Towards Recommending Accessibility Features on Mobile Devices

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ABSTRACT

Numerous accessibility features have been developed to increase who and how people can access computing devices. Increasingly, these features are included as part of popular platforms, *e.g.*, Apple iOS, Google Android, and Microsoft Windows. Despite their potential to improve the computing experience, many users are unaware of these features and do not know which combination of them could benefit them. In this work, we first quantified this problem by surveying 100 participants online (including 25 older adults) about their knowledge of accessibility and features that they could benefit from, showing very low awareness. We developed four prototypes spanning numerous accessibility categories (*e.g.,* vision, hearing, motor), that embody signals and detection strategies applicable to accessibility recommendation in general. Preliminary results from a study with 20 older adults show that proactive recommendation is a promising approach for better pairing users with accessibility features they could benefit from.

KEYWORDS

Accessibility; recommendation; mobile; disability; older adults

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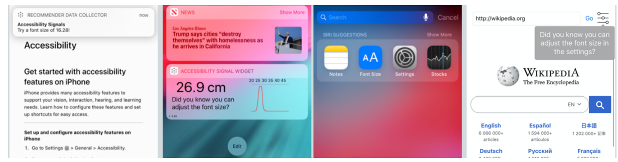

Figure 1: Many smartphone users are not aware of accessibility features that they could benefit from. We explored methods for detecting accessibility needs and surfacing them to the user.

1 INTRODUCTION

Over the past decades, numerous accessibility features have been developed so that people with a wide variety of abilities can use computing devices. Despite this, previous research suggests that many people who could benefit from these features do not know they exist and are unlikely to discover these features when they need them [7, 10].

The goal of our work is to explore methods for recommending accessibility features for people who may not know they could benefit from them. Our work focuses on recommending accessibility features based on how a user is interacting with a device. For instance, if the user is holding the device closer (or farther) than we would expect, that might indicate that they are having trouble seeing it, and could thus benefit from a font size increase. From our exploration, we find that many of the accessibility features available on today's smartphones can be activated using such mechanisms derived from behaviors detected based on device use.

We first present the results of a survey we conducted with 100 participants (including 25 older adults) demonstrating that very few people are aware of available accessibility features on their devices. We then select four common accessibility features drawn from each of the main categories of accessibility features (*e.g.,* vision, hearing, interaction and mobility) and develop prototype recommenders for them, which we initialize in a baseline study with 10 participants. Finally, we use these prototypes as design probes to further explore our concept of accessibility recommendation with 20 older adults.

2 RELATED WORK

Traditionally, the process of matching people to accessible technologies has been done by human experts or through recommendations of medical professionals. Such matching is typically done in specialized environments and is costly in terms of time and money. Access technologies tend to have low adoption rates [8], perhaps because potential users do not have sufficient time to see how they would work into their daily lives. Recent work has started to explore how to "detect" whether someone is likely to have a particular condition, which could be used to recommend that they consult an expert or even try out a particular assistive technology. Similarly, many mobile health sensing efforts have focused on providing low-cost alternatives for monitoring chronic symptoms, such as asthma [16], cystic fibrosis [14], and "screening" applications [9, 19, 20]. However, many of these approaches require active intervention on the user's part (*e.g.,* opening an app and performing a specialized screening procedure). Our approach to recommending accessibility aims to detect accessibility needs passively by monitoring natural interactions with unmodified applications.

There are many approaches to adapting and personalizing user interfaces to better serve user ability or context. A well-known example, SUPPLE, automatically generated UIs that optimize applications for expected user interactions based on a set of device

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constraints and interaction traces [11, 12]. Several other works [13, 15, 17, 18] related to ability-based design [21] are aimed at dynamically reconfiguring the user interface based on user ability or situation. While automatic personalization approaches can generate more accessible interfaces, it is often desirable to keep the default UI consistent and offer additional content and functionality through recommendation. This approach has the advantage of giving more control to users when customizing their interface and minimizing the effect of algorithm error.

3 ACCESSIBILITY AWARENESS SURVEY

We conducted an online survey with 100 people (through Pollfish [6]) to understand people's knowledge of accessibility features on their mobile phones. We were interested in understanding how people might react if they developed an accessibility need (as opposed to people who already had one), and so targeted a general population (*i.e.*, adults aged 18 and over in the United States).

To gauge participants' awareness of the accessibility affordances available on their smartphones, we asked them how they would configure or interact with their phone to make certain content more accessible. We chose four features spanning different accessibility categories (*e.g.,* vision, hearing, motor) and asked questions based on these features. Researchers chose features that were hypothesized to be good candidates for recommendation (*i.e.,* corresponded to an accessibility need that could be detected using our approach). For example, a question based on the "Font Size" feature was "How can you make the content on your screen larger and easier to view?" Survey-takers were told to answer the questions using their existing knowledge of smartphone features (or indicate "I don't know") and were explicitly told not to search for answers online or check external resources.

The survey responses were evaluated by a team of researchers taking into account solutions for different mobile platforms (*e.g.,* iOS, Android) and alternate feature configurations (*e.g.,* both Voice Control and AssistiveTouch can be used to automate gestures for motor-impaired users). On average only 10.3% of responses by participants allowed some type of content to be made more accessible. The final portion of our survey asked participants to describe the purpose of the Accessibility menu in their phone, and only less than a quarter of respondents were able to do so accurately. From the results from our awareness survey, we believe a smartphone that proactively recommends ways for increasing content accessibility would be appreciated by users who develop accessibility needs.

4 PROTOTYPE RECOMMENDERS

In this section, we describe four recommendation prototypes that we built to surface accessibility features beneficial to smartphone users. To understand how different usage behaviors were reflected in sensor data, we first conducted a baseline study where we recorded 10 participants (7M/3F, ages 24-40, mean age 32) performing a series of tasks on a smartphone (*e.g.,* watching a video, App Installation, Internet Scavenger Hunt) for 45 minutes. We used this dataset to inform our selection of signals and detection strategies for building our prototypes.

Font Size Recommender. Our "Font Size Recommender" recommends font size increases if the user holds their phone too close or too far from their face. We calculated viewing distance using the ARFaceAnchor objects returned by the ARFaceTrackingConfiguration [2]. We surfaced recommendations to the user for the Font Size and Larger Text features when the user is found to hold the phone outside of an expected viewing range. We chose to define our expected viewing range empirically, based on our baseline data collection ($M_d = 0.36m, \sigma_d = 0.049m$). We triggered a notification recommendation when the difference between the user's mean viewing distance and M_d exceeded a threshold, which we conservatively set to two standard deviations.

Subtitles & Captions Recommender. Hearing accessibility features available in iOS provide deaf and hard of hearing (DHH) users with affordances for accessing both real and virtual sounds (*e.g.,* hearing aid support, subtitles & closed captions) [5]. Our "Subtitles and Captions Recommender" monitors device volume levels to recommend hearing accessibility features, similar to other features such as watchOS decibel meter, which does so for environmental noise [3]. We implemented a background daemon that continuously monitored 1) whether audio was currently playing, 2) the volume level, and 3) the output device. In the data collected from our baseline study, the average volume level was $M_v = 47.1\%, \sigma_v = 16.3\%$. We surfaced a recommendation for the Subtitles & Captions feature when the user's listening volume was statistically greater (by a minimum of two standard deviations) than our baseline mean.

Side Button Click Speed Recommender. The default double-click speed on the side button can be difficult for many users with even slight motor impairments to successfully trigger. In recognition of this, the time allowed between clicks can be changed (increased) via the accessibility menu [4]. Our "Side Button Click Speed Recommender" recommends this feature to users when it observes a "near-miss" failed attempt. To do this, the recommender monitors interaction events from the system shell for repeated button presses that occurred within the slowest possible double-click threshold. The recommendation is made if the input is too slow to trigger based on the current threshold, but would have done so using a slower setting.

Grouped Recommenders. The previous three recommenders were triggered based on device usage data. Usage-based recommenders may be able to educate users about the existence of accessibility features, and grouped recommenders could help them expand and/or customize selected accessibility settings. Our grouped recommender prototype implemented a series of recommendation rules, two of which are shown below.

- AssistiveTouch → Side Button — If AssistiveTouch is enabled, the user might also benefit from the Side Button setting which can also make wider range of interactions accessible.
- Closed Captioning → Type to Siri — A Closed Captioning user may wish to interact with Siri using an alternative text-based modality.

5 STUDY WITH OLDER ADULTS

We conducted a study with 20 older adults (8M/10F/1 Prefer not disclose; ages 50-97) to investigate which signals our recommendation prototypes were able to detect. One participant later withdrew due to difficulty using the smartphone, so we excluded their data. We followed a procedure similar to the one used for our baseline data collection, where the usage session was shortened from 45 minutes to 30 minutes (by removing 2 of the 5 tasks) to make time for a brief interview afterwards about participants' views on the recommendations. During the interview, the researcher showed the participant several accessibility features and asked them to rate their usefulness on a 7-point Likert scale.

Using data collected from participants in our older adults study, we ran our prototypes to see if they would generate recommendations. Across the 3 features, our prototypes triggered 19 recommendations. Based on the participants' ratings of the features, they would have found 73.7% of those recommendations useful, 21.0% not useful, and 5.3% neutral.

Our Font Size prototype was triggered by 3 of the participants (all 3 wore glasses), who, on average, gave those features a usefulness rating of 6.3/7. The majority of triggers (66.7%) were caused by participants holding the phone at a viewing distance statistically further than observed in our baseline data, possibly due to presbyopia (far-sightedness), which is more common among older adults [1] Subtitles & Captions recommender was also implemented by performing statistical detection on the user's audio volume. In this case, the same threshold used for the Font Size recommender (two standard deviations) led to double the number of triggers. Those participants rated the Subtitles/Captioning features usefulness 4.8/7 on average. Compared to the other recommenders, the Click Speed prototype was triggered the most often. In total, 10 users performed a double-click at speeds which would not have been detected using the *Default* timing but would have using slower settings. Among users who triggered the recommender, the average usefulness rating was 4.7/7.

6 CONCLUSION

In our work, we show that "recommending accessibility" has the potential to improve usage experience of many smartphone users by increasing the adoption and awareness of accessibility technology. Even as numerous useful accessibility features have started to be included in the smartphones that people own, our survey demonstrated that very few people know about them or know which of those features they could benefit from using. Our work shows that on-device recommendation approaches can complement existing advocacy and awareness to increase awareness and adoption of accessibility technology. In future work, we plan to empirically compare different options for implementation and long-term evaluation, considering elements such as which options do users attend to, and which cause them to adopt the feature.

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