsed Twitter?
3. We used many methods to make Twitter images accessible. Which did you find the best? The worst?
4. Were you ever uneasy or felt like you didn't trust a description?
5. Would you continue using a tool like this?
6. What could be most improved about this tool? What worked well?
7. Do you think this tool would translate well to other social networks you use?
8. What else should we focus on to make social networks more accessible?