A Large-Scale Mixed-Methods Analysis of Blind and Low-vision Research in ACM and IEEE

Yong-Joon Thoo*
University of Fribourg
Fribourg, Switzerland
yongjoon.thoo@unifr.ch

Maximiliano Jeanneret Medina*†
HEG Arc, HES-SO // University of Applied Sciences Western Switzerland
Neuchâtel, Switzerland
maximiliano.jeanneret@he-arc.ch

Jon E. Froehlich
University of Washington
Seattle, Washington, USA
jonf@cs.washington.edu

Nicolas Ruffieux
University of Fribourg
Fribourg, Switzerland
nicolas.ruffieux@unifr.ch

Denis Lalanne
University of Fribourg
Fribourg, Switzerland
denis.lalanne@unifr.ch

ABSTRACT

Technologies for blind and low-vision (BLV) people have long been a focus of Human-Computer Interaction (HCI) and accessibility (ASSETS) research. To map and assess this cross-disciplinary field, prior literature reviews have focused on specific BLV research areas (*e.g.,* navigation assistance) or study methodologies (*e.g.,* qualitative methods). In this paper, we provide a more holistic examination, combining both quantitative bibliometric analyses with qualitative assessments. Using keyword queries of terms focused on the *human* (*e.g.*, people) and their *visual status* (*e.g.*, blind, low-vision), we first derived a dataset of 880 papers published between 2010-2022 from ACM and IEEE conferences and journals. We then apply a programmatic analysis of this dataset followed by a qualitative analysis of the 100 most-cited papers. Our findings highlight four major research areas: Accessibility at Home & on the Go, Non-Visual Interaction, Orientation & Mobility, and Education. We also capture the diversity of denominations used to refer to the BLV community and their co-occurrences, as well as computer systems targeting both *blind* and *low-vision* users with a focus on visual substitution. We close by suggesting areas for future work and hope to stimulate discussions in our field.

CCS CONCEPTS

• **General and reference** → **Surveys and overviews**; • **Social and professional topics** → **People with disabilities**; • **Human-centered computing** → *Accessibility technologies*; *HCI theory, concepts and models.*

KEYWORDS

blind; low-vision; visual impairment; systematic review; bibliographic coupling

ACM Reference Format:
Yong-Joon Thoo, Maximiliano Jeanneret Medina, Jon E. Froehlich, Nicolas Ruffieux, and Denis Lalanne. 2023. A Large-Scale Mixed-Methods Analysis of Blind and Low-vision Research in ACM and IEEE. In *The 25th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '23), October 22–25, 2023, New York, NY, USA.* ACM, New York, NY, USA, 20 pages. https://doi.org/10.1145/3597638.3608412

1 INTRODUCTION

The design and evaluation of technologies for people who are blind and low-vision (BLV)[1] has long been a focus of Human-Computer Interaction (HCI) research. In a recent HCI literature review, Mack *et al.* [72] found that BLV-related research is the largest accessibility focus published at CHI and ASSETS in the last three decades. BLV research in HCI itself is both large and diverse spanning topics and disciplines, including education [27, 79, 80], virtual environments for orientation and mobility training [47, 100], assistance for activities of daily living [18], navigation tasks [1, 43, 44] and object recognition [19, 139].

To assess and understand the scope and diversity of BLV-focused research, researchers have conducted a variety of literature reviews—often focused on a sub-topic such as navigation aids [63, 89, 97], specific technologies like inertial measurement units [93], or specific research methodologies [28]. Brulé *et al.* [28], for example, reviewed 178 BLV studies within ACM (CHI, ASSETS, TOCHI, TACCESS) venues to better understand empirical evaluation methods and develop study method guidelines for future work. While serving as partial inspiration for our own research, their analysis included only ACM venues, a more narrow focus on evaluation methods, and a limited keyword query set for their corpus.

*Both authors contributed equally to this research.
†Also with University of Fribourg.

[1] Disability language is nuanced, fluid, regional, cultural, and personal [5, 102]. Drawing from a recent study by Sharif *et al.* [102], we use *blind and low-vision* (BLV) people to refer to our primary target community.

ASSETS '23, October 22–25, 2023, New York, NY, USA

ACM ISBN 979-8-4007-0220-4/23/10.
https://doi.org/10.1145/3597638.3608412

Due to the exponential growth of scientific publications [21], bibliometric methods have been proposed as a complement to meta-analyses and structured literature reviews [124, 144]. These programmatic methods enable researchers to examine the relationship between disciplines as well as individual papers via science maps and help identify the most influential works algorithmically [124, 144]. To provide a wider coverage of BLV-related research areas and highlight recent technological trends, we leverage some of these automated techniques to analyze BLV-related studies in ACM or IEEE venues. Our key research questions include:

RQ1 *What* are the main research areas targeting BLV users?
RQ2 *What* are the main communities of focus considered in these studies (*e.g.,* low-vision, blind, not specified)?
RQ3 *What* are the main technological trends and devices used?
RQ4 *What* are the common interaction modalities employed with regards to the targeted end-users' visual abilities?

To address these questions, we first derived a study dataset via Scopus by adapting and extending previous keyword queries from Brulé *et al.* [28], Mack *et al.* [72], and Sharif *et al.* [103]. We limited our search to ACM and IEEE conferences and journals from 2010-2022 resulting in a dataset of 880 BLV papers. For analysis, we deductively and inductively developed a conceptual framework focused on the relationship between the user and the computer system as well as the issues addressed by the proposed solution (*e.g.,* digital/physical access, independence). Our findings are based on quantitative and qualitative analyses performed at two levels. First, we applied standard bibliometric techniques, including document bibliographic coupling analysis (DBCA) and text mining techniques to the documents' title, abstract, and author keywords (TAK). This enabled us to identify primary research areas, the diversity of BLV terminologies, and recent technological shifts. Second, we constructed a subset of the top-cited papers (*N*=100), which were selected proportional to the size of each research area. We then performed a manual coding on this subset to support a complementary, in-depth qualitative analysis.

Our findings highlight *Accessibility at Home & on the Go*, *Non-Visual Interaction*, *Orientation & Mobility*, and *Education* as the four major BLV research areas within ACM and IEEE. Moreover, in accordance with prior studies [28, 72], we highlight not only the diversity of terms used to denote the BLV community but also their co-occurrences within the same article. Finally, our analysis reveals a strong preference for vision substitution systems suitable to both *blind* and *low-vision* users as well as situations where no inputs are required or can be provided by the user. We close with a discussion of these findings and opportunities for future work.

In summary, our primary research contributions include: (1) a delineation of the most prominent research areas related to BLV across ACM and IEEE; (2) an evidence-based discussion of current gaps and opportunities for future work based on our findings; (3) an open-source programmatic analysis to support our two-level analysis[2].

2 BACKGROUND AND RELATED WORK

We first present a synthesis of BLV terminologies found in literature before summarizing prior BLV-focused literature reviews in HCI published between 2010-2022. Finally, we overview bibliometric methods and studies relevant to our work.

2.1 BLV Terminology Differences

Across regions, cultures, and research disciplines, the terms used to refer to the BLV community and even what constitutes "blind" *vs.* "low vision" differs. For instance, within the World Blind Union's list of national BLV federations [118], we note several instances where the terms "blind" or "visually impaired" are used to denote multiple levels of vision loss (*e.g.,* "American Foundation for the Blind", "Japan Federation of the Visually Impaired") in comparison with cases where "blind" and "low-vision" are mentioned separately (*e.g.,* "German Federation of the Blind and Partially Sighted").

In HCI, and more generally in computer science, BLV-focused papers commonly motivate their work by presenting WHO statistics (*e.g.,* [113, 115]). In the latest *World Report on Vision* published in 2019 [134], the WHO estimates that at least 2.2 billion people have some form of *visual impairment*[3] or blindness. Of these, 1 billion have a preventable vision-related condition. Grounded in the *International Classification of Functioning, Disability and Health* (ICF), the WHO explains that a *"vision impairment occurs when an eye condition affects the visual system and one or more of its vision functions"* [134].

Researchers in eye health and vision loss [22, 29, 87, 134] provide a more granular classification of visual impairments. For example, per this classification, the moderate and severe visual impairment categories are commonly referred to as *low-vision* [87]. Whilst these categories are mainly based on visual acuity, severe visual impairment and blindness can also be the consequence of a constriction of the visual field [134].

In the computer science community however, the terms used to refer to the BLV community are varied. For instance, it is common to find review papers that consider blind and low-vision people separately: *i.e.,* visually impaired people does not encompass blind people [17, 63, 113]. Based upon the primary source of the WHO [87], Brulé *et al.* [28] used the term *people with visual impairments* to denote different subsets of visual impairments with blindness considered a small subset. In other work, Mack *et al.* [72] used the term *blind and low-vision* (BLV) to encompass the two major categories as well as other commonly used terms (*i.e.,* "*visually impaired*", "*differently sighted*", or having "*vision loss*").

To provide terminology guidelines, Sharif *et al.* [102] recently reviewed the use of identity- (*e.g.,* disabled people) *vs.* person-first language (*e.g.,* people with disabilities). Their findings reveal that although 48.6% of disabled people indicated a minor preference for identity-first language, compared to 33.0% who favored person-first language, preferences vary across disability categories. Moreover, Sharif *et al.* [102] mention that the *National Federation of the Blind* (NFB) has, in recent years, started advocating for "blind and low-vision" (BLV) in place of "visually impaired" (VI).

Finally, the understanding of vision may be subject to change due to recent advances in vision-related disciplines. For instance, Kran *et al.* [65] discuss cortical vision impairments and the need to

[2] https://github.com/human-ist/BLV-research-analysis

[3] We acknowledge that categorizing visual differences as "impairments" is subject to debate. "Visual impairment" is a term and classification currently used by the WHO [134].

reassess the definition of *visual impairments*. For the remainder of this paper, we use terminology suggested by Sharif *et al.* [102, 103].

2.2 Related Literature Reviews

To reflect upon the growth of accessibility research and its extents, Mack *et al.* [72] recently conducted a large-scale survey of accessibility papers at CHI and ASSETS published between 1994-2019. While their dataset and analysis were not specifically on BLV research, Mack *et al.* found that 40% of all accessibility papers focused on BLV people. Such findings highlight the importance of BLV topics in the accessibility community and compels further reflective study, which we attempt in this work.

Prior BLV-focused reviews have focused largely on (1) specific subareas of BLV research (*e.g.,* the accessibility of commercial devices [3, 101] or trends in navigation assistance [63]), (2) the use of specific devices (*e.g.,* wearable devices to enhance safety and autonomy [97, 113]), or (3) methods used within the HCI community (*e.g.,* evaluation methods [28]). More specifically, prior analyses have reviewed the accessibility of commercial devices and their associated features (*e.g.,* touchscreens [3], text-entry features [101], virtual assistants [105], mobile applications [36]), as well as methods to enable BLV people to perceive and interact with graphical content [30, 115], learn mathematics [37, 78], and create mathematical content [78]. Others focused on navigation assistance, including overviews of trends and evaluation metrics [63], methods to navigate specific environments (*e.g.,* indoor environments [89]), and virtual environments to enable BLV people to enhance their orientation and mobility skills [38].

Finally, we highlight the aforementioned methodological review, performed by Brulé *et al.* [28] on CHI, ASSETS, TOCHI, and TACCESS papers between 1988-2019 (*N*=178), to determine the best practices in quantitative empirical evaluations of technologies for BLV. Their analysis highlights concerns regarding user evaluations, how the BLV participants are reported in these evaluations, and provides recommendations for conducting, reporting, and reviewing evaluations.

Our work is complementary to the above in that we conduct a field-, technology-, and method-agnostic analysis of BLV research to identify main research areas and trends.

2.3 Bibliometrics

Introduced six decades ago [62], *bibliometrics* refers to the quantitative study of published units, bibliographic units, or of the surrogates for either (*e.g.,* references) [26]. Bibliometric methods have two main uses: performance analysis and science mapping [144]. Performance analysis seeks to evaluate research activity such as the publication performance of individuals, institutions, or regions while science mapping aims to reveal the structure and dynamics of scientific fields [144]. Coarsely, the commonly accepted workflow to obtain science mappings consists of defining the research scope and then to collect, analyze, visualize, and interpret the data [7, 124, 144]. To do so, researchers can rely on a large variety of methods, techniques, and tools [7, 122, 144]. Clustering techniques are typically used to reveal research streams within a certain scientific domain and how they relate to each other [125]. Additionally, combining various bibliometric analyses can reveal details of research subjects for specific disciplines, as each bibliometric analysis exhibits certain advantages [33, 122, 124, 144].

The use of bibliometrics is gradually extending across disciplines [21] and is particularly suitable for science mapping when contributions are producing voluminous, fragmented, and controversial research streams [7]. Additionally, bibliometric analyses enable a third possible approach to conduct a literature review [122, 144], falling between the traditional qualitative and interpretive approach and the quantitative meta-analysis approach. Combining an interpretative literature review with bibliometrics can be illustrated by the "flesh and bones" metaphor, whereby researchers' interpretation of documents (the flesh) is added on the top of the field structure (the bones) revealed by a bibliometric analysis [122]. More specifically, bibliometric analyses initially precedes the researchers' interpretations, after which both processes become iterative [124].

Within the HCI community, researchers have benefited from a wide variety of bibliometric methods to support performance analysis and science mapping studies. For instance, Bartneck and Hu [15] used bibliometric methods to analyze the countries and organizations that contributed to the CHI conference. In the same line, Sandnes [96] recently explored the HCI research activity in the Nordic-Baltic Eight countries. By using automated text mining with probabilistic topic modeling, Gurcan *et al.* [46], explored the research trends in the developmental stages of the HCI studies over the past 60 years. Moreover, Wang *et al.* [127] analyzed the citation diversity in accessibility and HCI research while Sarsenbayeva *et al.* [98] provided visualization of the intellectual progress of accessibility research within HCI in the past two decades. Specifically within our research scope, Bhowmick *et al.* [17] performed a co-word analysis related to assistive technology for BLV. Surprisingly, and despite the advantages of references-based bibliometric methods to reveal the structure of a research field [33, 52, 122, 144], we found no study published in a leading HCI venue with the goal of delineating the BLV-related research field.

3 METHODOLOGY

The overarching goal of our review is to analyze and understand BLV-focused research in technology-oriented publication venues (ACM and IEEE). To perform our review, we drew on best practices from the bibliometrics literature [7, 122, 124, 144]. As illustrated in Figure 1, our review methodology follows the five-step process described by Zupic and Čater [144]: (1) Research design, (2) Compilation of bibliographic data, (3) Analysis, (4) Visualization, and (5) Interpretation.

3.1 Research Design

To answer our research questions, we applied bibliometric methods, programmatic analyses, and qualitative analyses. Overall, quantitative methods were applied to explore the field of research under various dimensions and to support our interpretations.

3.1.1 Choice of Appropriate Methods. To identify the main research areas related to BLV research, we primarily relied on a bibliometric technique entitled "documents bibliographic coupling analysis" (DBCA) [52]. Following bibliometrics best practices [33,

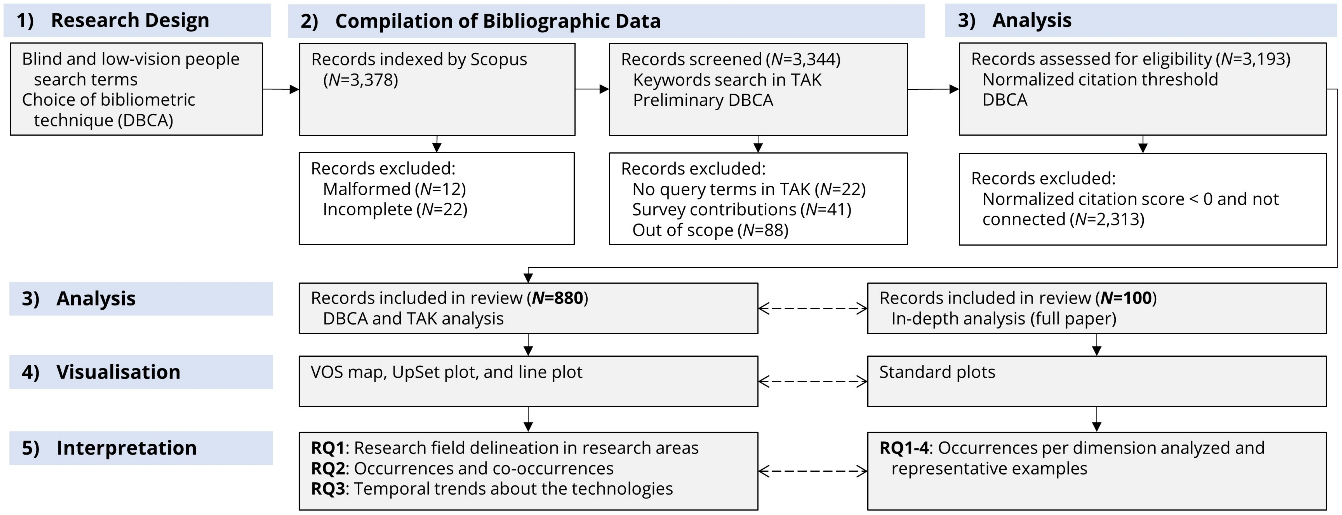

Figure 1: Our review methodology following the 5-step bibliometric workflow [144] shown as a modified Prisma Diagram [86]. Legend: Documents Bibliographic Coupling Analysis (DBCA); Title, Abstract, and Author Keywords (TAK).

122, 124, 144], we also combined the DBCA with other programmatic analyzes.

Documents Bibliographic Coupling Analysis. In DBCA, when two documents cite the same third document, those two documents are said to be bibliographically coupled [52]. The strength of their relationship is then determined by the number of references they share, where a high number of shared references indicates a strong relationship. Hence, this method can be seen as a measure of document similarity [52] and is especially helpful to gain insights into the intellectual structure of a recent or emerging literature [7, 23, 52, 122, 144]. The general process for bibliographic coupling [52] is to (1) identify a set of recent papers; (2) calculate the similarity between pairs of papers using bibliographic coupling counts; and (3) assign citing papers to clusters using the similarity values.

Programmatic Analyses. Inspired by prior works published in leading HCI venues [46, 49, 72, 102], we used several programmatic analysis techniques from Text Mining and Natural Language Processing disciplines with the goal to automatically analyze term frequencies. These terms could appear in the title, abstract, author keywords (TAK).

3.2 Compiling the Bibliometric Data

Below, we describe our data collection, screening, and document eligibility phases performed prior to applying bibliometric techniques.

3.2.1 Search Strategy and Query. To define our research scope, we relied on the Scopus (Elsevier) search query performed by Brulé *et al.* [28]. However, we extended their search query by adding common derivative terms of visual abilities, each referring to both identity- and person-first language [102] (*e.g.,* blind people, people with low-vision). The keywords were chosen to cover general but various forms of *visual impairments* according to the classification provided by the WHO [134]. The full search query is in Appendix A.

Additionally, to cover a wider scope than prior systematic literature reviews in HCI, we considered publications from either ACM or IEEE conferences or journals. ACM holds the leading conference (CHI, ASSETS) and journals (TOCHI, TACCESS) in HCI and accessibility and has a long history of designing computer systems for the BLV community [28, 72]. But IEEE conferences and journals also include new technology designs and studies aimed at the BLV community (*e.g.,* IEEE Transactions on Human-Machine Systems). As well, joint ACM/IEEE conferences (*e.g.,* HRI, CHASE, ICSE) could include relevant documents. For instance, via a preliminary search, we observed that seminal works have been published within both communities (*e.g.,* VizWiz [18] and VizWiz::LocateIt [19]).

We focused on 2010-2022 (inclusive) to gain insights into the most recent research areas and technology trends. According to Gurcan *et al.* [46] who reviewed the past 60 years of HCI, this period represents a new era in HCI development and is labelled as the "*pervasive era*". Moreover, DBCA yields better results for specific time frames [122, 144].

Furthermore, we selected Scopus as it provides the publications' data (*e.g.,* title, abstract, keywords, and references[4] [12]) to conduct a DBCA [7, 124, 143, 144], and offered a better coverage than Web of Science regarding our review scope.

Finally, the presence of a DOI was used as an inclusion constraint due to the importance to track and compare publications throughout the bibliometric workflow. The search query yielded 3,378 results. Additional details of this process can be found in supplementary materials.

[4]Currently, ACM DL and IEEE Xplore do not provide a way to download the publications data with their bibliographic references.

3.2.2 Conformity Check. Following our data retrieval process, we conducted several semi-automatic data analyses to identify documents irrelevant to our review. We automatically removed 12 publications due to formatting errors, four due to missing abstracts, 18 due to missing references, and 22 due to the presence of the research query terms solely in the *Index Keywords.* Furthermore, with a manual dictionary search (*e.g., systematic*, *review* terms) performed on the publications' TAKs, we rejected review papers (*e.g.,* [28, 72]) which, due to their nature, could typically have a higher citation or coupling score which would bias our results. These papers were, however, retained and included in our background section.

To identify irrelevant publications, without an error prone manual search, we then performed an automatic data cleaning of the bibliographic references (detailed below) and performed a preliminary DBCA with VOSviewer [125]. We identified 333 unconnected documents or outliers in the science map (cf. Section 2.3). After a manual review of these unconnected documents and outliers, as well as their neighbors in terms of connections and topics, we rejected 88 publications identified as false positives. Eliminated publications involved (1) topics neither related to the human nor a visual ability such as "*blind detection*", "*blind identification*", or "*blind user study*", (2) studies focused on color blindness/color vision deficiency (which is not always considered as part of "blind" or "low-vision" [71, 94, 121]), (3) publications without mention of BLV terms, and (4) eye condition detection. Similar to [54], we also noticed that works related to eye condition detection with computer systems are separate topics that are not directly related to BLV people (*e.g.,* eye disorders, cataract, retinopathy, glaucoma, macular degeneration).

At the end of this stage, we retained 3,193 documents (94.5%). A portion of this dataset (N=1,403) was then manually verified by two independent researchers (described below).

3.3 Analysis

We describe the filtering stage, as well as additional data cleaning, prior to applying the DBCA and conducting our programmatic analysis.

3.3.1 Bibliographic Data Cleaning, Normalization, and Threshold. **Reference Data Cleaning.** Due to data quality issues in scientific data sources [39], data cleaning is critical [124]. We therefore performed a semi-automatic data cleaning of references based on the fuzzy string similarity algorithm provided by ARTIREV [123].

Dataset Filtering. To obtain a reliable mapping of current research areas, researchers must choose relevant thresholds that cannot be selected *ex-ante* but rather require an iterative trial-and-error approach to determine optimal values [122, 124, 144]. In our case, we relied on a citation count threshold to retain the publications which attracted the most interest from researchers. More precisely, we performed a Z-score normalization on each paper's citation count with the total citation count per year of publication[5] and filtered documents with a normalized value under zero, resulting in 880 connected papers retained for our study. To validate our choice of threshold, we then compared two DBCA science maps (cf. Section 3.4.1)—the first corresponding to the dataset of 3,193 eligible papers and the second corresponding to the set of 880 connected papers— as well as their most cited documents and clusters.

Finally, after identifying the main research areas in our dataset, we identified the most cited papers within each research area based on their normalized citation score (cf. Subsection 3.5). We then extracted the top-cited papers in each research area proportional to the size of their corresponding area resulting in a subset of N=100 papers for our in-depth analysis.

3.3.2 Cleaning and Processing Title, Abstract, and Author Keywords (TAK). To clean the publications' TAK, we combined string manipulations, regular expressions, and part-of-speech tagging (similar to [49, 102]). For instance, we removed parts of the text that did not contain topical content (*e.g.,* copyright in abstracts) and retained only adjectives, adverbs, nouns, verb, punctuation marks, and other terms [20]. We then counted the frequency of unigrams, bigrams, trigrams, and fourgrams within the publications' TAKs. To do so, we used built-in Python packages and the natural language toolkit for Python (NLTK[6]). Then, similar to the approach taken by Mack *et al.* [72], we analyzed the list of terms and their frequency to develop a consolidated list of the most frequent groups of terms. Once we obtained this consolidated list, we counted occurrences with a custom-made frequency counter based on regular expressions.

3.4 Visualization

For the final dataset of 880 papers, we created and analyzed several data visualizations and settled on two forms (see Section 4). For the top 100 papers, our synthesis mainly relied on standard plots.

3.4.1 Science Mapping. To cluster and map the research field, we applied the association strength normalization method and the Leiden clustering algorithm using VOSviewer [125] v1.6.18. This combination of techniques is the most suitable way to identify research commonalities [116, 125]. Moreover, we note that, to obtain our final mappings, we used an iterative approach by conducting several trials with different parameters and respecting best practices in the bibliometric field [124, 125]. In the case of this study, we compared the resulting clusters at six levels of precision (from 0.5 to 1), created a memo (technique used in qualitative research where researchers note their interpretations throughout the process [124]) for each resulting map and settled upon a precision of 0.7.

3.4.2 UpSet Plot. To present the combinations of the terms denoting *people* and their *visual status*, we used UpSet plots [69]. As an alternative to a Venn diagram, an UpSet plot presents the sets, their intersections, and aggregates of intersections when the combinations are numerous.

3.5 Interpretation

As Figure 2 shows, we used bibliometric techniques to reveal clusters, as an intermediary step, prior to identifying research areas. In this sense, we do not fit the analysis to existing preconceptions, but rather used the acquired knowledge to enhance our findings [144].

[5]Because older publications tend to receive more citations over time, we ran a mean normalization per year to identify the most cited papers from each year. Typically, publications with a Z-score above 0 are the most cited amongst the papers published within the same year.

[6]https://www.nltk.org/

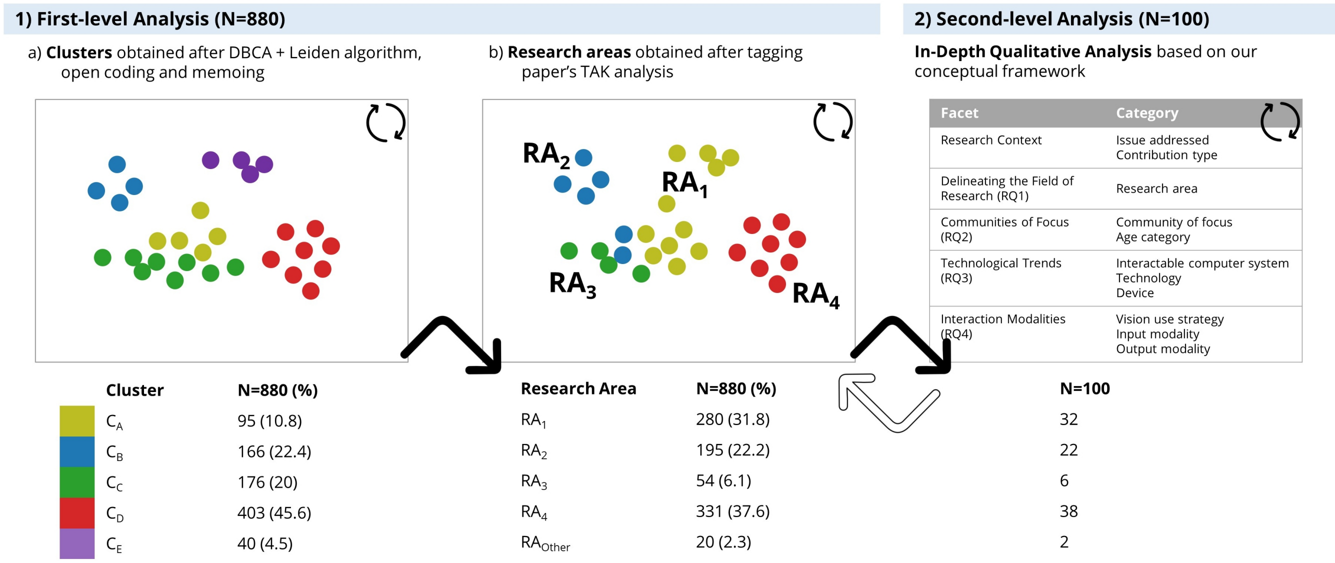

Figure 2: Focus on our Two Steps Interpretation. Legend: Documents Bibliographic Coupling Analysis (DBCA); Title, Abstract, and Author Keywords (TAK); Visualization of Science (VOS).

3.5.1 First-level Analysis. As the first step, we aim to delineate BLV-related research targets prior to an in-depth analysis. We distinguish a *cluster*, obtained after a automatic analysis (*i.e.,* VOSviewer [125]), from a *research area*, obtained after a qualitative analysis.

Open Coding of Clusters. An initial decomposition of the research field was obtained by bibliometric and clustering techniques (*i.e.,* DBCA, Leiden algorithm, VOS map, precision of 0.7, details in Section 3.4.1). Similar to [52], we performed a qualitative assessment of cluster compositions by highlighting their commonalities and differences. Each cluster was then labelled coarsely, after having conducted a content analysis (using publications' TAK data) of the most cited and central documents within each cluster, and a programmatic analysis. This interpretation was supported by an independent analysis performed in parallel by the first two authors, involving memoing [124].

Tagging Research Areas (N=880). Whilst the VOS map, followed by an analysis of the clusters, provided us with an overview of common themes within our dataset, "*science maps provide a starting point for analytical examination but are not an end in itself*" [144]. Moreover, while an automatic clustering of documents is a powerful technique [116], it is prone to limitations due to the data quality of references [123]. Given the manageable size of our dataset (N=880), we subsequently manually reviewed each publication's TAK to classify each publication within one research area. We should note that assigning a unique research area was complex, particularly for 60 out of the 880 papers (6.8%). At the end of this phase, the resulting research areas were presented to the research team for validation.

3.5.2 Second-level Analysis. As a second step, we developed a conceptual framework and performed an in-depth qualitative analysis of a selected set of publications.

In-Depth Qualitative Analysis (N=100). To analyze the subset of the 100 most-cited papers, two researchers independently coded each paper with the entire conceptual framework presented in Table 1. We used Krippendorff's alpha to examine inter-rater reliability. The coding procedure was then performed by the first two authors, both of whom are doing a PhD in HCI related to BLV. The first has a focus on designing training tools for BLV, has ongoing projects involving both BLV as well as low-vision specialists, and came from a robotics engineering background. The second aims to improve the accessibility of textbooks for people with low-vision, has a background in information systems, and possesses strong knowledge in bibliometrics. Both researchers conferred to discuss the divergences in coding, after which the convergence rate grew from α=0.95 to 0.99. Furthermore, our interpretations were presented to the remainder of the research team, composed of three additional members. Two of the members are professors in HCI, with over 40 years of combined HCI research experience, and the third is a professor in specialized education with a background in neuropsychology and ten years of clinical experience.

Conceptual Framework. To analyze both corpuses of research, we deductively and inductively developed a conceptual framework focused on the relationship between the user and the computer system as well as the context of use of the proposed solution (cf. Table 1). The dataset (N=880) has been analyzed by facets (research areas, human-computer) while the entire conceptual framework has been used to code the full papers (N=100).

4 RESULTS

In this section, we first describe the dataset (N=880) and the subset (N=100). We then present the results of our bibliometric and programmatic analyses as well as our in-depth interpretative analysis from manually coding the subset.

Table 1: Final Codebook with Eleven Code Categories. The (*) denotes that multiples codes are possible.

Category	Codes	Inspired by
Research area	Accessibility at Home & on the Go; Non-Visual Interaction; Education; Orientation & Mobility; Other	
Issue addressed (*)	Increasing independence; Increasing digital access; Increasing physical access; Increasing safety; Increasing understanding of users; Supporting communication; Personal informatics and changing behaviour; Other	[72]
Contribution type (*)	Empirical; Artefact; Methodological; Theoretical; Dataset; Survey	[28, 72]
Community of focus (*)	Blind or low-vision (BLV); Blind (B); Low-Vision (LV); Deafblind (DB); Sighted (S); Other (O)	[28, 72]
Age category (*)	Elderly (E); Adults (ADU); Adolescents (ADO); Children (C)	
Interactable computer system	Yes; No	
Technology (*)	Computer Vision; Navigation Assistance; Mobile; Web; Haptics; 3D Modeling/Printing; Human-based Computation; Speech Recognition; Augmented Reality; Virtual Reality; Speech-to-Text; Tactile graphics; Motion tracking; Natural Language Processing; Text-to-Speech; Signal Processing; Standalone; Other	
Device (*)	Mobile; Wearable; Personal Computer; Virtual Reality headset; Tangible object; Intelligent cane; Robot; N/S; Custom tactile interface; Computer Peripheral; Interactive tabletop; Voice-User Interface; Augmented Reality headset; Other	
Vision use strategy (*)	Enhancement; Substitution; Replacement; N/S; N/A	[74]
Input modality (*)	Touch; None; Speech; Gesture; N/S	[28, 49]
Output modality (*)	Audio; Haptic; Speech; Visual; Tactile; N/S; None; Other	[28, 49]

4.1 Dataset

Overall, our dataset (*N*=880) comprises works published in ACM and/or IEEE sponsored conferences and journals. Recall that these publications have been more cited than others within the research field according to their normalized citation score (Z-score).

4.1.1 Sponsor, Document Type, Main Venues, and Authorship. Table 2 shows that 495 (56.2%) studies were published within venues sponsored by ACM and that, overall, conference proceedings constitute the majority of publications (676, 76.8%).

Table 2: Frequency of the Documents per Conference/Journal Sponsor and Document Type.

Sponsor	Document Type	*N*=880 (%)	*N*=100
ACM	Journal Article	71 (8.1)	0
	Conference Paper	424 (48.2)	56
IEEE	Journal Article	133 (15.1)	30
	Conference Paper	246 (28)	11
Joint ACM/IEEE	Conference Paper	6 (0.7)	3

Surprisingly, the 880 papers were published in an expansive set of 240 venues. Of these, CHI (*N*=156, 17.7%) and ASSETS (*N*=141, 16%) are the most prevalent.

For the most-cited subset (*N*=100), the proportion of ACM and IEEE publications remains the same as the full dataset with 56 ACM papers and 44 IEEE. Interestingly, there are no TOCHI or TACCESS articles in the top 100. In terms of IEEE publications, journal articles were more popular than conference proceedings, accounting for 30% of the subset.

Regarding authorship, the papers of our dataset (*N*=880) were written by 2,458 unique authors with a mean of 4.2 authors per paper (*stdev*=1.9). Only a small number of authors (92, 0.04%) contributed papers to both ACM and IEEE.

4.1.2 Issue Addressed and Contribution Type. From our manual analysis of the most cited subset (*N*=100), the issue addressed included: increasing digital access (*N*=38), increasing independence (*N*=34), increasing physical access (*N*=30), increasing user understanding (*N*=25), increasing safety (*N*=21), communication support (*N*=8), supporting education (*N*=6), and other (*N*=4). Papers could be coded into multiple categories and generally addressed more than one issue (*median*=2, *stdev*=0.67) with the combination of increasing independence and physical access as most common. Additionally, papers within the *other* category focused on providing access to physical activities [81], training [108] and restoring vision [51, 129].

To address these problem areas, researchers primarily conducted empirical studies (*N*=93) and made artifact contributions (*N*=73). Empirical contributions focus on exploring user preferences or conducting an in-depth investigation of the use of a system whereas artifact contributions focus on the design and the implementation of a software artifact [133]. However, not all empirical investigations within our subset are related to a system in use and not all artifacts allow interactions. For instance, some contributions are purely technical and consist of an evaluation of a machine learning model (*e.g.,* [106]) whilst others present novel models or algorithms that were not integrated into an interactive system at the time of the study (*e.g.*, [6]). Furthermore, empirical and artifact contribution types frequently occurred in combination (*N*=59). Indeed, some papers typically comprise multiple steps, from the preliminary user study or the motivation study to the design, implementation, and evaluation of the artifact (*e.g.,* [18, 41, 135]).

The remaining contribution types occurred considerably less frequently with some papers (*N*=6) presenting a dataset (*e.g.,* [34, 45]). A low number of contributions are theoretical (*N*=2, *e.g.,* [80, 91]) or methodological (*N*=2, *e.g.,* [4]). These contributions often apply to a broader field of research than the one investigated here, such as accessibility research [104, 132].

4.2 Delineating the Field of Research

To describe *what* are the main research areas regarding the BLV community, we first summarize our bibliometric findings. Then, we present our delineation of the research field by highlighting some of the most popular (*i.e.,* based on their normalized citation score) studies within each research area.

4.2.1 Bibliometric and Statistical Analysis. The delineation of the field, obtained after a DBCA performed on the 880 ACM/IEEE conference proceedings and journal articles, is presented as a VOS map in Figure 3 with the proportions of papers per cluster and their most frequent terms shown in Table 3.

This map highlights the organization of the research corpus into five clusters and two poles with clusters A, B, and C grouped towards the left while clusters D and E are located towards the right. Cluster A is central and organized around the foundational VizWiz publication by Bigham *et al.* [18] whereas cluster B is relatively dense with several important nodes related to accessibility, such as Wu *et al.* [135], Stangl *et al.* [110], and Power *et al.* [91]. Cluster C is transversal to the left part of the map and contains publications related to interaction within different contexts (*e.g.,* education settings). Moreover, cluster D, situated in the right lower corner, is dense and related to navigation assistance systems. Finally, cluster E has a limited number of documents and contains the most cited work of the dataset: a paper on automatic visual question answering published in ICCV by Antol *et al.* [6].

Whilst this map organizes the research field into five clusters, we note the close proximity between the clusters and many overlaps which may be explained by shared common terms (cf. Table 3).

4.2.2 Interpretative Analysis. To delineate the research field, we first relied on the DBCA, from the previous step, and manually tagged the 880 publications according to a main research area. From this analysis, we identified four primary research areas:

Accessibility at Home & on the Go (*N*=280). This research area aims to help BLV people in various daily life activities involving visual content. Such activities are performed in digital(*e.g.,* image, videos or visualizations on the web [56, 73, 110, 120]) and real-world contexts (*e.g.,* at home or outdoors [18, 55]) where the aids provided can be human powered [18, 24], machine powered [55, 135], or human-machine powered [18, 41].

First, we highlight pioneering works related to Visual Question Answering (VQA). Most notably, the project VizWiz [18] enables blind people to recruit remote sighted individuals to assist them with visual issues in almost real-time. This project has since evolved into VizWiz Social [24], which transitions away from generic crowdsourcing to a friendsourcing strategy, highlighting the importance of knowing the asker as well as privacy considerations. Human-powered solutions (*e.g.,* crowdsourcing) have proven to be a valuable and scalable solution [18, 24]. On the technical side, computer systems rely heavily on machine learning or deep learning methods to understand user input as well as generate image descriptions. More specifically, researchers developed VQA [6] and TextVQA datasets and models [106]. However, to address the limitations of automatic VQA, task-specific datasets have been used for training. Hence, Gurari *et al.* [45] proposed the first goal-oriented VizWiz VQA dataset where visual questions originate from blind people.

The description of visual content is also strongly connected to mainstream social applications [24] such as Facebook [135] and Twitter [41, 82]. Challenges faced by BLV regarding visual contents are widely documented [24, 110]. Another important and related topic area is personal object recognizers (*e.g.,* ReCog [2]), face recognizers [83], or text readers [138] which can be integrated in wearable and mobile technologies. Such works are closely linked to predominantly technical contributions focusing on text localization (*e.g.,* [137]) or image quality evaluation (*e.g.,* [55]).

Non-Visual Interaction (*N*=195). Non-visual interaction research is composed of publications that rely on non-visual modalities to enable BLV individuals to interact with or through computer systems. Speech [10, 25, 67, 92] and touch [48, 53, 59, 85, 109, 136] modalities received the most interest.

The speech modality is investigated through voice personal assistants within mainstream devices (*e.g.,* Apple Siri, Amazon Alexa, Amazon Echo) [10, 92] which have rapidly become pervasive in households (as smart speakers) as well as on-the-go (as mobile apps) [25]. Such devices provide a voice-user interface (VUI) with human-to-machine and machine-to-human speech communication. Whilst the speech modality may be, by default, an accessible means of interaction for BLV people [92], studies highlight the limitations of this modality when used by blind people [10] as well as the lack of consideration of this demographic within VUI guidelines [25]. On the other hand, the touch modality is provided via mainstream technologies such as touchscreens [59] as well as via assistive technologies such as braille, or wearable devices [85] where the primary goal of the research is to support communication [85]. Although both of these modalities are not often investigated simultaneously, multimodal interfaces are integrated within mobile devices [40]. Finally, exercise games (exergames) are developed to promote physical activities (*e.g.,* VI-Tennis [81]).

Education (*N*=54). Education research comprises technology development and/or studies that aim to provide educational support to BLV students. We distinguish between special needs education, where the studies are tailored to students and their disabilities, and inclusive education where BLV students and their peers are provided with the same education. Inclusive learning has primarily been studied via a collaborative learning approach including robotics [79], voice user interfaces [80], physical programming languages [114], and multi-sensory interactive maps [27]. Additionally,

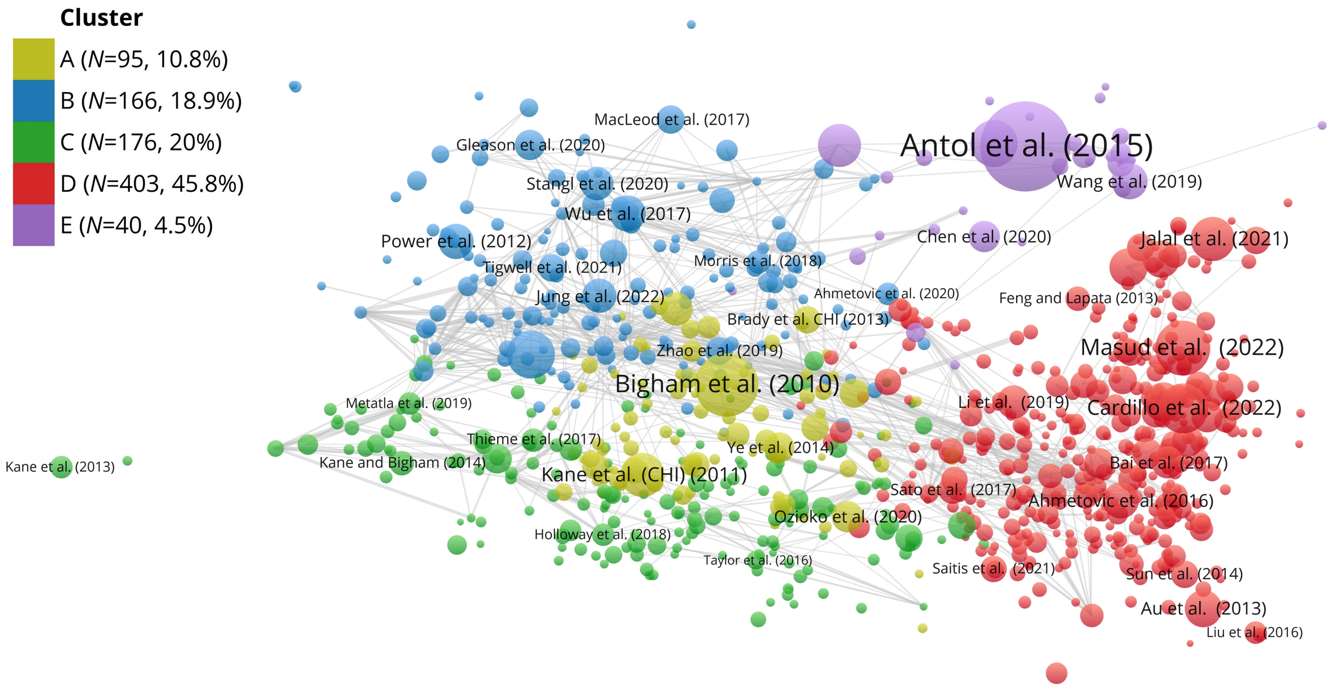

Figure 3: The VOS map [125] of 880 ACM/IEEE conference proceedings and journal articles using DBCA. The research field is organised into five clusters (A to E). For clarity, the map is centered and 100 node labels plus 1000 connections (in grey) are presented. The size of nodes corresponds to the normalized citation score. The distance between two nodes reflects the DBCA relational strength between the items.

Table 3: An overview of the five clusters. We report three bibliometric indices: the mean number of incoming citations (*i.e.,* citation count, CC), its normalized score (Z score), and the mean total links strength (TLS) plus the most frequent terms per cluster. TLS denotes the total number of shared references of a document with other documents in the set.

Cluster	# papers (%)	Mean CC (Z score)	Mean TLS	Most Frequent Terms (in # papers TAK)
A	95 (10.8)	27.7 (1)	122.9	app (50), accessibility (48), phone (41), interact (41), assistive technology (26), mobile (40), touch (37), text entry (13), touch screen (11)
B	166 (18.9)	22.4 (0.7)	127.3	accessibility (111), app (91), text (63), face (61), screen reader (53), assistive technology (41), computer vision (18)
C	176 (20)	24.6 (1)	252.8	access (128), interact (78), tactile (75), work (70), stem (67), information (61), assistive technology (34), tactile graphics (21), user interface (21)
D	403 (45.6)	46.5 (1.3)	152.1	system (275), navigation (198), environment (198), computer vision (54), obstacle detection (44), electronic travel aid (42), white cane (41)
E	40 (4.5)	90.3 (1.7)	104.6	model (35), app (30), deep learning (9), computer vision (9), visual question answering (6), restore partial vision (4)
Total/Mean	**880**	**30.9 (1)**	**151.9**	

other studies focused on special needs education settings during their evaluations[7] [57, 64]. Due to their abstract nature and their intensive reliance on the visual modality, science, technology, engineering, and mathematics (STEM) disciplines have been ideal places to use tangible technologies. More specifically, tangible interfaces [57, 64, 114] and 3D printed objects [57] have been explored to enable BLV students to learn programming languages. Moreover, multiple researchers emphasized the benefits of not only involving BLV but also specialists (*e.g.,* teacher, educators, caretakers) in the development process [27, 64, 79, 80]. Furthermore, when it comes to the pedagogical aspect, collaborative learning is often put into practice [27, 64, 79, 80, 114].

[7]We note however that some of these solutions could potentially be used in inclusive learning settings as sometimes discussed by the authors.

Orientation & Mobility (*N*=331). Orientation & Mobility research (O&M) aims to improve the independence and safety of BLV during O&M tasks. Papers typically describe a solution that is composed of one or more of the following modules: the localization of the user [1, 70], the detection of eventual obstacles along the path [14, 70, 139] and/or the provision of reliable instructions or feedback to guide the BLV user (via audio [1, 61, 139] or haptic [14, 70] feedback). Such goals are achieved via the combination of a variety of sensors, devices (*e.g.,* smartphones [1, 99, 112], tablets [70]) and technologies (*e.g.,* Bluetooth low energy [1] or deep learning [139]). Some systems aim to provide navigation assistance in indoor [14, 70, 99], outdoor [139] environments or both [1], others focus on navigation in crowded environments [61] or on object/obstacle detection and/or localization [139]. Moreover, we highlight the design, development and clinical evaluation of navigation aids [16] as well as collaboration with vision specialists [9].

Another part of the research in this area aims to understand how BLV people use navigation aids and to provide insights to guide future designs (e.g. [130, 131]). To a lesser extent, tools to support blind as well as deaf-blind public transit riders are developed [11] as well as investigating vehicle-pedestrian communication [35].

Other (*N*=20). In this category, we found papers related to artificial vision which generally have a low bibliographic coupling with regards to the other research areas. However, we highlight the study of White *et al.* [129], which consists of exploring subsystems to be included in computer-mediated assistive vision systems (*e.g.,* prosthetic vision devices). Moreover, scene semantic recognition models [51] are envisioned to be used in machine vision systems (*e.g.,* artificial eyes).

4.3 Communities of Focus

Here we focus on *what* forms of visual abilities are primarily considered and language usage.

4.3.1 Title, Abstract, and Author Keywords (TAK) Analysis. To conduct this analysis, we counted the binary occurrences of terms denoting BLV, low-vision, or blind people in the title, abstract, and author keywords (TAK) of the full *N*=880 dataset. We merged common denominations, used by authors, into seven groups differentiated by the populations and language preferences (Table 4). Furthermore, we note 47 instances where none of these terms were found in the TAKs. This may be due to our strict counting method where terms such as *"blind navigation"* are discarded. The terms or groups of terms found in the remaining 833 (94.66%) TAKs are presented in Figure 4.

Across the 833 papers, a vast majority of papers (*N*=715; 85.8%) mentioned at least one of the BLV terms (IFL, PFL and BLV multi.) provided in Table 4 to cover multiple visual abilities. Furthermore, these terms are frequently mentioned in tandem with a more precise visual ability definition (*e.g.,* 89 occurrences of Blind (IFL) and 42 of Blind (PFL))—see *Intersection size* in Figure 4.

4.3.2 Interpretative Analysis. To gain insights into the communities of focus in the top 100 subset, we present the results of our manual coding, which includes target end-users, vision instructors, and education specialists. For visual ability, we attempted to code

Table 4: The identified denomination categories, with language preference and examples, from the TAKs of the *N*=880 dataset. The term "people" denotes several terms such as "child", "developer", "person", "those". Grammar key: | = or.

Category	Examples
BLV (PFL)	people w/ {visual impairments | vision impairments | visual disabilities | vision disabilities | vision loss | mixed visual abilities}; people who are visually impaired
BLV (IFL)	visually {impaired | disabled | challenged} people; the visually impaired
BLV multi. (IFL)	blind {and | or} {vision impaired | visually impaired | low vision | low-vision | partially sighted} people
B (PFL)	people w/ blindness; people who are blind
B (IFL)	blind {people | population}; the blind
LV (PFL)	people w/ {low-vision | low vision}; people who have low vision
LV (IFL)	{low-vision | low vision | partially sighted} people

specific forms of *visual impairments* based on the WHO classification [134] (*e.g., low-vision*, *blind*). However, this was not possible due to a lack of disclosed details. Many papers target both *blind* and *low-vision* people and include non-specific ability terms (*e.g.,* "*visually impaired users*", "*blind and visually impaired people*"). Thus, we added the code *blind and low-vision* to cover such cases. The results of our analysis are shown on the left-hand side of Figure 5.

Our findings highlight six communities with *blind and low-vision* as the most prevalent (*N*=50), which propose technological solutions for both *blind* and *low-vision* people [41, 110] and/or that are inclusive to people with mixed visual abilities [27, 79, 80, 114]. A focus solely on the *blind* community is also common (*N*=36) with papers such as VizWiz [18], NavCog [1] and derivative research (*e.g.,* NavCog3 [99], VizWiz Social [24]). *Low-vision* people are also considered (*N*=6) with studies regarding virtual [141] and augmented reality [142] as well as understanding how *low-vision* people access computing devices [111]. We also note the presence of *sighted* people (*N*=12) in studies where the goal is for: education and/or to promote inclusive learning [64, 79, 80, 114]; understanding how sighted people perceive *blind* people [130]; alerting/notifying other pedestrians [61] or family members [32]. Moreover, we note research that also aims to aid the *deafblind* community [11, 42, 85] and *other* disabilities (*e.g.,* motor, sensory and cognitive impairments [92]).

Finally, we also coded the age categories of the participants included in these studies. Our analysis reveals that the communities included during the evaluation or design phases of these studies are mainly adults between the ages of 18+ to 65 (*N*=55). People who are 65+ years are considered 10 times, followed by adolescents/teenagers between 13-18 years of age (*N*=8), and children (*N*=7). Moreover, our coding highlights that 30 studies either do not report participant ages (not specified, N/S) or did not include users (not applicable, N/A).

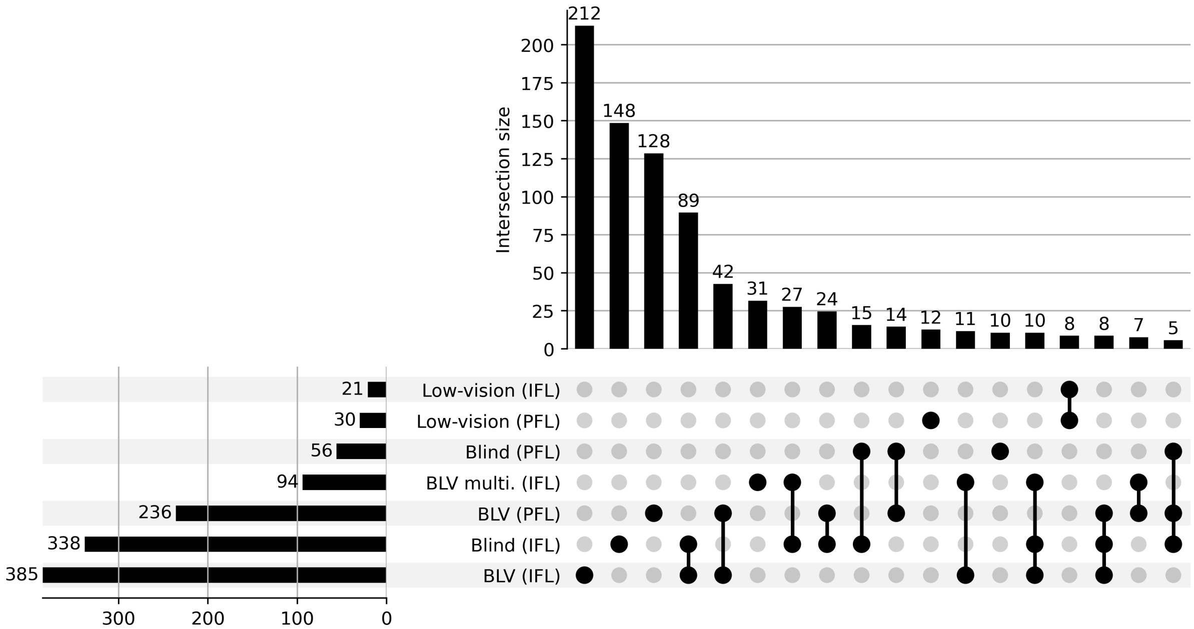

Figure 4: An UpSet plot [69] highlighting common denominations, as well as their language preferences, occurring at least 10 times and intersecting at least five times.

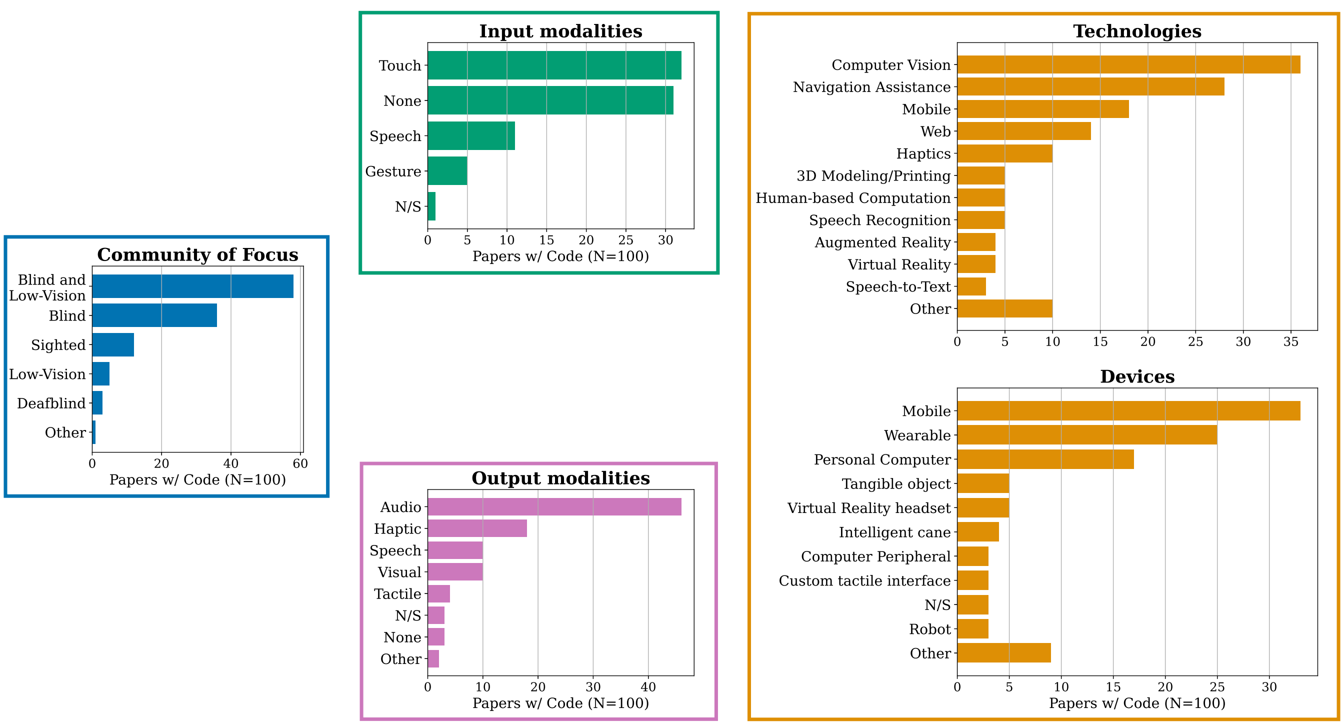

Figure 5: Qualitative Coding (*N*=100) presenting five categories focusing on Human-Computer Interaction. On the left, communities of focus (*Human*), on the right Technologies and Devices (*Computer*), as well as Input and Output Modalities (*Interaction*) in the middle.

4.4 Technological Trends

In this section, we examine technological trends in BLV research since 2010.

4.4.1 Title, Abstract, and Keywords (TAK) Analysis. To analyze recent technological trends, we first counted term occurrences in the TAKs of 880 papers where each term could be a unigram, a bigram, a trigram, or a fourgram. Based on term frequency, we then created a consolidated list of the most prominent technologies and normalized their frequency by the total number of papers per year. As we aim to review interaction modalities separately (cf. Section 4.5), we excluded terms related to interaction from this part of our analysis.

Figure 6 presents the top technological trends since 2010. Mobile technology is most prevalent (*N*=224, 25.5%) followed by computer vision (*N*=116, 15.8%), wearable (*N*=106, 12%), navigation assistance technologies (*N*=106, 12%), artificial intelligence (*N*=70, 8%), and web (*N*=67, 7.6%).

Regarding recent technological shifts, we observe an increase in mixed reality since 2015 and artificial intelligence since 2016. Other technology groups have less discernible temporal patterns.

4.4.2 Interpretative Analysis. For our qualitative analysis of the 100 most-cited papers (*N*=100), we were interested in categorizing the main technologies and devices considered (cf. right-hand side of Figure 5). Due to the large variety of technical solutions and hardware, as well as the necessity to sometimes infer the presence of certain technologies within a solution, we decided to code classes of technologies based on their purpose. For instance, certain machine/deep learning models are used for *Computer Vision* applications and were thus coded as *Computer Vision.* Additionally, artificial intelligence has become embedded in many computer systems, devices, and technologies, and are sometimes difficult to infer from publications. As such, when papers use AI-based technologies (*e.g.,* speech-to-text, text-to-speech, screen readers) which are already part of a commercial device, we coded the main technology as part of the category of devices used (*e.g.,* mobile touchscreens were coded under *mobile*).

Our findings (Figure 5) highlight that *Computer Vision*-based solutions [2, 6, 18, 128, 139] were heavily favored (*N*=36) followed by systems that suggest a novel form of *Navigation Assistance* [1, 43, 60, 61]. The latter denotes systems that aim to either: locate the user (localization) [1, 43]; plan a safe path to a desired destination (path-planning) [1, 43]; enable user to avoid obstacles [60, 61] (obstacle/collision detection and navigation around the obstacle); or a combination of these modules [1, 43]. As such systems can typically use *Computer Vision* to achieve the desired task [139], we coded studies where the main contribution is a novel *Computer Vision* model for navigation assistance under both *Computer Vision* and *Navigation Assistance* categories. Additionally, we note studies focused on using technologies available on commercial mobile devices such as smartphones and/or tablets. For instance, past studies have focused on investigating how *blind* people use touchscreens [59], designing an accessible keyboard on smartphones [109] and enabling *blind* people to recognize personal objects [2].

This is in line with the devices portion of Figure 5, where we observe that the top three devices used in these studies consist of classes of commercial devices such as mobile devices (smartphone [1, 18] and tablets [59, 70]), wearable devices (*e.g.,* smartglasses [32, 139], a sensor belt [60]), or personal computers [41].

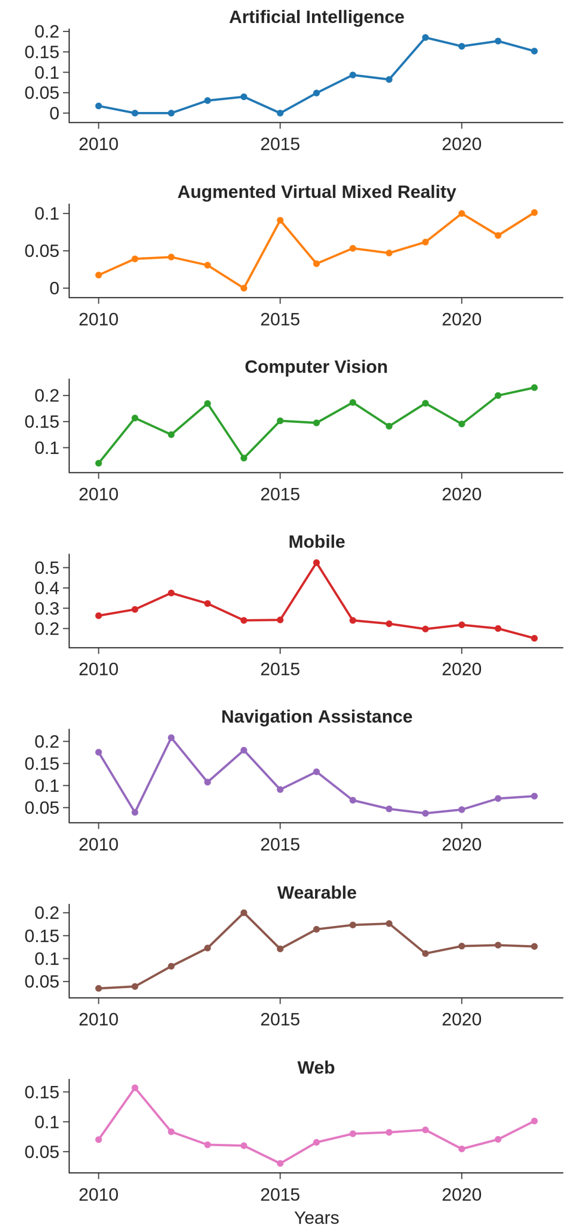

Figure 6: Main Technological Trends from 2010-2022 (*N*=880).

4.5 Interaction Modalities

In this subsection, we focus on the interaction aspect of our conceptual framework, *i.e.,* input/output modalities and the visual use strategy. For each of these aspects, multiple codes are possible (*e.g.,* audio and haptic feedback). Here, we report only our qualitative analysis of the data subset (*N*=100).

To perform this analysis, we considered only the studies that presented or evaluated a computer system with which an end-user could interact. This excluded 30 papers, including datasets (*e.g.,* [6, 45, 106]), models where no interactable component was initially proposed (*e.g.,* [6, 106, 128]) and studies/surveys for understanding where the focus is not on an artefact (*e.g.,* [91, 110, 120, 131]).

4.5.1 Interpretative Analysis. Of the remaining papers (*N*=70), non-speech audio was by far the most prominent output modality [2, 18, 59, 61] (*N*=46, cf. Figure 5), followed by haptic feedback [44, 108, 140] (*N*=18) with visual feedback included in only 10 papers [4, 139, 141]. The focus on non-visual feedback is further highlighted by the fact that 61 of the studies considered visual substitution rather than visual enhancement strategies (*N*=8) with one study which did not specify the output(s). However, we also identified two studies that considered both visual substitution and visual enhancement technologies depending on the end-user [13, 139]. One paper included both olfaction and taste [27] where the authors filled tangible objects with "scents" and/or "tastes" (coded as *Other*).

Regarding input modalities (cf. Figure 5), touch (*e.g.,* via a computer peripheral [4, 64, 107] or touchscreen [58, 59, 84]) was considered 32 times. However, we also highlight the preponderance of computer systems that do not require a specific input from users (*N*=31). These systems typically involve functionalities (*e.g.,* object detection and/or navigation assistance [60, 61, 139], alt-text generation [41]) that are performed automatically without any required intervention during use. Moreover, we identified studies that considered speech [10, 18, 92] input (*N*=11), as well as studies that use specific gestures [90, 108, 140] as inputs (*N*=5).

Finally, we note that certain computer systems are intended to be used in complement with other ones. In particular, within the studies included in the interpretative analysis, authors commonly stated that their system either could or should be used in complement with another assistive technology or device such as screen readers [18, 41, 135], magnifiers [57, 120] or traditional white canes [31, 77, 88].

5 DISCUSSION

Our findings illustrate the diversity of research regarding BLV people but also key trends and tendencies within our field. To help guide future research, we summarize our findings per research question (RQ) and discuss potential directions for future work.

5.1 RQ1: Main Research Areas

Our iterative process, combining bibliometrics as well as qualitative data analyses, revealed four main research areas: *Accessibility at Home & on The Go*, *Non Visual Interaction*, *Education*, and *Orientation & Mobility*. While in line with prior literature reviews [17, 28, 72], our contribution highlights the proximity of research clusters and provides a high-level delineation of interactive computer systems devoted to BLV. We also reveal that seminal BLV research is published in both ACM (*e.g.,* [1, 18]) or IEEE (*e.g.,* [6, 45]) sponsored conferences and journals.

5.1.1 Health-Related Outliers. Within the scope of our review, we focused on BLV people and their interactions with computer-based systems. Upon analysis of the *others* category (*N*=20; Section 4.2.2), in addition to the outliers discarded during the screening and eligibility phase (Section 3.2), we found that half of the studies focused on vision restoration/machine vision systems or simulating visual conditions. For instance, papers focused on technical contributions [51, 129] that could be further integrated within computer-mediated assistive vision systems (*e.g.*, "artificial eye", "bionic vision"). This research area has been mentioned as a future trends by Bhomwick *et al.* [17] who explicitly searched "visual prosthesis".

Moreover, a subset of studies within our *other* category focused on developing systems to simulate various eye conditions [8, 66, 68, 119], either related to or that can lead to *blindness* or *low-vision.* Whilst we do not advocate the substitution of real user feedback by these simulations and, as encouraged by Mankoff et al. [75], strive to actively involve BLV participants in research, the proposed solutions and upcoming developments in this field may contribute to greater public awareness and understanding of BLV conditions.

5.2 RQ2: Communities of Focus

The aim of our second research question was to determine *what* are the main forms of visual abilities considered in BLV research? The analytical process to answer this question quickly became daunting due to the variety of language preferences used across papers to denote the BLV community, as reported in previous literature reviews [28, 72] and as shown in Figure 4. However, we recognize that authors may use such a variety of terms—even within a single paper—to facilitate the indexing in scientific databases and gain further visibility.

Although our in-depth analysis of the target end-users highlights a tendency to find solutions which may be usable by both *blind* and *low-vision* communities (cf. Figure 5), the lack of a visual ability reporting standard becomes problematic when comparing user evaluations between studies and for scientific replication. Additionally, such information could become valuable when attempting to gain insights into factors that could affect the BLV community's adoption of a given technology. Studies such as Williams *et al.* [131] and Saitis *et al.* [95] also suggest additional factors, external to visual ability, that could influence how the BLV use assistive technology (*e.g.*, navigation behaviors [131], cognitive-emotional state of navigating in unfamiliar environments [95]).

In the following subsections, we first discuss how research could reflect upon potential guidelines for future research followed by a discussion of factors, aside from visual abilities, that could yield promising areas for future work.

5.2.1 Reporting Participants' Visual Abilities. To gather and report participants' visual abilities, prior guidelines in the literature (*e.g.,* Brulé *et al.* [28]) encourage using the WHO classification [134]. However, this classification is mainly based on visual acuity and may not provide sufficient insights into participants' use of their residual vision. For instance, Htike *et al.* [50] evaluated the usability of visual augmentations for low-vision people and found that individuals with similar levels of visual acuity perceived different benefits due to their distinct preferences and techniques when using their residual vision. Moreover, reporting the visual status of participants may be subject to data privacy regulations as well as to what authors believe may factor into their work.

We therefore encourage the HCI community to collectively reflect and discuss potential guidelines regarding *what* information about BLV participants should be collected and reported and *how* this information should be gathered. Moreover, this discussion could benefit from external perspectives by involving people across disciplines who work closely with BLV people, such as low-vision therapists and teachers, who could enable us to better understand which factors or data could be gathered and/or how they could influence our designs. Additionally, disciplinary insights may lead to novel research areas that aim to not directly help BLV but the people who work closely with them.

Finally, although information regarding the participants' ages may be sensitive and not always available, we argue that such information could be of value to better understand which age group may be more susceptible to adopt a proposed solution as well as the technologies and devices involved.

5.3 RQ3: Technological Trends

The goal of our third research question is to determine *what* are the main technological trends and devices considered in BLV research.

Recently, Gurcan *et al.* [46] reviewed 60 years of HCI research and determined that there were certain "developmental stages" that are closely related to technological shifts. For instance, Bhomwick *et al.* [17] noted a "Mobility and Accessible Environments" research community actively involved in developing systems based on machine learning, computer vision, and pattern recognition. Unsurprisingly, our analysis therefore highlights that artificial intelligence has become a dominant technology within HCI research over the last decade (mentioned in about 15% of 880 publications' TAKs). For instance, whereas the initial *VizWiz* [18] publication did not use machine learning to achieve Visual Question Answering, researchers (*e.g.*, [6, 45, 76, 106]) have since expanded upon this concept by combining computer vision, natural language processing, and knowledge representation modules.

Finally, we also note the increase of interest in topics such as augmented reality (*e.g.,* [13, 142]) and virtual reality (*e.g.,* [108, 140]). For instance, recent studies have proposed solutions based on such technologies not only for navigation assistance [13, 142] but also for orientation and mobility training [140] using either visual enhancement [13] or visual substitution [13, 108, 140, 142] strategies.

5.4 RQ4: Interactions and Use of Vision

Our final question aimed to determine *what* the common interaction modalities are in the BLV literature and *if/how* they consider the users' visual abilities?

Whilst we commend the diversity of solutions proposed by the HCI community, our results in Section 4.5 highlight instances where assistance and feedback/outputs are generated automatically without requiring or enabling the user to provide input. Moreover, given the heavy focus on both *blind and low-vision* or *blind* people highlighted in Section 4.3.2, the lack of interest for solutions with visual feedback (Section 4.5) seems consistent with prior studies [50, 111] which highlighted the potential lack of consideration of residual vision of target end-users and their desire to use it. Furthermore, the study conducted by Szpiro *et al.* [111] emphasizes how "*different visual abilities lead to different interactions with technology*" and the desire of *low-vision* participants to be able to control/adapt the technology in use to their needs. Moreover, several works mentioned that users with similar visual statuses possess "individual differences/preferences" in terms of navigation [50, 131] and interaction [84] behaviors.

We therefore encourage future research on how to enable users to gain more control of the assistance that is provided. For instance, studies could explore: the ability to adapt the feedback or even switch off certain outputs based on users' preferences; the ability to query the system to obtain additional information if/when required; and the ability to provide feedback to the system if they have trouble understanding the feedback that is being provided.

Finally, whilst our study delineated interaction modalities found in our subset of studies (N=70), our work does not report on the multimodality of proposed solutions. This could be the subject of future reviews to understand the potential benefits of multiple input and/or output modalities on the BLV community.

6 LIMITATIONS AND FUTURE WORK

The primary limitation of our work stems from our research query which may not encompass the diversity of terms used in BLV research (*e.g.,* specific visual conditions). Moreover, our document retrieval process used Scopus which, similar to other scientific databases, contains data quality issues [39]. For instance, we noticed cases where certain publications within our scope contained either missing or incorrect data that had to be revised manually. These limitations may have impacted the number of retained publications, our bibliometric thresholds, and thus our findings.

In accordance with the findings from Brulé *et al.* [28] and Mack *et al.* [72], we highlight the diversity of terms used to denote the BLV community as well as, in some cases, a tendency not to specify the form(s) of *visual impairments* or the visual abilities of participants or end users. The heterogeneity in reporting visual abilities may have impacted the documents retrieved from our research query, our coding phase, and thus the results.

Additionally, the screening phase may be prone to subjectivity due to the researchers' interpretations made on the title, abstract, and author keywords on a portion of the total number of retrieved documents that were valid. However, to reduce this limitation, we performed an independent evaluation aided by bibliometric techniques that attempted to identify outliers within our dataset.

Furthermore, the normalization based on the citation count as well as the clustering based on DBCA can lead us to neglect papers that, although haven't yet gained much interest within the HCI community, yield promising future research areas. Whilst our analysis included studies from both ACM and IEEE sponsored venues, we focused on a sponsor-agnostic delineation of the most prominent research areas. However, a comparison of research methods and technological trends between ACM and IEEE could provide additional insights into our field. Moreover, given the interdisciplinary nature of accessibility research [126], investigating BLV research through additional bibliometric techniques (*e.g.,* co-citation analysis) could highlight the diverse schools of thought [117, 122].

Finally, our results could lead to future analyses into our field. For instance, whereas our work presents a general overview of the field and highlights four main research areas, there may be several subareas which could be subject of their own review (*e.g.,* physical activities and leisure, training tools for BLV, inclusive education). Moreover, an identification of these subareas (*e.g.,* indoor/outdoor navigation, transport access, visual question answering, web accessibility) could be used to conduct additional technology or domain specific literature reviews. Finally, future work could contribute to literature by investigating other aspects of accessibility such as the evolution of BLV related terminologies over time or the analysis of the accessibility of the documents themselves.

7 CONCLUSION

In this paper, we conducted a two-part analysis of BLV research from ACM and IEEE sponsored conferences and journals between 2010-2022. Via a synthesis and programmatic analysis of 880 papers followed by an in-depth analysis of the top 100 most-cited subset, we contribute insights into four major research areas, communities of focus, technologies, and interaction modalities. Whilst our findings highlight a large variety of innovative solutions and research for the BLV community, we also discuss potential future fields of research that may gain more popularity with advancement of technology and suggest areas for improvement. For instance, we encourage discussions regarding how to collect and report visual ability status. We hope that our review will serve as a valuable resource for researchers and practitioners interested in improving the lives of BLV people and will help promote discussions on the future of our field.

ACKNOWLEDGMENTS

We thank our colleagues Simon Ruffieux, Karim Aebsicher from the Human-IST Institute, and Cédric Baudet from HEG Arc, for their support and feedback over the course of this study as well as the participants of the Swiss ACM SIGCHI Chapter workshop.

REFERENCES

[1] Dragan Ahmetovic, Cole Gleason, Chengxiong Ruan, Kris Kitani, Hironobu Takagi, and Chieko Asakawa. 2016. NavCog: A Navigational Cognitive Assistant for the Blind. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '16)*. Association for Computing Machinery, New York, NY, USA, 90–99. https://doi.org/10.1145/2935334.2935361

[2] Dragan Ahmetovic, Daisuke Sato, Uran Oh, Tatsuya Ishihara, Kris Kitani, and Chieko Asakawa. 2020. ReCog: Supporting Blind People in Recognizing Personal Objects. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376143

[3] Nancy Alajarmeh. 2021. Non-visual access to mobile devices: A survey of touchscreen accessibility for users who are visually impaired. *Displays* 70 (2021), 102081. https://doi.org/10.1016/j.displa.2021.102081

[4] Jérémy Albouys-Perrois, Jérémy Laviole, Carine Briant, and Anke M Brock. 2018. Towards a Multisensory Augmented Reality Map for Blind and Low Vision People: A Participatory Design Approach. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3173574.3174203

[5] Erin E. Andrews, Robyn M. Powell, and Kara Ayers. 2022. The evolution of disability language: Choosing terms to describe disability. *Disability and Health Journal* 15, 3 (2022), 101328. https://doi.org/10.1016/j.dhjo.2022.101328

[6] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C. Lawrence Zitnick, and Devi Parikh. 2015. VQA: Visual Question Answering. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*.

[7] Massimo Aria and Corrado Cuccurullo. 2017. bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics* 11, 4 (2017), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

[8] Halim Cagri Ates, Alexander Fiannaca, and Eelke Folmer. 2015. Immersive Simulation of Visual Impairments Using a Wearable See-through Display. In *Proceedings of the Ninth International Conference on Tangible, Embedded, and Embodied Interaction* (Stanford, California, USA) *(TEI '15)*. Association for Computing Machinery, New York, NY, USA, 225–228. https://doi.org/10.1145/2677199.2680551

[9] Anthea Wain Sy Au, Chen Feng, Shahrokh Valaee, Sophia Reyes, Sameh Sorour, Samuel N. Markowitz, Deborah Gold, Keith Gordon, and Moshe Eizenman. 2013. Indoor Tracking and Navigation Using Received Signal Strength and Compressive Sensing on a Mobile Device. *IEEE Transactions on Mobile Computing* 12, 10 (2013), 2050–2062. https://doi.org/10.1109/TMC.2012.175

[10] Shiri Azenkot and Nicole B Lee. 2013. Exploring the Use of Speech Input by Blind People on Mobile Devices. In *Proceedings of the 15th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '13)*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/2513383.2513440

[11] Shiri Azenkot, Sanjana Prasain, Alan Borning, Emily Fortuna, Richard E Ladner, and Jacob O Wobbrock. 2011. Enhancing Independence and Safety for Blind and Deaf-Blind Public Transit Riders. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. Association for Computing Machinery, New York, NY, USA, 3247–3256. https://doi.org/10.1145/1978942.1979424

[12] Jeroen Baas, Michiel Schotten, Andrew Plume, Grégoire Côté, and Reza Karimi. 2020. Scopus as a curated, high-quality bibliometric data source for academic research in quantitative science studies. *Quantitative Science Studies* 1, 1 (02 2020), 377–386. https://doi.org/10.1162/qss_a_00019 arXiv:https://direct.mit.edu/qss/article-pdf/1/1/377/1760882/qss_a_00019.pdf

[13] Jinqiang Bai, Shiguo Lian, Zhaoxiang Liu, Kai Wang, and Dijun Liu. 2017. Smart Guiding Glasses for Visually Impaired People in Indoor Environment. *IEEE Trans. on Consum. Electron.* 63, 3 (aug 2017), 258–266. https://doi.org/10.1109/TCE.2017.014980

[14] Federica Barontini, Manuel G. Catalano, Lucia Pallottino, Barbara Leporini, and Matteo Bianchi. 2021. Integrating Wearable Haptics and Obstacle Avoidance for the Visually Impaired in Indoor Navigation: A User-Centered Approach. *IEEE Transactions on Haptics* 14, 1 (2021), 109–122. https://doi.org/10.1109/TOH.2020.2996748

[15] Christoph Bartneck and Jun Hu. 2009. Scientometric Analysis of the CHI Proceedings. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. Association for Computing Machinery, New York, NY, USA, 699–708. https://doi.org/10.1145/1518701.1518810

[16] Shripad Bhatlawande, Manjunatha Mahadevappa, Jayanta Mukherjee, Mukul Biswas, Debabrata Das, and Somedeb Gupta. 2014. Design, Development, and Clinical Evaluation of the Electronic Mobility Cane for Vision Rehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22, 6 (2014), 1148–1159. https://doi.org/10.1109/TNSRE.2014.2324974

[17] Alexy Bhowmick and Shyamanta M. Hazarika. 2017. An insight into assistive technology for the visually impaired and blind people: state-of-the-art and future trends. *Journal on Multimodal User Interfaces* 11, 2 (June 2017), 149–172. https://doi.org/10.1007/s12193-016-0235-6

[18] Jeffrey P Bigham, Chandrika Jayant, Hanjie Ji, Greg Little, Andrew Miller, Robert C Miller, Robin Miller, Aubrey Tatarowicz, Brandyn White, Samual White, and Tom Yeh. 2010. VizWiz: Nearly Real-Time Answers to Visual Questions. In *Proceedings of the 23nd Annual ACM Symposium on User Interface Software and Technology (UIST '10)*. Association for Computing Machinery, New York, NY, USA, 333–342. https://doi.org/10.1145/1866029.1866080

[19] Jeffrey P Bigham, Chandrika Jayant, Andrew Miller, Brandyn White, and Tom Yeh. 2010. VizWiz::LocateIt - enabling blind people to locate objects in their environment. In *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops*. 65–72. https://doi.org/10.1109/CVPRW.2010.5543821

[20] Steven Bird, Ewan Klein, and Edward Loper. 2009. *Natural Language Processing with Python* (1st ed.). O'Reilly Media, Inc.

[21] Lutz Bornmann and Rüdiger Mutz. 2015. Growth Rates of Modern Science : A Bibliometric Analysis Based on the Number of Publications and Cited References. *Journal of the Association for Information Science and Technology* 66, 11 (2015), 2215–2222. https://doi.org/10.1002/asi

[22] Rupert R A Bourne, Seth R Flaxman, Tasanee Braithwaite, Maria V Cicinelli, Aditi Das, Jost B Jonas, Jill Keeffe, John H Kempen, Janet Leasher, Hans Limburg, Kovin Naidoo, Konrad Pesudovs, Serge Resnikoff, Alex Silvester, Gretchen A Stevens, Nina Tahhan, Tien Y Wong, Hugh R Taylor, Rupert Bourne, Peter Ackland, Aries Arditi, Yaniv Barkana, Banu Bozkurt, TASANEE BRAITHWAITE, Alain Bron, Donald Budenz, Feng Cai, Robert Casson, Usha Chakravarthy, Jaewan Choi, Maria Vittoria Cicinelli, Nathan Congdon, Reza Dana, Rakhi Dandona, Lalit Dandona, Aditi Das, Iva Dekaris, Monte Del Monte, Jenny Deva, Laura Dreer, Leon Ellwein, Marcela Frazier, Kevin Frick, David Friedman, Joao Furtado, Hua Gao, Gus Gazzard, Ronnie George, Stephen Gichuhi, Victor Gonzalez,

Billy Hammond, Mary Elizabeth Hartnett, Minguang He, James Hejtmancik, Flavio Hirai, John Huang, April Ingram, Jonathan Javitt, Jost Jonas, Charlotte Joslin, Jill Keeffe, John Kempen, Moncef Khairallah, Rohit Khanna, Judy Kim, George Lambrou, Van Charles Lansingh, Paolo Lanzetta, Janet Leasher, Jennifer Lim, Hans LIMBURG, Kaweh Mansouri, Anu Mathew, Alan Morse, Beatriz Munoz, David Musch, Kovin Naidoo, Vinay Nangia, MARIA PALAIOU, Maurizio Battaglia Parodi, Fernando Yaacov Pena, Konrad Pesudovs, Tunde Peto, Harry Quigley, Murugesan Raju, Pradeep Ramulu, Serge Resnikoff, Alan Robin, Luca Rossetti, Jinan Saaddine, MYA SANDAR, Janet Serle, Tueng Shen, Rajesh Shetty, Pamela Sieving, Juan Carlos Silva, Alex Silvester, Rita S Sitorus, Dwight Stambolian, Gretchen Stevens, Hugh Taylor, Jaime Tejedor, James Tielsch, Miltiadis Tsilimbaris, Jan van Meurs, Rohit Varma, Gianni Virgili, Jimmy Volmink, Ya Xing Wang, Ning-Li Wang, Sheila West, Peter Wiedemann, Tien Wong, Richard Wormald, and Yingfeng Zheng. 2017. Magnitude, temporal trends, and projections of the global prevalence of blindness and distance and near vision impairment: a systematic review and meta-analysis. *The Lancet Global Health* 5, 9 (2017), e888–e897. https://doi.org/10.1016/S2214-109X(17)30293-0

[23] Kevin W Boyack and Richard Klavans. 2010. Co-Citation Analysis, Bibliographic Coupling, and Direct Citation: Which Citation Approach Represents the Research Front Most Accurately? *Journal of the American Society for Information Science and Technology* 61, 12 (2010), 2389–2404. https://doi.org/10.1002/asi.21419

[24] 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)*. Association for Computing Machinery, New York, NY, USA, 1225–1236. https://doi.org/10.1145/2441776.2441915

[25] Stacy M Branham and Antony Rishin Mukkath Roy. 2019. Reading Between the Guidelines: How Commercial Voice Assistant Guidelines Hinder Accessibility for Blind Users. In *The 21st International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '19)*. Association for Computing Machinery, New York, NY, USA, 446–458. https://doi.org/10.1145/3308561.3353797

[26] R. N. Broadus. 1987. Toward a definition of "bibliometrics". *Scientometrics* 12, 5-6 (1987), 373–379. https://doi.org/10.1007/BF02016680

[27] Emeline Brule, Gilles Bailly, Anke Brock, Frederic Valentin, Grégoire Denis, and Christophe Jouffrais. 2016. MapSense: Multi-Sensory Interactive Maps for Children Living with Visual Impairments. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 445–457. https://doi.org/10.1145/2858036.2858375

[28] Emeline Brulé, Brianna J. Tomlinson, Oussama Metatla, Christophe Jouffrais, and Marcos Serrano. 2020. Review of Quantitative Empirical Evaluations of Technology for People with Visual Impairments. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376749

[29] Matthew J. Burton, Jacqueline Ramke, Ana Patricia Marques, Rupert R.A. Bourne, Nathan Congdon, Iain Jones, Brandon A.M. Ah Tong, Simon Arunga, Damodar Bachani, Covadonga Bascaran, Andrew Bastawrous, Karl Blanchet, Tasanee Braithwaite, John C. Buchan, John Cairns, Anasaini Cama, Margarida Chagunda, Chimgee Chuluunkhuu, Andrew Cooper, Jessica Crofts-Lawrence, William H. Dean, Alastair K. Denniston, Joshua R. Ehrlich, Paul M. Emerson, Jennifer R. Evans, Kevin D. Frick, David S. Friedman, João M. Furtado, Michael M. Gichangi, Stephen Gichuhi, Suzanne S. Gilbert, Reeta Gurung, Esmael Habtamu, Peter Holland, Jost B. Jonas, Pearse A. Keane, Lisa Keay, Rohit C. Khanna, Peng Tee Khaw, Hannah Kuper, Fatima Kyari, Van C. Lansingh, Islay Mactaggart, Milka M. Mafwiri, Wanjiku Mathenge, Ian McCormick, Priya Morjaria, Lizette Mowatt, Debbie Muirhead, Gudlavalleti V.S. Murthy, Nyawira Mwangi, Daksha B. Patel, Tunde Peto, Babar M. Qureshi, Solange R. Salomão, Virginia Sarah, Bernadetha R. Shilio, Anthony W. Solomon, Bonnielin K. Swenor, Hugh R. Taylor, Ningli Wang, Aubrey Webson, Sheila K. West, Tien Yin Wong, Richard Wormald, Sumrana Yasmin, Mayinuer Yusufu, Juan Carlos Silva, Serge Resnikoff, Thulasiraj Ravilla, Clare E. Gilbert, Allen Foster, and Hannah B. Faal. 2021. The Lancet Global Health Commission on Global Eye Health: vision beyond 2020. *The Lancet Global Health* 9, 4 (April 2021), e489–e551. https://doi.org/10.1016/S2214-109X(20)30488-5

[30] Matthew Butler, Leona M Holloway, Samuel Reinders, Cagatay Goncu, and Kim Marriott. 2021. Technology Developments in Touch-Based Accessible Graphics: A Systematic Review of Research 2010-2020. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3411764.3445207

[31] Emanuele Cardillo, Changzhi Li, and Alina Caddemi. 2022. Millimeter-Wave Radar Cane: A Blind People Aid With Moving Human Recognition Capabilities. *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology* 6, 2 (2022), 204–211. https://doi.org/10.1109/JERM.2021.3117129

[32] Wan-Jung Chang, Liang-Bi Chen, Chia-Hao Hsu, Jheng-Hao Chen, Tzu-Chin Yang, and Cheng-Pei Lin. 2020. MedGlasses: A Wearable Smart-Glasses-Based Drug Pill Recognition System Using Deep Learning for Visually Impaired Chronic Patients. *IEEE Access* 8 (2020), 17013–17024. https://doi.org/10.1109/ACCESS.2020.2967400

[33] Yu Wei Chang, Mu Hsuan Huang, and Chiao Wen Lin. 2015. Evolution of research subjects in library and information science based on keyword, bibliographical coupling, and co-citation analyses. *Scientometrics* 105, 3 (2015), 2071–2087. https://doi.org/10.1007/s11192-015-1762-8

[34] Jieshan Chen, Chunyang Chen, Zhenchang Xing, Xiwei Xu, Liming Zhu, Guoqiang Li, and Jinshui Wang. 2020. Unblind Your Apps: Predicting Natural-Language Labels for Mobile GUI Components by Deep Learning. In *Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering (ICSE '20)*. Association for Computing Machinery, New York, NY, USA, 322–334. https://doi.org/10.1145/3377811.3380327

[35] Mark Colley, Marcel Walch, Jan Gugenheimer, Ali Askari, and Enrico Rukzio. 2020. Towards Inclusive External Communication of Autonomous Vehicles for Pedestrians with Vision Impairments. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376472

[36] Arthur Floriano Barbosa Andrade de Oliveira and Lucia Vilela Leite Filgueiras. 2018. Developer Assistance Tools for Creating Native Mobile Applications Accessible to Visually Impaired People: A Systematic Review. In *Proceedings of the 17th Brazilian Symposium on Human Factors in Computing Systems* (Belém, Brazil) *(IHC 2018)*. Association for Computing Machinery, New York, NY, USA, Article 16, 9 pages. https://doi.org/10.1145/3274192.3274208

[37] José Enrique Llamazares De Prado, Ana Rosa Arias Gago, and Mar Estrada López. 2019. Theorical Review of the Teaching of Mathematics in Student with Visual Functional Diversity. In *Proceedings of the Seventh International Conference on Technological Ecosystems for Enhancing Multiculturality* (León, Spain) *(TEEM'19)*. Association for Computing Machinery, New York, NY, USA, 201–208. https://doi.org/10.1145/3362789.3362806

[38] Agebson Rocha Façanha, Ticianne Darin, Windson Viana, and Jaime Sánchez. 2020. O&M Indoor Virtual Environments for People Who Are Blind: A Systematic Literature Review. *ACM Trans. Access. Comput.* 13, 2 (aug 2020). https://doi.org/10.1145/3395769

[39] Fiorenzo Franceschini, Domenico Maisano, and Luca Mastrogiacomo. 2016. The museum of errors/horrors in Scopus. *Journal of Informetrics* 10, 1 (2016), 174–182. https://doi.org/10.1016/j.joi.2015.11.006

[40] Nicholas A Giudice, Hari Prasath Palani, Eric Brenner, and Kevin M Kramer. 2012. Learning Non-Visual Graphical Information Using a Touch-Based Vibro-Audio Interface. In *Proceedings of the 14th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '12)*. Association for Computing Machinery, New York, NY, USA, 103–110. https://doi.org/10.1145/2384916.2384935

[41] Cole Gleason, Amy Pavel, Emma McCamey, Christina Low, Patrick Carrington, Kris M Kitani, and Jeffrey P Bigham. 2020. Twitter A11y: A Browser Extension to Make Twitter Images Accessible. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376728

[42] Ulrike Gollner, Tom Bieling, and Gesche Joost. 2012. Mobile Lorm Glove: Introducing a Communication Device for Deaf-Blind People. In *Proceedings of the Sixth International Conference on Tangible, Embedded and Embodied Interaction* (Kingston, Ontario, Canada) *(TEI '12)*. Association for Computing Machinery, New York, NY, USA, 127–130. https://doi.org/10.1145/2148131.2148159

[43] 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 (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3290605.3300246

[44] João Guerreiro, Daisuke Sato, Saki Asakawa, Huixu Dong, Kris M Kitani, and Chieko Asakawa. 2019. CaBot: Designing and Evaluating an Autonomous Navigation Robot for Blind People. In *The 21st International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '19)*. Association for Computing Machinery, New York, NY, USA, 68–82. https://doi.org/10.1145/3308561.3353771

[45] Danna Gurari, Qing Li, Abigale J. Stangl, Anhong Guo, Chi Lin, Kristen Grauman, Jiebo Luo, and Jeffrey P. Bigham. 2018. VizWiz Grand Challenge: Answering Visual Questions from Blind People. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 3608–3617. https://doi.org/10.1109/CVPR.2018.00380

[46] Fatih Gurcan, Nergiz Ercil Cagiltay, and Kursat Cagiltay. 2021. Mapping Human–Computer Interaction Research Themes and Trends from Its Existence to Today: A Topic Modeling-Based Review of past 60 Years. *International Journal of Human–Computer Interaction* 37, 3 (2021), 267–280. https://doi.org/10.1080/10447318.2020.1819668

[47] Sangsun Han, Pilhyoun Yoon, Miyeon Ha, and Kibum Kim. 2022. VR Wayfinding Training for People with Visual Impairment using VR Treadmill and VR Tracker. In *2022 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. 596–597. https://doi.org/10.1109/VRW55335.2022.00149

[48] Leona Holloway, Kim Marriott, and Matthew Butler. 2018. Accessible Maps for the Blind: Comparing 3D Printed Models with Tactile Graphics. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3173574.3173772

[49] Kasper Hornbæk, Aske Mottelson, Jarrod Knibbe, and Daniel Vogel. 2019. What Do We Mean by "Interaction"? An Analysis of 35 Years of CHI. *ACM Trans. Comput.-Hum. Interact.* 26, 4 (2019). https://doi.org/10.1145/3325285

[50] Hein Min Htike and Tom H. Margrain. 2021. Augmented reality glasses as an orientation and mobility aid for people with low vision: A feasibility study of experiences and requirements. In *Conference on Human Factors in Computing Systems - Proceedings*. Association for Computing Machinery. https://doi.org/10.1145/3411764.3445327

[51] Ahmad Jalal, Abrar Ahmed, Adnan Ahmed Rafique, and Kibum Kim. 2021. Scene Semantic Recognition Based on Modified Fuzzy C-Mean and Maximum Entropy Using Object-to-Object Relations. *IEEE Access* 9 (2021), 27758–27772. https://doi.org/10.1109/ACCESS.2021.3058986

[52] Bo Jarneving. 2007. Bibliographic coupling and its application to research-front and other core documents. *Journal of Informetrics* 1, 4 (2007), 287–307. https://doi.org/10.1016/j.joi.2007.07.004

[53] Chandrika Jayant, Christine Acuario, William Johnson, Janet Hollier, and Richard Ladner. 2010. V-Braille: Haptic Braille Perception Using a Touch-Screen and Vibration on Mobile Phones. In *Proceedings of the 12th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '10)*. Association for Computing Machinery, New York, NY, USA, 295–296. https://doi.org/10.1145/1878803.1878878

[54] Maximiliano Jeanneret Medina, Denis Lalanne, and Cédric Baudet. 2022. Human-Computer Interaction in Artificial Intelligence for Blind and Vision Impairment : An Interpretative Literature Review Based on Bibliometrics. In *IHM '22 Adjunct*.

[55] Bin Jiang, Jiachen Yang, Zhihan Lv, and Houbing Song. 2019. Wearable Vision Assistance System Based on Binocular Sensors for Visually Impaired Users. *IEEE Internet of Things Journal* 6, 2 (2019), 1375–1383. https://doi.org/10.1109/JIOT.2018.2842229

[56] Crescentia Jung, Shubham Mehta, Atharva Kulkarni, Yuhang Zhao, and Yea-Seul Kim. 2022. Communicating Visualizations without Visuals: Investigation of Visualization Alternative Text for People with Visual Impairments. *IEEE Transactions on Visualization and Computer Graphics* 28, 1 (2022), 1095–1105. https://doi.org/10.1109/TVCG.2021.3114846

[57] Shaun K Kane and Jeffrey P Bigham. 2014. Tracking @stemxcomet: Teaching Programming to Blind Students via 3D Printing, Crisis Management, and Twitter. In *Proceedings of the 45th ACM Technical Symposium on Computer Science Education (SIGCSE '14)*. Association for Computing Machinery, New York, NY, USA, 247–252. https://doi.org/10.1145/2538862.2538975

[58] Shaun K. Kane, Meredith Ringel Morris, Annuska Z. Perkins, Daniel Wigdor, Richard E. Ladner, and Jacob O. Wobbrock. 2011. Access Overlays: Improving Non-Visual Access to Large Touch Screens for Blind Users. In *Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology* (Santa Barbara, California, USA) *(UIST '11)*. Association for Computing Machinery, New York, NY, USA, 273–282. https://doi.org/10.1145/2047196.2047232

[59] Shaun K Kane, Jacob O Wobbrock, and Richard E Ladner. 2011. Usable Gestures for Blind People: Understanding Preference and Performance. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. Association for Computing Machinery, New York, NY, USA, 413–422. https://doi.org/10.1145/1978942.1979001

[60] Robert K. Katzschmann, Brandon Araki, and Daniela Rus. 2018. Safe Local Navigation for Visually Impaired Users With a Time-of-Flight and Haptic Feedback Device. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 26, 3 (2018), 583–593. https://doi.org/10.1109/TNSRE.2018.2800665

[61] Seita Kayukawa, Keita Higuchi, João Guerreiro, Shigeo Morishima, Yoichi Sato, Kris Kitani, and Chieko Asakawa. 2019. BBeep: A Sonic Collision Avoidance System for Blind Travellers and Nearby Pedestrians. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300282

[62] M. M. Kessler. 1963. Bibliographic Coupling Between Scientific Papers. *American Documentation* 14, 1 (1963), 10–25. https://doi.org/10.1002/asi.5090140103

[63] Sulaiman Khan, Shah Nazir, and Habib Ullah Khan. 2021. Analysis of Navigation Assistants for Blind and Visually Impaired People: A Systematic Review. *IEEE Access* 9 (2021), 26712–26734. https://doi.org/10.1109/ACCESS.2021.3052415

[64] Varsha Koushik, Darren Guinness, and Shaun K Kane. 2019. StoryBlocks: A Tangible Programming Game To Create Accessible Audio Stories. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300722

[65] Barry S. Kran, Linda Lawrence, D. Luisa Mayer, and Gena Heidary. 2019. Cerebral/Cortical Visual Impairment: A Need to Reassess Current Definitions of Visual Impairment and Blindness. *Seminars in Pediatric Neurology* 31 (2019), 25–29. https://doi.org/10.1016/j.spen.2019.05.005 Cortical Visual Impairment.

[66] Katharina Krösl, Carmine Elvezio, Matthias Hürbe, Sonja Karst, Steven Feiner, and Michael Wimmer. 2020. XREye: Simulating Visual Impairments in Eye-Tracked XR. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. 830–831. https://doi.org/10.1109/VRW50115.2020.00266

[67] Barbara Leporini, Maria Claudia Buzzi, and Marina Buzzi. 2012. Interacting with Mobile Devices via VoiceOver: Usability and Accessibility Issues. In *Proceedings of the 24th Australian Computer-Human Interaction Conference* (Melbourne, Australia) *(OzCHI '12)*. Association for Computing Machinery, New York, NY, USA, 339–348. https://doi.org/10.1145/2414536.2414591

[68] James Lewis, David Brown, Wayne Cranton, and Robert Mason. 2011. Simulating Visual Impairments Using the Unreal Engine 3 Game Engine. In *Proceedings of the 2011 IEEE 1st International Conference on Serious Games and Applications for Health (SEGAH '11)*. IEEE Computer Society, USA, 1–8. https://doi.org/10.1109/SeGAH.2011.6165430

[69] Alexander Lex, Nils Gehlenborg, Hendrik Strobelt, Romain Vuillemot, and Hanspeter Pfister. 2014. UpSet: Visualization of Intersecting Sets. *IEEE Transactions on Visualization and Computer Graphics* 20, 12 (2014), 1983–1992. https://doi.org/10.1109/TVCG.2014.2346248

[70] Bing Li, Juan Pablo Muñoz, Xuejian Rong, Qingtian Chen, Jizhong Xiao, Yingli Tian, Aries Arditi, and Mohammed Yousuf. 2019. Vision-Based Mobile Indoor Assistive Navigation Aid for Blind People. *IEEE Transactions on Mobile Computing* 18, 3 (2019), 702–714. https://doi.org/10.1109/TMC.2018.2842751

[71] Wanda Li and David R Flatla. 2019. 30 Years Later: Has CVD Research Changed the World?. In *Proceedings of the 21st International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '19)*. Association for Computing Machinery, New York, NY, USA, 584–590. https://doi.org/10.1145/3308561.3354612

[72] Kelly Mack, Emma McDonnell, Dhruv Jain, Lucy Lu Wang, Jon E. Froehlich, and Leah Findlater. 2021. What Do We Mean by "Accessibility Research"? A Literature Survey of Accessibility Papers in CHI and ASSETS from 1994 to 2019. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3411764.3445412

[73] 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)*. Association for Computing Machinery, New York, NY, USA, 5988–5999. https://doi.org/10.1145/3025453.3025814

[74] Kanak Manjari, Madhushi Verma, and Gaurav Singal. 2020. A survey on Assistive Technology for visually impaired. *Internet of Things* 11 (2020), 100188. https://doi.org/10.1016/j.iot.2020.100188

[75] Jennifer Mankoff, Gillian R. Hayes, and Devva Kasnitz. 2010. Disability Studies as a Source of Critical Inquiry for the Field of Assistive Technology. In *Proceedings of the 12th International ACM SIGACCESS Conference on Computers and Accessibility* (Orlando, Florida, USA) *(ASSETS '10)*. Association for Computing Machinery, New York, NY, USA, 3–10. https://doi.org/10.1145/1878803.1878807

[76] Daniela Massiceti, Samreen Anjum, and Danna Gurari. 2022. VizWiz Grand Challenge Workshop at CVPR 2022. *SIGACCESS Access. Comput.* 133, Article 1 (aug 2022), 1 pages. https://doi.org/10.1145/3560232.3560233

[77] Usman Masud, Tareq Saeed, Hunida M. Malaikah, Fezan Ul Islam, and Ghulam Abbas. 2022. Smart Assistive System for Visually Impaired People Obstruction Avoidance Through Object Detection and Classification. *IEEE Access* 10 (2022), 13428–13441. https://doi.org/10.1109/ACCESS.2022.3146320

[78] Paúl Mejía, Luiz César Martini, Felipe Grijalva, Julio César Larco, and Juan Carlos Rodríguez. 2021. A Survey on Mathematical Software Tools for Visually Impaired Persons: A Practical Perspective. *IEEE Access* 9 (2021), 66929–66947. https://doi.org/10.1109/ACCESS.2021.3076306

[79] Oussama Metatla, Sandra Bardot, Clare Cullen, Marcos Serrano, and Christophe Jouffrais. 2020. Robots for Inclusive Play: Co-Designing an Educational Game With Visually Impaired and Sighted Children. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376270

[80] Oussama Metatla, Alison Oldfield, Taimur Ahmed, Antonis Vafeas, and Sunny Miglani. 2019. Voice User Interfaces in Schools: Co-Designing for Inclusion with Visually-Impaired and Sighted Pupils. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3290605.3300608

[81] Tony Morelli, John Foley, Luis Columna, Lauren Lieberman, and Eelke Folmer. 2010. VI-Tennis: A Vibrotactile/Audio Exergame for Players Who Are Visually Impaired. In *Proceedings of the Fifth International Conference on the Foundations of Digital Games (FDG '10)*. Association for Computing Machinery, New York, NY, USA, 147–154. https://doi.org/10.1145/1822348.1822368

[82] 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": Understanding Twitter's Evolving Accessibility to Blind Users. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery,

New York, NY, USA, 5506–5516. https://doi.org/10.1145/2858036.2858116

[83] Laurindo Britto Neto, Felipe Grijalva, Vanessa Regina Margareth Lima Maike, Luiz César Martini, Dinei Florencio, Maria Cecília Calani Baranauskas, Anderson Rocha, and Siome Goldenstein. 2017. A Kinect-Based Wearable Face Recognition System to Aid Visually Impaired Users. *IEEE Transactions on Human-Machine Systems* 47, 1 (2017), 52–64. https://doi.org/10.1109/THMS.2016.2604367

[84] João Oliveira, Tiago Guerreiro, Hugo Nicolau, Joaquim Jorge, and Daniel Gonçalves. 2011. Blind People and Mobile Touch-Based Text-Entry: Acknowledging the Need for Different Flavors. In *The Proceedings of the 13th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '11)*. Association for Computing Machinery, New York, NY, USA, 179–186. https://doi.org/10.1145/2049536.2049569

[85] Oliver Ozioko, Prakash Karipoth, Marion Hersh, and Ravinder Dahiya. 2020. Wearable Assistive Tactile Communication Interface Based on Integrated Touch Sensors and Actuators. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 28, 6 (2020), 1344–1352. https://doi.org/10.1109/TNSRE.2020.2986222

[86] Matthew J. Page, Joanne E. McKenzie, Patrick Bossuyt, Isabelle Boutron, Tammy C. Hoffmann, Cynthia D. Mulrow, Larissa Shamseer, Jennifer M. Tetzlaff, Elie Akl, Sue E. Brennan, Roger Chou, Julie Glanville, Jeremy M. Grimshaw, Asbjørn Hróbjartsson, Manoj M. Lalu, Tianjing Li, Elizabeth W. Loder, Evan Mayo-Wilson, Steve McDonald, Luka McGuinness, Lesley A. Stewart, James Thomas, Andrea C. Tricco, Vivian A. Welch, Penny Whiting, and David Moher. 2021. The prisma 2020 statement: An updated guideline for reporting systematic reviews. *Medicina Fluminensis* 57, 4 (2021), 444–465. https://doi.org/10.21860/medflum2021_264903

[87] Donatella Pascolini and Silvio Paolo Mariotti. 2012. Global estimates of visual impairment: 2010. *British Journal of Ophthalmology* 96, 5 (2012), 614–618. https://doi.org/10.1136/bjophthalmol-2011-300539

[88] Kailas Patil, Qaidjohar Jawadwala, and Felix Che Shu. 2018. Design and Construction of Electronic Aid for Visually Impaired People. *IEEE Transactions on Human-Machine Systems* 48, 2 (2018), 172–182. https://doi.org/10.1109/THMS.2018.2799588

[89] Darius Plikynas, Arūnas Žvironas, Marius Gudauskis, Andrius Budrionis, Povilas Daniušis, and Ieva Sliesoraitytė. 2020. Research advances of indoor navigation for blind people: A brief review of technological instrumentation. *IEEE Instrumentation & Measurement Magazine* 23, 4 (2020), 22–32. https://doi.org/10.1109/MIM.2020.9126068

[90] Lorenzo Porzi, Stefano Messelodi, Carla Mara Modena, and Elisa Ricci. 2013. A Smart Watch-Based Gesture Recognition System for Assisting People with Visual Impairments. In *Proceedings of the 3rd ACM International Workshop on Interactive Multimedia on Mobile & Portable Devices* (Barcelona, Spain) *(IMMPD '13)*. Association for Computing Machinery, New York, NY, USA, 19–24. https://doi.org/10.1145/2505483.2505487

[91] Christopher Power, André Freire, Helen Petrie, and David Swallow. 2012. Guidelines Are Only Half of the Story: Accessibility Problems Encountered by Blind Users on the Web. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Austin, Texas, USA) *(CHI '12)*. Association for Computing Machinery, New York, NY, USA, 433–442. https://doi.org/10.1145/2207676.2207736

[92] Alisha Pradhan, Kanika Mehta, and Leah Findlater. 2018. "Accessibility Came by Accident": Use of Voice-Controlled Intelligent Personal Assistants by People with Disabilities. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3173574.3174033

[93] Karla Miriam Reyes Leiva, Milagros Jaén-Vargas, Benito Codina, and José Javier Serrano Olmedo. 2021. Inertial Measurement Unit Sensors in Assistive Technologies for Visually Impaired People, a Review. *Sensors* 21, 14 (2021). https://doi.org/10.3390/s21144767

[94] Madalena Ribeiro and Abel J P Gomes. 2019. Recoloring Algorithms for Colorblind People: A Survey. *ACM Comput. Surv.* 52, 4 (2019). https://doi.org/10.1145/3329118

[95] Charalampos Saitis and Kyriaki Kalimeri. 2021. Multimodal Classification of Stressful Environments in Visually Impaired Mobility Using EEG and Peripheral Biosignals. *IEEE Transactions on Affective Computing* 12, 1 (2021), 203–214. https://doi.org/10.1109/TAFFC.2018.2866865

[96] Frode Eika Sandnes. 2021. A bibliometric study of human–computer interaction research activity in the Nordic-Baltic Eight countries. *Scientometrics* 126, 6 (2021), 4733–4767. https://doi.org/10.1007/s11192-021-03940-z

[97] Aline Darc Piculo Dos Santos, Ana Harumi Grota Suzuki, Fausto Orsi Medola, and Atiyeh Vaezipour. 2021. A Systematic Review of Wearable Devices for Orientation and Mobility of Adults With Visual Impairment and Blindness. *IEEE Access* 9 (2021), 162306–162324. https://doi.org/10.1109/ACCESS.2021.3132887

[98] Zhanna Sarsenbayeva, Niels van Berkel, Danula Hettiachchi, Benjamin Tag, Eduardo Velloso, Jorge Goncalves, and Vassilis Kostakos. 2023. Mapping 20 years of accessibility research in HCI: A co-word analysis. *International Journal of Human-Computer Studies* 175 (2023), 103018. https://doi.org/10.1016/j.ijhcs.2023.103018

[99] Daisuke Sato, Uran Oh, Kakuya Naito, Hironobu Takagi, Kris Kitani, and Chieko Asakawa. 2017. NavCog3: An Evaluation of a Smartphone-Based Blind Indoor Navigation Assistant with Semantic Features in a Large-Scale Environment. In *Proceedings of the 19th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '17)*. Association for Computing Machinery, New York, NY, USA, 270–279. https://doi.org/10.1145/3132525.3132535

[100] Yoshikazu Seki and Tetsuji Sato. 2011. A Training System of Orientation and Mobility for Blind People Using Acoustic Virtual Reality. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 19, 1 (2011), 95–104. https://doi.org/10.1109/TNSRE.2010.2064791

[101] Huniya Shahid, Munam Ali Shah, Bilal Khalid Dar, and Fizzah Fizzah. 2018. A Review of Smartphone's Text Entry for Visually Impaired. In *2018 24th International Conference on Automation and Computing (ICAC)*. 1–7. https://doi.org/10.23919/IConAC.2018.8749128

[102] Ather Sharif, Aedan Liam McCall, and Kianna Roces Bolante. 2022. Should I Say "Disabled People" or "People with Disabilities"? Language Preferences of Disabled People Between Identity- and Person-First Language. In *Proceedings of the 24th International ACM SIGACCESS Conference on Computers and Accessibility* (Athens, Greece) *(ASSETS '22)*. Association for Computing Machinery, New York, NY, USA, Article 10, 18 pages. https://doi.org/10.1145/3517428.3544813

[103] Ather Sharif, Ploypilin Pruekcharoen, Thrisha Ramesh, Ruoxi Shang, Spencer Williams, and Gary Hsieh. 2022. "What's Going on in Accessibility Research?" Frequencies and Trends of Disability Categories and Research Domains in Publications at ASSETS. In *Proceedings of the 24th International ACM SIGACCESS Conference on Computers and Accessibility* (Athens, Greece) *(ASSETS '22)*. Association for Computing Machinery, New York, NY, USA, Article 46, 5 pages. https://doi.org/10.1145/3517428.3550359

[104] Kristen Shinohara, Cynthia L. Bennett, Wanda Pratt, and Jacob O. Wobbrock. 2018. Tenets for Social Accessibility. *ACM Transactions on Accessible Computing* 11, 1 (2018), 1–31. https://doi.org/10.1145/3178855

[105] Clauirton Siebra, Walter Correia, Marcelo Penha, Jefte Macedo, Jonysberg Quintino, Marcelo Anjos, Fabiana Florentin, Fabio Q. B. da Silva, and Andre L M Santos. 2018. Virtual Assistants for Mobile Interaction: A Review from the Accessibility Perspective. In *Proceedings of the 30th Australian Conference on Computer-Human Interaction* (Melbourne, Australia) *(OzCHI '18)*. Association for Computing Machinery, New York, NY, USA, 568–571. https://doi.org/10.1145/3292147.3292232

[106] Amanpreet Singh, Vivek Natarajan, Meet Shah, Yu Jiang, Xinlei Chen, Dhruv Batra, Devi Parikh, and Marcus Rohrbach. 2019. Towards VQA Models That Can Read. In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 8309–8318. https://doi.org/10.1109/CVPR.2019.00851

[107] Alexa F. Siu, Son Kim, Joshua A. Miele, and Sean Follmer. 2019. ShapeCAD: An Accessible 3D Modelling Workflow for the Blind and Visually-Impaired Via 2.5D Shape Displays. In *Proceedings of the 21st International ACM SIGACCESS Conference on Computers and Accessibility* (Pittsburgh, PA, USA) *(ASSETS '19)*. Association for Computing Machinery, New York, NY, USA, 342–354. https://doi.org/10.1145/3308561.3353782

[108] Alexa F. Siu, Mike Sinclair, Robert Kovacs, Eyal Ofek, Christian Holz, and Edward Cutrell. 2020. Virtual Reality Without Vision: A Haptic and Auditory White Cane to Navigate Complex Virtual Worlds. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376353

[109] Caleb Southern, James Clawson, Brian Frey, Gregory Abowd, and Mario Romero. 2012. An Evaluation of BrailleTouch: Mobile Touchscreen Text Entry for the Visually Impaired. In *Proceedings of the 14th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '12)*. Association for Computing Machinery, New York, NY, USA, 317–326. https://doi.org/10.1145/2371574.2371623

[110] Abigale Stangl, Meredith Ringel Morris, and Danna Gurari. 2020. "Person, Shoes, Tree. Is the Person Naked?" What People with Vision Impairments Want in Image Descriptions. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376404

[111] Sarit Felicia Anais Szpiro, Shafeka Hashash, Yuhang Zhao, and Shiri Azenkot. 2016. How People with Low Vision Access Computing Devices: Understanding Challenges and Opportunities. In *Proceedings of the 18th International ACM SIGACCESS Conference on Computers and Accessibility*. Association for Computing Machinery, New York, NY, USA, 171–180. https://doi.org/10.1145/2982142.2982168

[112] Ruxandra Tapu, Bogdan Mocanu, Andrei Bursuc, and Titus Zaharia. 2013. A Smartphone-Based Obstacle Detection and Classification System for Assisting Visually Impaired People. In *2013 IEEE International Conference on Computer Vision Workshops*. 444–451. https://doi.org/10.1109/ICCVW.2013.65

[113] Ruxandra Tapu, Bogdan Mocanu, and Titus Zaharia. 2020. Wearable assistive devices for visually impaired: A state of the art survey. *PATTERN RECOGNITION LETTERS* 137, SI (sep 2020), 37–52. https://doi.org/10.1016/j.patrec.2018.10.031

[114] Anja Thieme, Cecily Morrison, Nicolas Villar, Martin Grayson, and Siân Lindley. 2017. Enabling Collaboration in Learning Computer Programing Inclusive of Children with Vision Impairments. In *Proceedings of the 2017 Conference on Designing Interactive Systems (DIS '17)*. Association for Computing Machinery, New York, NY, USA, 739–752. https://doi.org/10.1145/3064663.3064689

[115] Márcio Josué Ramos Torres and Regina Barwaldt. 2019. Approaches for diagrams accessibility for blind people: a systematic review. In *2019 IEEE Frontiers in Education Conference (FIE)*. 1–7. https://doi.org/10.1109/FIE43999.2019.9028522

[116] V. A. Traag, L. Waltman, and N. J. van Eck. 2019. From Louvain to Leiden: guaranteeing well-connected communities. *Scientific Reports* 9, 1 (2019), 1–12. https://doi.org/10.1038/s41598-019-41695-z arXiv:1810.08473

[117] Caleb M. Trujillo and Tammy M. Long. 2018. Document co-citation analysis to enhance transdisciplinary research. *Science Advances* 4, 1 (2018), 1–9. https://doi.org/10.1126/sciadv.1701130

[118] World Blind Union. 2023. World Blind Union Membership Categories. https://worldblindunion.org/members-and-partners/membership-information/ Accessed: Jul. 7, 2023.

[119] Jani Väyrynen, Ashley Colley, and Jonna Häkkilä. 2016. Head Mounted Display Design Tool for Simulating Visual Disabilities. In *Proceedings of the 15th International Conference on Mobile and Ubiquitous Multimedia* (Rovaniemi, Finland) *(MUM '16)*. Association for Computing Machinery, New York, NY, USA, 69–73. https://doi.org/10.1145/3012709.3012714

[120] Violeta Voykinska, Shiri Azenkot, Shaomei Wu, and Gilly Leshed. 2016. How Blind People Interact with Visual Content on Social Networking Services. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing (CSCW '16)*. Association for Computing Machinery, New York, NY, USA, 1584–1595. https://doi.org/10.1145/2818048.2820013

[121] W3C. 2016. Accessibility Requirements for People with Low Vision. https://www.w3.org/TR/low-vision-needs/ Accessed: Jan. 9, 2023.

[122] Isabelle Walsh and Alexandre Renaud. 2017. Reviewing the literature in the IS field: Two bibliometric techniques to guide readings and help the interpretation of the literature. *Systèmes d'information & management* 22, 3 (2017), 75–115. https://doi.org/10.3917/sim.173.0075

[123] Isabelle Walsh, Alexandre Renaud, Maximiliano Jeanneret Medina, Cédric Baudet, and Gaëtan Mourmant. 2022. ARTIREV: An Integrated Bibliometric Tool to Efficiently Conduct Quality Literature Reviews. *Systèmes d'information & management* 27, 4 (2022), 5–50. https://doi.org/10.3917/sim.224.0005

[124] Isabelle Walsh and Frantz Rowe. 2022. BIBGT: combining bibliometrics and grounded theory to conduct a literature review. *European Journal of Information Systems* (2022), 1–22. https://doi.org/10.1080/0960085x.2022.2039563

[125] Ludo Waltman, Nees Jan van Eck, and Ed C.M. Noyons. 2010. A unified approach to mapping and clustering of bibliometric networks. *Journal of Informetrics* 4, 4 (2010), 629–635. https://doi.org/10.1016/j.joi.2010.07.002

[126] Liyang Wang, Jinxin Zhao, and Liangjun Zhang. 2021. NavDog: Robotic Navigation Guide Dog via Model Predictive Control and Human-Robot Modeling. In *Proceedings of the 36th Annual ACM Symposium on Applied Computing (SAC '21)*. Association for Computing Machinery, New York, NY, USA, 815–818. https://doi.org/10.1145/3412841.3442098

[127] Lucy Lu Wang, Kelly Mack, Emma J McDonnell, Dhruv Jain, Leah Findlater, and Jon E Froehlich. 2021. A Bibliometric Analysis of Citation Diversity in Accessibility and HCI Research. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems (CHI EA '21)*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3411763.3451618

[128] Xiaobing Wang, Yingying Jiang, Zhenbo Luo, Cheng-Lin Liu, Hyunsoo Choi, and Sungjin Kim. 2019. Arbitrary Shape Scene Text Detection With Adaptive Text Region Representation. In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 6442–6451. https://doi.org/10.1109/CVPR.2019.00661

[129] Jack White, Tatiana Kameneva, and Chris McCarthy. 2022. Vision Processing for Assistive Vision: A Deep Reinforcement Learning Approach. *IEEE Transactions on Human-Machine Systems* 52, 1 (2022), 123–133. https://doi.org/10.1109/THMS.2021.3121661

[130] Michele A Williams, Caroline Galbraith, Shaun K Kane, and Amy Hurst. 2014. "Just Let the Cane Hit It": How the Blind and Sighted See Navigation Differently. In *Proceedings of the 16th International ACM SIGACCESS Conference on Computers & Accessibility (ASSETS '14)*. Association for Computing Machinery, New York, NY, USA, 217–224. https://doi.org/10.1145/2661334.2661380

[131] Michele A Williams, Amy Hurst, and Shaun K Kane. 2013. "Pray before You Step out": Describing Personal and Situational Blind Navigation Behaviors. In *Proceedings of the 15th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '13)*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/2513383.2513449

[132] Jacob O. Wobbrock, Shaun K. Kane, Krzysztof Z. Gajos, Susumu Harada, and Jon Froehlich. 2011. Ability-based design: Concept, principles and examples. *ACM Transactions on Accessible Computing* 3, 3 (2011), 1–27. https://doi.org/10.1145/1952383.1952384

[133] Jacob O. Wobbrock and Julie A. Kientz. 2016. Research Contributions in Human-Computer Interaction. *Interactions* 23, 3 (apr 2016), 38–44. https://doi.org/10.1145/2907069

[134] World Health Organization (WHO). 2019. *World report on vision*. Vol. 214. 1–160 pages.

[135] 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)*. Association for Computing Machinery, New York, NY, USA, 1180–1192. https://doi.org/10.1145/2998181.2998364

[136] Koji Yatani, Nikola Banovic, and Khai Truong. 2012. SpaceSense: Representing Geographical Information to Visually Impaired People Using Spatial Tactile Feedback. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '12)*. Association for Computing Machinery, New York, NY, USA, 415–424. https://doi.org/10.1145/2207676.2207734

[137] Chucai Yi and Yingli Tian. 2012. Localizing Text in Scene Images by Boundary Clustering, Stroke Segmentation, and String Fragment Classification. *IEEE Transactions on Image Processing* 21, 9 (2012), 4256–4268. https://doi.org/10.1109/TIP.2012.2199327

[138] Chucai Yi, Yingli Tian, and Aries Arditi. 2014. Portable Camera-Based Assistive Text and Product Label Reading From Hand-Held Objects for Blind Persons. *IEEE/ASME Transactions on Mechatronics* 19, 3 (2014), 808–817. https://doi.org/10.1109/TMECH.2013.2261083

[139] Jiaming Zhang, Kailun Yang, Angela Constantinescu, Kunyu Peng, Karin Muller, and Rainer Stiefelhagen. 2022. Trans4Trans: Efficient Transformer for Transparent Object and Semantic Scene Segmentation in Real-World Navigation Assistance. *IEEE Transactions on Intelligent Transportation Systems* 23, 10 (2022), 19173 – 19186. https://doi.org/10.1109/TITS.2022.3161141 46.24.01; LK 01.

[140] Yuhang Zhao, Cynthia L. Bennett, Hrvoje Benko, Edward Cutrell, Christian Holz, Meredith Ringel Morris, and Mike Sinclair. 2018. Enabling People with Visual Impairments to Navigate Virtual Reality with a Haptic and Auditory Cane Simulation. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3173574.3173690

[141] Yuhang Zhao, Edward Cutrell, Christian Holz, Meredith Ringel Morris, Eyal Ofek, and Andrew D Wilson. 2019. SeeingVR: A Set of Tools to Make Virtual Reality More Accessible to People with Low Vision. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3290605.3300341

[142] Yuhang Zhao, Elizabeth Kupferstein, Hathaitorn Rojnirun, Leah Findlater, and Shiri Azenkot. 2020. The Effectiveness of Visual and Audio Wayfinding Guidance on Smartglasses for People with Low Vision. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376516

[143] Junwen Zhu and Weishu Liu. 2020. A tale of two databases: the use of Web of Science and Scopus in academic papers. *Scientometrics* 123, 1 (2020), 321–335. https://doi.org/10.1007/s11192-020-03387-8 arXiv:2002.02608

[144] Ivan Zupic and Tomaž Čater. 2015. Bibliometric Methods in Management and Organization. *Organizational Research Methods* 18, 3 (2015), 429–472. https://doi.org/10.1177/1094428114562629

A BIBLIOMETRIC ANALYSIS DETAILS

Scopus advanced query that resulted in N=3,378 documents.

Terms: `TITLE-ABS-KEY ("visually impaired" OR "with vis* impair*" OR "with vis* disabilit*" OR "eye disorder*" OR "vis* disorder*" OR "partially sighted" OR "partial vision" OR "blind people" OR "blind person*" OR "blind user*" OR "with blindness" OR deafblind OR deaf-blind OR "low vision people" OR "low vision person*" OR "low vision user*" OR "with low vision")`

Conference proceedings: `AND DOCTYPE ("cp") AND SRCTYPE ("p") AND (CONFSPONSORS (acm OR "association for computing machinery" OR ieee OR "institute of electrical and electronics engineers") OR SRCTITLE (acm OR "association for computing machinery" OR ieee OR "institute of electrical and electronics engineers") OR ABS (acm OR "association for computing machinery" OR ieee OR "institute of electrical and electronics engineers"))`

Journal articles: `AND DOCTYPE ( "ar" ) AND SRCTYPE ( "j" ) AND SRCTITLE ( acm OR "association for computing machinery" OR ieee OR "institute of electrical and electronics engineers")`

Year, Language, Publication Stage, and DOI: `AND PUBYEAR > 2009 PUBYEAR < 2023 AND LANGUAGE ( "english" ) AND PUBSTAGE ( "final" ) AND DOI ( "10.*" )`