Characterizing and Predicting Engagement of Blind and Low-Vision People with an Audio-Based Navigation App

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ABSTRACT

Audio-based navigation technologies can help people who are blind or have low vision (BLV) with more independent navigation, mobility, and orientation. We explore how such technologies are incorporated into their daily lives using machine learning models trained on the engagement patterns of over 4,700 BLV people. For mobile navigation apps, we identify user engagement features like the duration of first-time use and engagement with spatial audio callouts that are greatly relevant to predicting user retention. This work contributes a more holistic understanding of important features associated with user retention and strong app usage, as well as insight into the exploration of ambient surroundings as a compelling use case for assistive navigation apps. Finally, we provide design implications to improve the accessibility and usability of audio-based navigation technology.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in accessibility**.

KEYWORDS

user engagement, blind navigation, spatial audio, app engagement prediction, behavior modeling, user modeling, machine learning, mobile apps

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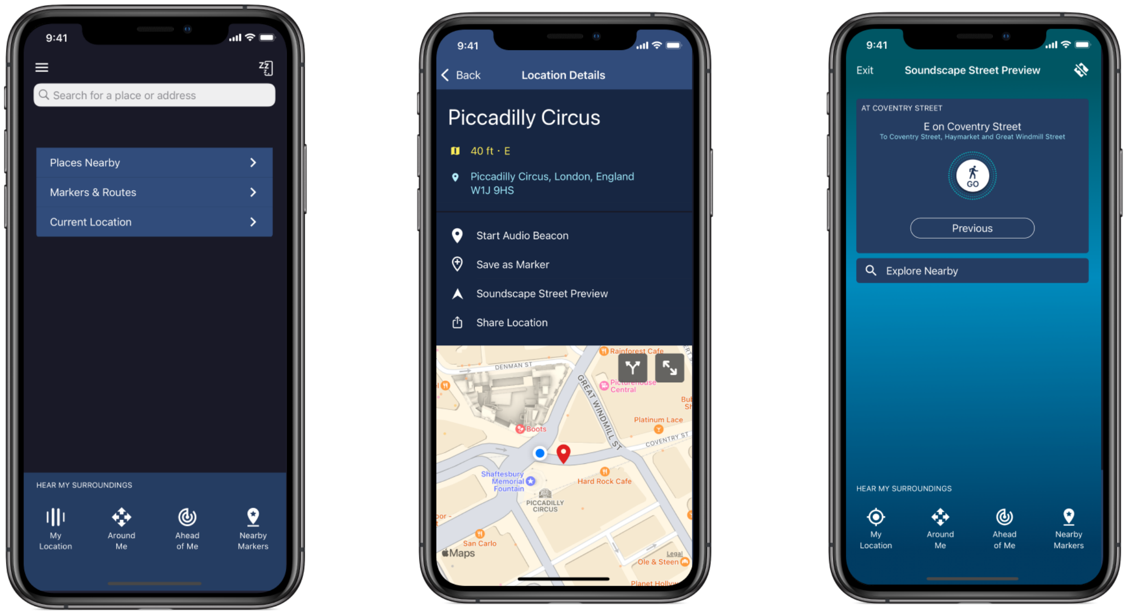
1 INTRODUCTION

Creating mental maps and being able to navigate from place to place are crucial parts of everyday life [1, 10]. However, people who are blind or have low vision often struggle with safe, efficient, and independent navigation [9], as vision plays a critical role in identifying points of interest (POIs), landmarks, and directions. Recent navigational technologies, especially audio-based virtual experiences, use audio cues to enhance people's mental maps of their surroundings [6] and thereby allow BLV people to navigate more independently and confidently [18]. Many prototypes of navigation technology to aid BLV people have been developed, incorporating everything from GPS to computer vision to help with wayfinding, indoor navigation, and more [3, 5, 7, 12]. However, current research on these navigation technologies has mostly explored the engagement in controlled laboratory settings [8, 18], small-scale interviews and qualitative research [13], or field tests that involve one-time navigation tasks [11]. As such, little is known on a wider scale about how BLV people actually engage with technology for navigation, exploration, and mobility in their everyday lives. In addition, while there is some work on mobile app engagement in the context of consumer and retail apps [16, 21], health apps [4, 20], and educational apps [2, 14], little research thus far has focused on engagement with navigational apps specifically.

This work aims to quantify the engagement behaviors of BLV people with Microsoft's Soundscape (see Fig. 1), an audio-based navigation app that gives people real-time audio information about their surroundings. We aim to analyze the app's logged data in order



(a) Home screen **(b) Location details and options screen** **(c) Street preview screen**

Figure 1: Screenshots of Soundscape app highlighting some of the main functions: (a) finding a specific destination, (b) exploring surroundings and setting markers at locations of interest, and (c) previewing the route to a destination.

to predict gaps in usage for BLV people. In particular, we evaluate the efficacy of machine learning models in predicting usage of the app and identify engagement features that are highly predictive of retention. We assess the usage patterns of those who stay with the app and those who drop off. Ultimately, we contribute to a better understanding of navigational technology engagement and usage prediction, while also providing insights informing the design of such technologies to become more accessible and useful for BLV people.

2 METHODOLOGY

2.1 Microsoft Soundscape

The data analyzed in this work was comprised of user activity logs of Microsoft Soundscape[1]. Unlike more traditional step-by-step navigation apps, Soundscape employs a user's location and activity to provide 3D descriptive audio cues that enhance ambient awareness and provide more context about an environment. Among other capabilities, users can hear spatialized audio callouts as they pass various intersections and landmarks (e.g, shops and buildings of interest) (see Fig.1a), and can set an audio beacon originating from a set destination (see Fig.1b). Additionally, users can preview locations of interest by simulating navigation to the location via audio (see Fig.1c), as well as saving locations as markers for easier future access (see Fig.1b).

2.2 Data Collection and Processing

The data set is composed of activity logs of 15,171 users collected from January 30, 2021 to July 29, 2021. The collection contains 6,193,229 logged user events, each tagged with anonymized user IDs. Each event captures a user action, such as a certain button clicked or an audio callout, along with its associated user ID, timestamp, and meta-information like the location context, type of button, and so on. All data were extracted in adherence to user privacy policies (e.g. the context of a user's location, such as 'food and groceries' may be recorded, but GPS data is never logged).

To analyze the data, we perform several cleaning and filtering steps. Because the engagement behavior of those who have used the app for years is likely different from those who have just begun using Soundscape, we filter out users whose first use date is before January 30, 2021 (the first day of data we have access to). In this way, we only consider users for whom we have all app engagement data. In addition, we filter out data from users who started using the app after June 29, 2021, to ensure that we have at least one month of data per user.

Finally, we identify the vision level of users based on the app accessibility settings. Accessibility features include larger text size, bold text, color-inverted text, gray-scale text, darker system colors, VoiceOver, speak screen, and speak selection. Users are classified as blind if they do not enable visual assistance features but enable audio assistance features. Otherwise, users are classified as having low vision if they enable any visual assistance features, and those who do not enable any accessibility settings are classified as sighted. After these filtering steps, the data set consists of 1,083,016 records across 7,085 users (2,549 blind, 2,176 low-vision, and 2,360 sighted). As we are interested in the engagement and behavior of BLV users, this work only analyzes data from users classified as blind or low-vision (4,725 users). Future work may

[1]https://www.microsoft.com/en-us/research/product/soundscape/

consider other user categorizations that capture more complex relationships between different types of users, such as sighted users who teach the app to BLV people.

2.3 Modeling Engagement Retention

This work aims to recognize gaps in usage of BLV users, with a particular focus on the relevance of the first week of engagement with the app in characterizing and predicting future usage. We formalize this task as a binary classification problem: given a set of engagement features $\{f_j\}$ from user u's first week (7 days) of app usage, we study whether user u will return and use the app at least once after the first week and within the first month (30 days). We decided to focus on the first week of use as prior work has shown that the first week contains critical information regarding long-term retention [15]. Our final dataset contains 4,494 users who return after their first week of use, and 2,591 users who do not return.

To analyze engagement features in the context of machine learning, this work leverages Adaptive Boosting (AdaBoost) [19], which has been shown to achieve comparable performance to some deep learning methods even with imbalanced datasets [22]. In earlier explorations, we also evaluated other methods like Random Forest and Support Vector Machines, but AdaBoost yielded superior classification performance. In particular, we used sklearn[2] libraries and implemented grid search to tune hyper-parameters with stratified 10-fold cross-validation and 3 repeats on the training data. The range of learning rates was from 0.0001 to 0.1, the maximum number of estimators was from 50 to 500, and the boosting algorithm was SAMME.R. To evaluate the performance of the model, we computed Area Under the Curve (AUC), precision, recall, weighted F1 score, and accuracy. Since we have an imbalanced dataset, we optimize for the weighted F1 score during hyper-parameter tuning. We compare the model against two other baseline classifiers: 1) *Random*, where the class label is assigned randomly to each data point, and 2) *Most Frequent*, where the most frequent label in the training set is assigned to the testing set.

We extracted a total of 106 features from each user's first seven days following their first use of the app. A comprehensive list of all 106 features used in the model, as well as their aggregate means and deviations before normalization, can be found in the supplemental material. To systematically analyze different types of user information and help draw insights into in-app behavior, we derived a feature taxonomy that combines individual user and app usage features into 16 groups. These groups were formed based on findings from prior navigation technology research and usability work which identifies relevant categories such as temporal factors, navigation-related features, and exploration-related features [18, 24]. The selection of these groups was also influenced by the types of collected data and intended app activities such as completing a tutorial or engaging with street preview mode.

- **Temporal Features**: captures temporal aspects of app usage (e.g. number of app events during the day vs. night ('numEveningEvents'), weekday vs. weekend). While more granular features like time of day and seasonality could provide useful retention information as well, we decided to exclude them due to the exploratory nature of this work.
- **Demographic Features**: contains demographic information about the user (e.g. country, vision level).
- **Device Settings**: includes information related to the device (e.g. phone vs. tablet ('deviceType'), type of audio outputs).
- **Street Preview**: captures actions in the app's street preview mode, such as the number of button clicks and callouts while previewing a location of interest ('numStreetPreviewEvents'), and if a user used the street preview functionality in their first week of use ('usedStrPr').
- **Screen Engagement**: captures user engagement with different screens of the app (e.g. help and settings screens).
- **First Use Experience**: captures users' in-app behaviors during their first time using the app, such as the number of seconds spent in the app during the first use ('firstUseDuration'), or whether the user completed the out-of-the-box experience ('finishedOOBE').
- **Callout Experience**: captures the number, type, and context of spatial audio callouts that the user encounters, such as the number of callouts the user hears at along-road locations ('numAlongRoadLocCallouts').
- **Tutorial Engagement**: captures the engagement with the app's tutorials (e.g. adding markers, setting a beacon).
- **Search Activity**: details user engagement with the app's search functionality (e.g. searching for nearby stores).
- **Marker Activity**: captures the number, type, and context of location markers that the user saves.
- **Beacon Activity**: captures the number, type, and context of destination beacons that the user navigates to.
- **Button Engagement**: captures user engagement with the four main buttons of the app, which allow the user to set a desired destination as well as hear the current location, nearby landmarks, and nearby POIs.
- **App State**: captures the number of events for which the app is in an active state (interacting with buttons and search functionality), background state (hearing callouts while navigating to a destination), or inactive state ('numEventsInInactiveAppState').
- **Navigation Mode**: captures the user's activity while using the app (e.g. walking, in a car, cycling).
- **Retention Features**: records user retention information from the first week of app usage (e.g. the time between the first and the most recent time of app use ('daysBetweenFirstAndMostRecentUse'), the percentage of active use within the first week ('percentActiveDaysInWeek1').
- **External Engagement**: captures details about how users interact with other people outside the app (e.g. sharing locations, engaging with a location sent by others).

3 RESULTS

3.1 How accurately can we determine whether users will return?

Table 1 shows the means and standard deviations of the AdaBoost model performance metrics, averaged across 10 model iterations. As shown, *AdaBoost* outperforms both baseline classifiers in F1, accuracy, precision, and AUC. In particular, *AdaBoost* achieves large improvements of 44.45% and 53.43% for F1 and accuracy compared to the *Random* baseline, and 35.47% and 12.41% for F1 and accuracy

[2] https://scikit-learn.org/

compared to the *Most Frequent* baseline. However, *AdaBoost* had a recall score of 0.428, comparable to the 0.488 recall score of the *Random* baseline, indicating that the proposed model tends to miss some returning users but those that are labeled as such tend to be correct. *AdaBoost* also outperformed other methods like Random Forest and SVMs, which yielded F1 scores of 63.5% and 65.0% and accuracy scores of 64.5% and 67.4%, respectively.

3.2 What are some of the signals of long-term retention?

To achieve more understanding about how BLV users engage with Soundscape, this section analyzes the importance of each of the engagement features. To do so, we identify the features that were consistently selected by *AdaBoost* across 10 random training/testing splices of the data and compute their average weights as an indication of their importance (see Table 2).

All of the *Retention Features* as well as the *First Use Experience* features were consistently selected by AdaBoost across all the iterations. This indicates that users' time spent in the app within the first week, including the percentage of days they used the app ('percentActiveDaysInWeek1') and the time between their first and last use of the app ('daysBetweenFirstAndMostRecentUse'), as well as behaviors exhibited within their first time using the app, such as the duration of their first use of the app ('firstUseDuration'), can be predictive of long-term retention. In addition, the nature of the user's engagement with specific aspects of the app's functionality, like callouts and street preview mode, appear to be important in determining retention. Multiple features from the *Callout Experience*, *Street Preview*, and *App State* feature groups appear in the model's most important features.

Callout Experience: Informative audio callouts give the user additional context about the environment, such as a particular building to the right or an intersection ahead. Real-time location callouts were identified by the model as being particularly discriminative for retention prediction: 58.00% of those who return to the app after the first week encounter along-road location callouts, compared to only 31.70% of those who drop. On average, users who return to the app after the first week engage with far more callouts in their first week than those who drop (136 and 31 average callouts per user, respectively), though this may be a result of spending more time using the app. In general, engaging with more callouts indicates that a user is walking around and navigating more, as callouts only occur when a user encounters a landmark, intersection, or other POI. Examining the context of callout occurrences, we note that various types of callouts like beacon callouts (callouts that occur along the route as users navigate to a particular destination), along-road location callouts, and automatic callouts appear to be important in predicting user retention.

Automatic callouts translate the visual process of taking in one's surroundings and noting landmarks while passing by into an audio format; they occur as a user explores an area without clicking on specific buttons or navigating to a particular location. Automatic callouts at POIs comprise 49.06% of the aggregate callouts for users who return after the first week, more than the 43.37% for users who drop off. In addition, automatic callouts at street intersections comprise 10.48% of the aggregate callouts for those who return after the first week, also more than the 7.64% for users who drop off. While automatic callouts at intersections may occur less frequently than those at POIs because it is likely that most users pass far more POIs than intersections on a walk, increased engagement with automatic callouts suggests an interest in technology that facilitates exploration rather than just navigation from one point to another.

App State: As mentioned previously, there are three potential app states: active, background, and inactive. On average, those who returned to the app after their first week tend to use the app in a background state a higher percentage of the time when compared to those who dropped after their first week. Those who returned to the app spent 19.1% of their app usage time in a background state, whereas those who drop spent only 13.4% of their usage in the background state. These results align with our insights about callout activity, pointing to the use of Soundscape for exploring ambient surroundings during user journeys rather than active route planning that involves in-app actions like button clicks or typing.

Street Preview: Prior user studies have posited that exploring new locations, testing the walkability of various areas, and increasing confidence in navigational capability are compelling use cases for virtually previewing locations [18]. Our findings corroborate these insights: 24.8% of users who returned after the first week engaged with the app's virtual street previewing functionality, compared to only 16.3% of the users who dropped off after the first week. Of those who used the street preview functionality, 52.6% of the users who came back after their first week engaged in virtual exploration (i.e. clicking 'Ahead of Me', 'Around Me', 'Nearby Markers' buttons) compared to just 42.5% of those who dropped off.

3.3 What are some of the most informative types of app usage features?

To gain more understanding about what groups of features are more informative for predicting user retention, we performed ablation experiments in which the *AdaBoost* model classified users using only one feature group at a time. Table 3 shows the performance results for each of the feature groups, sorted by decreasing F1 score.

Retention Features yielded the best performance with an F1 score of 0.727 and an accuracy of 0.74, which is comparable to the performance of the model with all features (F1 score of 0.741 and accuracy of 0.761). This indicates that a user's first experiences with Soundscape are crucial to their continued use of the app, which is consistent with previous research on the importance of mobile systems that provide a good first impression and generate a positive first-time user experience [23]. This feature group was followed by *Device Settings*, which consists of the user's device type and headset states. Examining the device settings features more closely, we note three main types of audio output: speaker, Bluetooth, and headphones. Of these three, only the Bluetooth and headphones allow users to experience the 3D spatial audio capacity of the app; for example, the audio callout for a location on the right would enter through the right ear. In our data, a higher percentage of those who return to the app after their first week use Bluetooth or headphones most frequently (22.91% and 11.17%, respectively) compared to those who drop off (18.76% use Bluetooth and 7.81% use headphones most frequently). This points to the potential importance of the 3D spatial audio experience for BLV

Table 1: Summary of the prediction results for user retention based on the first week of use. The best performance is highlighted in boldface.

Model	F1	Accuracy	Precision	Recall	AUC
AdaBoost	**.741 (.015)**	**.761 (.013)**	**.716 (.033)**	.428 (.03)	**.673 (.017)**
Random	.513 (.013)	.496 (.014)	.318 (.012)	**.488 (.023)**	.494 (.013)
Most Frequent	.547 (0)	.677 (0)	0 (0)	0 (0)	.5 (0)

Table 2: Most important individual features in the context of user retention prediction.

Rank	Feature Name	Group	Average Importance
1	firstUseDuration	First Use Experience	1.000
2	daysBetweenFirstAndMostRecentUse	Retention Features	0.862
3	percentActiveDaysInWeek1	Retention Features	0.384
4	deviceType	Device Settings	0.373
5	finishedOOBExperience	First Use Experience	0.350
6	usedStreetPreview	Street Preview	0.301
7	numStreetPreviewEvents	Street Preview	0.281
8	numEventsInInactiveAppState	App State	0.264
9	numAlongRoadLocationCallouts	Callout Experience	0.196
10	numEveningEvents	Temporal Features	0.187
11	country	Demographic Features	0.186
12	numBeaconCallouts	Callout Experience	0.176
13	numUnpairedAudioEvents	Device Settings	0.114
14	numAutomaticCallouts	Callout Experience	0.110
15	numCallouts	Callout Experience	0.102
16	numEventsInBackgroundAppState	App State	0.081

users to orient themselves accurately within their environment and to build cognitive maps that support more confident, independent navigation.

Interestingly, *Tutorial Engagement* features yield poor performance (.557 F1 score), indicating that the nature of a user's engagement with in-app tutorials is not particularly informative to predicting longer-term retention. Tutorials are found within the app, providing step-by-step instructions to complete basic actions in the app like setting an audio destination beacon to move toward or creating a marker to note a landmark of interest. In contrast, we find that *Callout Experience* features, which allow people to use the app in a more hands-on, exploratory manner, yield better performance in retention prediction (.7 F1 score). This aligns with prior work that has identified exploration as a compelling use case for navigation technology for BLV people [18], Together, these results indicate that the differentiating behavior between users who return to the app and users who drop off is returning users' engagement with more real-time exploration rather than completion of structured in-app tutorials. However, it is important to keep in mind that the weaker predictive power of tutorial engagement features may alternatively arise from a lack of tutorial usage across all users due to factors like poor usability of the tutorials or difficulty in finding them within the app.

4 DISCUSSION

This work formalizes the task of retention prediction in navigational technology for BLV people by leveraging interaction data logs from Microsoft's Soundscape app. We first identify a feature taxonomy consisting of 16 feature groups from users' first week of app usage and build models to predict whether they will return to the app within a month. The proposed method outperforms other baseline methods, and shows that features like first-week retention, audio settings, and style of app usage are particularly important for predicting future retention behavior. In addition, in-app audio callouts of landmarks and POIs, as well as virtual location previewing, are important app use cases whose increased usage points to higher retention. Interestingly, the use of tutorials does not seem to predict higher retention, showing that users may prefer to try the app in the wild rather than engaging with structured tutorials at home.

This work extends previous research by discovering that usage patterns like the duration of first-time usage and consistency of use within the first week are highly predictive of longer-term retention. These insights may help researchers leverage models trained on a user's first week of activity to identify users who are likely to drop off. For instance, designers of navigation technology can potentially provide personalized messages or highlight important

Table 3: Comparison of *AdaBoost* performance on predicting user retention when we only consider one feature group. The best performance is highlighted in boldface.

Feature Group	F1	Accuracy	Precision	Recall	AUC
Retention Features	**.727**	**.74**	.635	.465	**.668**
Device Settings	.711	.726	.606	.43	.648
Temporal Features	.708	.737	.678	.35	.635
Navigation Mode	.707	.714	.568	**.479**	.653
App State	.701	.732	.671	.334	.628
Callout Experience	.7	.715	.586	.43	.641
Screen Engagement	.695	.713	.59	.41	.634
Button Engagement	.686	.694	.53	.451	.63
Beacon Activity	.684	.709	.585	.343	.614
Marker Activity	.669	.706	.627	.297	.599
First Use Engagement	.649	.701	.605	.213	.573
Search Activity	.632	.695	.598	.17	.558
Street Preview	.589	.68	.553	.083	.524
Tutorial Engagement	.557	.679	.566	.016	.505
External Engagement	.554	.679	**.701**	.011	.504
Demographic Features	.547	.677	.1	0	.5

in-app functionality to users whose behavior in the first week indicates that they may stop using the app. This predictive modeling of retention can help address two main issues with user prompting. Namely, traditional usage reminders like calls and texts have been correlated with more usage of mobile apps, but these reminders are often sent after a usage gap has already been observed and the user may already have stopped engaging [17]. Predictive modeling can preemptively identify and engage with users likely to stop using the app in the short-term. On the other hand, sending too many reminders or notifications can lead to a decrease in usage [17], and thus predictive models can help designers implement personalized reminders that are tailored more specifically toward individual users and their usage patterns. For example, as our predictive models point to the importance of callout usage and 3D spatial audio experiences in determining retention, Soundscape may improve user engagement by sending users personalized notifications that highlight the unique callout feature or perhaps prompt them to put on headphones. Of course, in implementing these insights from prediction models, it is important to be mindful of the multiplicity of experiences and preferences of BLV people. For example, hearing ambient environmental sounds are especially important for many BLV people in spatially orienting themselves, which in turn may contribute to hesitancy about using noise-canceling Bluetooth or wired headphones.

This work probes user behavior of Microsoft's Soundscape app, but more research is needed to evaluate how well our insights may generalize to other audio-based navigation technology or other mobile apps. In addition, this work focused on analyzing app interaction logs, but future work may consider conducting deeper usability evaluations that incorporate user feedback, as well as semi-structured interviews with users of audio-based virtual navigation technology. Finally, our results indicate that the first interactions of users with Soundscape can inform the likelihood of their continued use of the app, though further research may need to consider how user behavior changes in the longer-term.

5 CONCLUSION

Our research represents an initial endeavor to better understand and characterize the interactions of BLV people with mobile navigation technology on a larger scale. In the future, similar studies may provide further insight into how context-aware navigation technologies can help BLV people achieve more comfort and independence as they navigate day-to-day life.

REFERENCES

[1] Christian Bongiorno, Yulun Zhou, Marta Kryven, David Theurel, Alessandro Rizzo, Paolo Santi, Joshua Tenenbaum, and Carlo Ratti. 2021. Vector-based pedestrian navigation in cities. *arXiv preprint arXiv:2103.07104* (2021).

[2] Rishabh Chatterjee, Michael Madaio, and Amy Ogan. 2020. Predicting Gaps in Usage in a Phone-Based Literacy Intervention System BT - Artificial Intelligence in Education, Ig Ibert Bittencourt, Mutlu Cukurova, Kasia Muldner, Rose Luckin, and Eva Millán (Eds.). Springer International Publishing, Cham, 92–105.

[3] Hsuan-Eng Chen, Yi-Ying Lin, Chien-Hsing Chen, and I-Fang Wang. 2015. BlindNavi: A Navigation App for the Visually Impaired Smartphone User. Figure 1 (2015), 19–24. https://doi.org/10.1145/2702613.2726953

[4] Ken Cheung, Wodan Ling, Chris J Karr, Kenneth Weingardt, Stephen M Schueller, and David C Mohr. 2018. Evaluation of a recommender app for apps for the treatment of depression and anxiety: an analysis of longitudinal user engagement. *Journal of the American Medical Informatics Association* 25, 8 (aug 2018), 955–962. https://doi.org/10.1093/jamia/ocy023

[5] Sakmongkon Chumkamon, Peranitti Tuvaphanthaphiphat, and Phongsak Keeratiwintakorn. 2008. A blind navigation system using RFID for indoor environments. *5th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, ECTI-CON 2008* 2 (2008), 765–768. https://doi.org/10.1109/ECTICON.2008.4600543

[6] Gregory D Clemenson, Antonella Maselli, Alexander J Fiannaca, Amos Miller, and Mar Gonzalez-Franco. 2021. Rethinking GPS navigation: creating cognitive maps through auditory clues. *Scientific reports* 11, 1 (2021), 1–10.

[7] Giovanni Fusco, Seyed Ali Cheraghi, Leo Neat, and James M Coughlan. 2020. An Indoor Navigation App Using Computer Vision and Sign Recognition. In *Computers Helping People with Special Needs*, Klaus Miesenberger, Roberto Manduchi, Mario Covarrubias Rodriguez, and Petr Penaz (Eds.). Springer International Publishing, Cham, 485–494.

[8] Nicholas A. Giudice, Benjamin A. Guenther, Toni M. Kaplan, Shane M. Anderson, Robert J. Knuesel, and Joseph F. Cioffi. 2020. Use of an Indoor Navigation System by Sighted and Blind Travelers. *ACM Transactions on Accessible Computing* 13, 3 (2020). https://doi.org/10.1145/3407191

[9] Reginald G. Golledge, Roberta L. Klatzky, and Jack M. Loomis. 1996. *Cognitive Mapping and Wayfinding by Adults Without Vision.* Santa Barbara Geographical Press. 215–246 pages. https://doi.org/10.1017/s0003161500052470

[10] Mar Gonzalez-Franco, Gregory D Clemenson, and Amos and Miller. 2021. How GPS Weakens Memory—and What We Can Do about It. *Scientific American* (2021). https://www.scientificamerican.com/article/how-gps-weakens-memory-mdash-and-what-we-can-do-about-it/

[11] João Guerreiro, Dragan Ahmetovic, Daisuke Sato, Kris Kitani, and Chieko Asakawa. 2019. Airport Accessibility and Navigation Assistance for People with Visual Impairments. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3290605.3300246

[12] João José, Miguel Farrajota, João M. Rodrigues, and J. M. Hans du Buf. 2011. The smart vision local navigation aid for blind and visually impaired persons. *International Journal of Digital Content Technology and its Applications* 5, 5 (2011), 362–375. https://doi.org/10.4156/jdcta.vol5.issue5.40

[13] Vaishnav Kameswaran, Alexander J. Fiannaca, Melanie Kneisel, Amy Karlson, Edward Cutrell, and Meredith Ringel Morris. 2020. Understanding In-Situ Use of Commonly Available Navigation Technologies by People with Visual Impairments. In *The 22nd International ACM SIGACCESS Conference on Computers and Accessibility* (Virtual Event, Greece) *(ASSETS '20)*. Association for Computing Machinery, New York, NY, USA, Article 28, 12 pages. https://doi.org/10.1145/3373625.3416995

[14] Natalia Kucirkova, David Messer, Kieron Sheehy, and Carmen Fernández Panadero. 2014. Children's engagement with educational iPad apps: Insights from a Spanish classroom. *Computers & Education* 71 (2014), 175–184. https://doi.org/10.1016/j.compedu.2013.10.003

[15] Yu-Hsuan Lin, Si-Yu Chen, Pei-Hsuan Lin, An-Shun Tai, Yuan-Chien Pan, Chang-En Hsieh, and Sheng-Hsuan Lin. 2020. Assessing User Retention of a Mobile App: Survival Analysis. *JMIR mHealth and uHealth* 8, 11 (nov 2020), e16309–e16309. https://doi.org/10.2196/16309

[16] Christopher J Parker and Huchen Wang. 2016. Examining hedonic and utilitarian motivations for m-commerce fashion retail app engagement. *Journal of Fashion Marketing and Management: An International Journal* 20, 4 (jan 2016), 487–506. https://doi.org/10.1108/JFMM-02-2016-0015

[17] Xuan-Lam Pham, Thi-Huyen Nguyen, Wu-Yuin Hwang, and Gwo-Dong Chen. 2016. Effects of Push Notifications on Learner Engagement in a Mobile Learning App. In *2016 IEEE 16th International Conference on Advanced Learning Technologies (ICALT)*. 90–94. https://doi.org/10.1109/ICALT.2016.50

[18] Anne Spencer Ross, Paul G Allen, Edward Cutrell, Alex Fiannaca, Melanie Kneisel, and Meredith Ringel Morris. 2019. Use Cases and Impact of Audio-Based Virtual Exploration. (2019). https://doi.org/10.1145/3290607.XXXXXXX

[19] Robert E Schapire. 2013. Explaining adaboost. In *Empirical inference*. Springer, 37–52.

[20] Katrina J Serrano, Kisha I Coa, Mandi Yu, Dana L Wolff-Hughes, and Audie A Atienza. 2017. Characterizing user engagement with health app data: a data mining approach. *Translational behavioral medicine* 7, 2 (jun 2017), 277–285. https://doi.org/10.1007/s13142-017-0508-y

[21] Preeti Tak and Mansi Gupta. 2021. Examining Travel Mobile App Attributes and Its Impact on Consumer Engagement: An Application of S-O-R Framework. *Journal of Internet Commerce* 20, 3 (jul 2021), 293–318. https://doi.org/10.1080/15332861.2021.1891517

[22] Putthiporn Thanathamathee and Chidchanok Lursinsap. 2013. Handling Imbalanced Data Sets with Synthetic Boundary Data Generation Using Bootstrap Re-Sampling and AdaBoost Techniques. *Pattern Recogn. Lett.* 34, 12 (sep 2013), 1339–1347. https://doi.org/10.1016/j.patrec.2013.04.019

[23] Joe Welinske. 2014. *Developing user assistance for mobile apps.* Lulu. com.

[24] Liu Yang, Susan T. Dumais, Paul N. Bennett, and Ahmed Hassan Awadallah. 2017. Characterizing and Predicting Enterprise Email Reply Behavior. In *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval* (Shinjuku, Tokyo, Japan) *(SIGIR '17)*. Association for Computing Machinery, New York, NY, USA, 235–244. https://doi.org/10.1145/3077136.3080782