Beyond Canes and Guide Dogs: A Review of 40 Years of Robotics for Wayfinding, Navigating, and Orienting Assistance for People with Visual Impairments

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Abstract:

Robotic aids that enrich the lives of Persons with Visual Impairments (PwVI) are becoming increasingly popular. Their development is motivated by the significant navigational challenges faced by PwVI, which negatively impact their independence and quality of life. Additionally, traditional tools such as white canes, guide dogs, and tactile maps, although useful, lack the adaptability and situational awareness that robots can provide. This survey presents the first comprehensive review of robotic solutions for wayfinding, spanning over 150 works in the past 40 years. We propose unifying definitions of *wayfinding* and *robotic wayfinding* drawing from the fields of robotics, human factors, urban theory, and several other social sciences, and provide a rigorous classification along the axes of embodiment, communication, sensing, and user evaluation. Informed by the gaps in the literature, we provide a critical analysis of six research questions, including factors in device design trends, evolution of unidirectional and bidirectional communication mediums, and robustness of system evaluations and user studies. Furthermore, we analyze and compare state-of-the-art approaches spanning human-robot interaction, advanced perception pipelines, and experimental design. We identify limitations and open challenges for developing robotic wayfinding solutions and outline recommendations for future research directions. The full annotated dataset and detailed taxonomy for all surveyed papers are published in the Inter-university Consortium for Political and Social Research (ICPSR) repository: https://doi.org/10.3886/E235425V1. Additional resources can be found on our project website: https://wayfinding-robots.github.io.

Keywords: Human-Robot Interaction, Assistive Device, Robotic Wayfinding, Robot-Assisted Wayfinding, Assistive Navigation, Guide Dog Robot, Haptic feedback, Accessibility, Interaction Design, Blind and Low Vision

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Contents

1 Introduction

Intelligent software and devices, such as robots, have been increasingly used by and designed for people living with disabilities, including those with blindness, low vision, and other visual impairments [30, 314]. Although these technologies have the potential to augment the abilities of people with disabilities, their usability and acceptance depend in part on the ease of interaction between the device and the user [266]. As scenarios involving human-robot interaction (HRI) become increasingly prevalent, it is important to consider how robots can better coexist and interact with people to enhance everyday life experiences [127–129, 135–137]. One promising avenue of application for these growing capabilities in HRI lies in the development and deployment of systems designed to support and assist persons with visual impairments (PwVI)[5] in navigating daily life [30].

The World Health Organization (WHO) reported that across the globe there are over 2.2 billion people living with some form of visual impairment [242]. Visual impairments[6] can be defined based on visual acuity and subdivided into four categories: (1) mild vision loss (visual acuity worse than 6/12), (2) moderate vision loss (visual acuity worse than 6/18), (3) severe vision loss (visual acuity worse than 6/60), and (4) blindness (visual acuity worse than 3/60) [241]. Note that such a definition of visual impairment, which is derived from a measure of the presenting visual acuity, can include correctable visual impairments[7] (*e.g.*, refractively). Of these 2.2 billion people, $\sim 15\%$ (some 338.3 million) have moderate to severe visual impairments or blindness and may experience severe disruptions in routine tasks [42].

PwVI may experience challenges with orientation and navigation, which restrict their independence and can lead to a decrease in overall quality of life [186, 200], resulting from a reduced ability to perform Instrumental Activities of Daily Living (IADLs) such as cooking and transportation [34, 113, 188, 264]. Naturally, methods to combat such disruptions and improve the lives of PwVI have been developed. These efforts can be broadly described as: (1) augmenting quality of life and independence, and (2) improving medical care such as scanning, prevention, and treatment. This review focuses on the former category of solutions: namely, designing robotic assistants to address the problem of wayfinding for PwVI. We term this effort as working towards *Robotic Wayfinding* and formally define it below in Def. 2. Readers interested in the latter effort can refer to the following works and comprehensive reviews: [85, 250, 273, 311, 357].

Traditional tools to augment the quality of life of PwVI include white canes, guide dogs, and static tactile maps [30]. Although these tools are greatly beneficial, they have limitations: (1) white canes convey limited information within a small radius around the user near ground level (*e.g.*, they are unable to communicate fine-grained tactile information such as wet floors or detect hazards at head-height) [100, 255]; (2) guide dogs are both costly and time-consuming to train, and have a limited working life [139]; and (3) tactile maps are not portable nor easy to use [146]. An alternative natural solution is the technique of *shorelining*, whereby PwVI may follow a wall (*e.g.*, walltrailing [300]) or other edges with their hands and/or white cane in order to navigate a non-familiar space [178].

[5] We recognize that there are varying terminologies used for the visually impaired community both from outside and within across disciplines and regions; further, there is ambiguity around the preference for disability-first versus person-first identification by those within the community [314]. In the course of our review, we encountered a variety of labels, including (people who are) Blind and Low Vision (pBLV, BLV, or B/LV) [111, 124, 307], People with Low Vision (PLV) [368], Persons with Visual Impairments (PwVI or PVI) [200, 201], Visually Impaired People (VIP) [192, 267], Blind or Visually Impaired (BVI) [168, 169], Blind and Visually Impaired People (BVIP) [305], the Visually Impaired or Vision-Impaired (VI) [94, 332, 359], and the Blind [155, 216]. We will refer to members of the blind, low vision, and visually impaired communities as *Persons with Visual Impairments (PwVI)* hereafter (see also Fig. 2 for supporting quantitative data of this choice). We encourage future studies in this area to adopt similar verbiage in pursuit of terminology standardization.

[6] Although other types of visual impairments exist that may affect daily life (such as color vision deficiency or amblyopia), they are beyond the scope of this review. We direct the reader to Grant and Moseley [114] and Aydindoğan et al. [17] as a starting point for more information on the impacts of other visual impairments on life and avenues through which technology can assist.

[7] For the purposes of this review, the term *visual impairment* generally will pertain to the subset of more severe visual impairments unless otherwise noted, *e.g.*, with respect to visual feedback in Sec. 3.4.1.

However, shorelining is generally a less preferred option because of inefficiencies in time and path length [139]. Human guides and companions can address many of the limitations of these traditional tools and methods, but the resulting reliance on another person contributes to the loss of independence for PwVI [24, 163].

Navigating the world in which we inhabit is innately human. The task of *wayfinding* dates back to the age of seafarers, who voyaged across the seas guided by the stars, bird migration, tidal patterns, and smells of the ocean, among others [33, 97, 109]. Despite this storied history, there is no single clear definition of the term. The first documented use of the term *wayfinding* was as a seemingly magical ability possessed by some individuals to successfully navigate through space better than most [89]. Later, the term *wayfinding*, minus any apparent wizardry, was introduced into urban theory as similar to the concept of legibility, where a city's landmarks and pathways are clearly and easily accessible [207]. Over time, the term wayfinding has been adopted by the PwVI community to encompass a shifting variety of components — some or all of which are often combined into complex systems to create holistic solutions [131, 200].

Included in this toolbox are:

1. ***path planning*** for designing a path to some destination [22, 340, 359], often paired with (1) obstacle detection [11] and/or (2) obstacle avoidance [299, 330, 358]
2. ***localization***, the sense of knowing one's location within an environment [293] and ***orientation***, the sense of knowing the direction one is facing and how one moves through space[8] [182]
3. ***scene understanding*** to provide context about the environment through mapping and interpretation [83, 253] and for aiding users to understand spatial relationships and build a mental map [131, 267] of their surroundings
4. ***semantic translation*** to bridge high-level semantic information (*e.g*., resistance induced on a white cane to inform an object's size or texture) low-level reactive control (*e.g*., a guide dog making minor corrections while maintaining the user's goal of walking along a straight sidewalk) for more actionable assistance [139, 168, 169]
5. ***environment familiarity***, the amount to which a person recognizes their surroundings (which may be familiar, semi-familiar, or unfamiliar) [105, 151]
6. ***object-goal (last-mile) navigation*** to guide the user to precisely reach the goal rather than a general vicinity [2, 248, 272, 288, 330, 333].

We propose a unifying definition of wayfinding, in which we extract the thematic essence from these varying definitions:

Definition 1. *Wayfinding* for PwVI is the process of navigating with implicit or explicit cues about routes and/or salient environmental features to augment one's orientation and localization throughout travel.

Explicit cues can manifest as speech or Braille displays, while implicit cues may be interactive forces, such as the tension transmitted through a dog leash [58]. Note that in many social science fields, wayfinding is commonly referred to as *Orientation and Mobility* (O&M) [247]. Wayfinding is an action and skill of utmost importance for PwVI as it enables a critical component of motion throughout daily life [264] and underpins the ability to perform IADLs that are often visually demanding [34, 113, 188, 264]. Wayfinding can be facilitated by a human guide or through the use of tools, such as a white cane or guide dog, all of which are intended to support the independence of PwVI [173, 345]. Beyond these low-tech tools, new systems make use of technology found in vehicles and mobile phones, such as GPS, Bluetooth (BLE), accelerometers, cameras, and more, including colloquial robots [174, 200, 205, 330, 360].

[8] For added comprehension, we note that the layman term "sense of direction" can be thought of as a combination of what we term as path planning, localization, orientation, and environmental familiarity [67].

However, development for these use cases is not without challenges. Some PwVI prefer a discreet device that does not single them out in a crowd, leading to the design of disguised systems [330]. Systems that speak or otherwise emit sound to the user [159, 200] (refer to Table 1 for a complete list) may be difficult to hear in noisy environments, or may reveal destinations or tasks that the user may wish to keep private. Furthermore, (non-bone-conductive) earbuds and headphones obstruct the hearing of environmental cues, restricting a primary avenue for PwVI environmental perception [30, 149]. Beyond *how* to communicate with the user, there is little standardization about *what* to communicate. Specifically, there is a lack of both standardization and comprehension of which environment features and specific items are important for navigation and detection for a given user [107, 150] which underscores the need for a well-tailored approach toward clear and unambiguous guidance [200, 237, 341].

This leads us to the following definition of robot-assisted wayfinding:

Definition 2. A *wayfinding robot* is a device that assists PwVI by:

1. enabling localization and orientation within their environment, and
2. facilitating navigation through their surroundings.

and that is imbued with the ability to:

1. perceive their environment through some set of sensors (*e.g.*, LiDAR, RGB-D camera, force sensor)
2. sustain communication with the user through any combination of modalities (*e.g.*, natural language, haptics)

We note that Def. 2 excludes non-robotic solutions such as smartphone applications, static environmental hardware (*e.g.*, BLE, RFID, and UWB beacons), and passive or non-reactive tactile maps. There is ample prior work within the enumerated areas of exclusion — we invite interested readers to peruse the below works and reviews that address these areas. Specifically, some reviews explore works that rely primarily on devices such as cellphones and tablets [6, 91]. Additionally, there are many specific works that propose various phone and app-based solutions [9, 29, 53, 92, 93, 95, 153, 202, 229, 230, 275, 320]. For further discussion on the use of static tactile maps and static hardware (such as RFID or BLE beacons) installed in the environment, refer to Rocha et al. [268] and de Fatima X.M. Almeida et al. [75]. Discussions of such beacons in the realm of public transportation specifically are provided by Sangale et al. [274]. Please refer to Real and Araujo [262] and Tapu et al. [308] for reviews of primarily wearables and/or mobile apps.

In this review, we cover works regarding robotic wayfinding spanning 40 years, from 1984 to halfway through February 2024 (as detailed in Sec. 2.1). Most relevant to ours is the concurrent contemporaneous work by Wei et al. [336]; although the authors provide a valuable review of 76 papers covering several HRI contexts for PwVI, our work further extends the field by (1) *breadth* in the curation of a corpus of papers that is twice as large over the same time interval of the past four decades, and (2) *depth* in the analysis of robotic wayfinding and navigation assistance — an area of particular relevance to interactions between humans and robots as well as real-world deployment challenges. Also similar to our review, Thiyagarajan et al. [312] is limited in that the focus is primarily on describing (1) several specific sensing-enabled devices (*e.g.*, augmented white canes) and (2) predominantly commercially available robots and how they might be or are applied to working with PwVI. Furthermore, they do not provide a comprehensive analysis of unidirectional or bidirectional human-robot communication mechanisms. Finally, somewhat related are Kyrarini et al. [184] and El sheikh [90], though both focus on a narrow investigative scope and/or time interval, covering two years and five papers, respectively. Parker et al. [247] focused on reviewing how to conduct wayfinding experiments, intentionally omitting robotics solutions. These gaps inform our review and analyses.

Within this survey, a vast breadth and depth of topics and analyses are covered throughout Secs. 3 and 4. While this review does cover augmented canes in depth, we refer the reader to Mai et al. [208]

for a more extensive analysis of the limitations and futures of solely augmented canes. Comprehensive analyses of *indoor* route planning methods for PwVI are provided by Nimalika Fernando and Murray [238]. For a more detailed review addressing particular aspects of indoor and outdoor route planning and assistive spatial orientation technologies, see Fernandes et al. [99]. For further discussions tailored towards leveraging SLAM [87] for the assistance of PwVI, we refer the reader to Bamdad et al. [23]. While robotic quadrupeds for the assistance of PwVI are covered in depth in this review (Sec. 3.2.1), we refer the reader to Hong et al. [132] for a more extensive analysis on solely the potential for robotic quadrupeds in wayfinding, contrasting to requirements and needs of live guide dogs [19].

The remainder of this paper is organized as follows. In Sec. 2 we provide an overview of our literature review process. Section 3 details our findings to our research questions (RQs) with analysis on the different components of wayfinding for PwVI, keeping Defs. 1 and 2 in mind:

- RQ1 What are the historical and current trends in the area of wayfinding robotics (*e.g.*, growth in publication volume, shifts in direction and technologies)?
- RQ2 What robotic solutions exist to address the different components of wayfinding?
- RQ3 What methods of sensing/perception are commonly used in these robotic solutions?
- RQ4 What methods of communication are commonly used in these robotic solutions?
- RQ5 How are the different robotic solutions evaluated for real-world use? What type of metrics do they use?
- RQ6 For whom are the robotic solutions designed, and who was involved in the evaluation?

We include many categorical tables detailing the different taxonomies for robot-assisted wayfinding solutions. Finally, we conclude with our findings on the current landscape and future directions of wayfinding for PwVI in Sec. 4. To the best of our knowledge, we are the first to provide a comprehensive review of robotics for wayfinding for PwVI at this scale.

The main contributions of this literature review are as follows:

1. Unifying definitions for *Wayfinding for Persons with Visual Impairments* and *Robotic Wayfinding assistants*.
2. A comprehensive review of over 150 published works on robotic solutions for wayfinding.
3. Robust categorizations of all robot-assisted wayfinding solutions along the axes of formulation, technologies used, guidance, communication, and interaction methods, and evaluation.
4. Open-source, structured, and annotated data released in the Inter-university Consortium for Political and Social Research (ICPSR) data repository (Pohovey et al. [251]), with further resources on our project page[9].
5. A discussion of limitations and open challenges for future work in robotically-assisted wayfinding.

2 Survey Methodology

2.1 Search Process

Papers for this literature review were collected via comprehensive queries of both Scopus and Google Scholar search engines, ensuring a wide capture of relevant publications across various venues and publishers. Owing to the intrinsic multidisciplinary nature of the field, our review incorporates literature from various publishers, including IEEE, ACM, and Springer, as well as across various venues. Many papers have been published in peer-reviewed conferences and journals, although we have also included several preprints. Our review encompasses papers published (or uploaded to

[9] https://wayfinding-robots.github.io

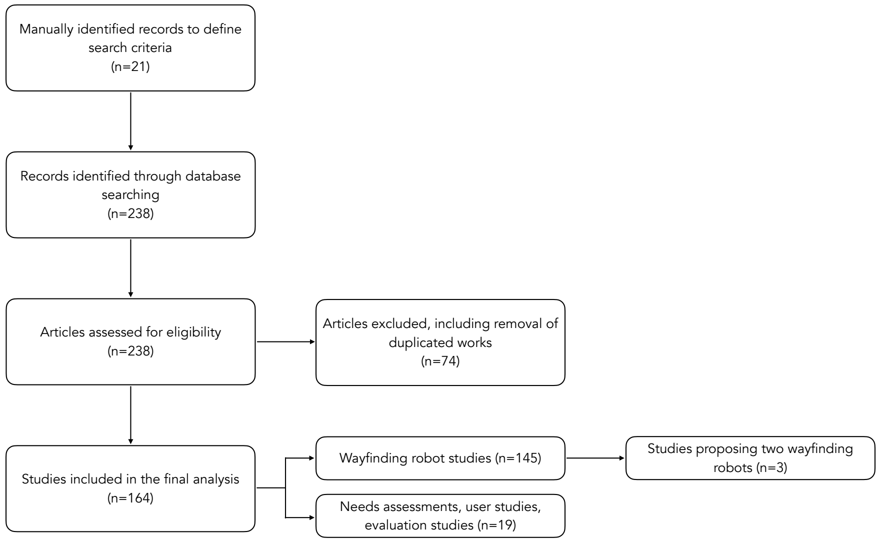

Figure 1: Flowchart visualization of the screening procedure hierarchy.

preprint repositories such as arXiv) between 1984 and the time that this search was conducted, early February 2024.

2.2 Selection and Screening

A data-driven approach toward classification and grouping was employed, whereby similar themes and topics were allowed to surface by the natural content of the reviewed papers, guided by our research questions (RQs) discussed above in Sec. 1. We followed a similar screening and elimination methodology to that of Moher et al. [220], so as to enumerate all related works regarding the topic of robotic wayfinding assistance. In this screening procedure, we employed a three-tiered hierarchy as shown in Fig. 1.

In the first phase of our literature search, we conducted a preliminary, non-systematic process to establish a controlled ontology. Driven with the purpose of creating a set of relevant keywords, no specific predefined technical terms beyond *e.g*., "visual impairment", "cane", "robot", "blind" were employed; instead, guided by senior researchers, we manually curated a set of 21 papers [12, 21, 44, 65, 76, 88, 168, 169, 174, 195, 238, 293, 307, 314, 322, 328, 330, 332, 342, 352, 360]. This selection was designed to be representative of the literature, targeting recent reviews, foundational, and state-of-the-art works, some of which were previously known to the research team. Using this gathered set of keywords, we crafted a well-structured logical query for titles, abstracts, and keywords as follows:

```
( navigat* OR wayfind* OR way-find* OR guid* OR localiz* OR orient* )
AND ( ( ( visual* OR vision* ) AND impair* ) OR (blind OR ( low AND
vision ) ) )
```

where * denotes a wildcard character sequence, allowing for strings such as *visual impairment* and *visually impaired* as well as different tenses of the verb *to guide*, among others. To enable a more scalable search method, we divided the initial query into 4 overlapping subsets among a group of 4 readers. This division minimized the risk of missing relevant works in the search collection process while simultaneously distributing workload. Specifically, each reader is assigned one of the following four variations of the complete initial query:

1. `( navigat* OR wayfind* OR way-find*) AND ( ( ( visual* OR vision* ) AND impair* ) OR ( blind OR ( low AND vision ) ) )`

2. `( wayfind* OR way-find* OR guid*) AND ( ( ( visual* OR vision* ) AND impair* ) OR ( blind OR ( low AND vision ) ) )`
3. `( localiz* OR orient* ) AND ( ( ( visual* OR vision* ) AND impair* ) OR ( blind OR ( low AND vision ) ) )`
4. `( navigat* OR orient* ) AND ( ( ( visual* OR vision* ) AND impair* ) OR ( blind OR ( low AND vision ) ) )`

Notably, we did not include search terms such as "robot" or "cane" in this structured query, as we observed a vast array of terminology used by authors to describe what we defined as a robotic wayfinding assistant in Def. 2; it was not feasible to include all of them.

Broadly, our search methodology followed that of Ye and Robert [354]. Owing to the aforementioned lack of universally accepted vocabulary, we avoided crafting a single restricting search query, which may be prone to unintended exclusions. Instead, we manually reviewed all results on the search engine result pages, continuing until we reached a page where no results met our search relevance. However, rather than adding all results on all pages like Ye and Robert [354], we loosely screened by title and abstract, adding all work that may match our search criteria. This initial screening across different search engines yielded an initial collection of 232 papers. A further six were identified through other sources (such as referral), for a total of 238 papers. In the second screening procedure, we conducted a more rigorous filtering evaluation by further analyzing the title, abstract, figures, images of each article. Specifically, we examined whether the work addressed wayfinding and robotic wayfinding as defined in Defs. 1 and 2 respectively, *e.g.*, via proposing a new system or experimental results. After removing duplicate entries (*i.e.*, repeated papers collected by multiple readers), we conclude with a reduction to a set of 164 papers. Of this amount, 145 were wayfinding robots and 19 were needs assessments or studies of previously proposed wayfinding robots. Three of these papers include two distinct wayfinding robots, giving a total of 148 wayfinding robots.

With this final selection of papers, 10 readers were involved in the detailed review and reading for this survey. All readers have a background in robotics and/or human-robot interaction. The number of papers read by each person ranged from 1 to 35, with a mean of 16.4 and a median of 14.5. To ensure consistency and reduce subjectivity or bias in the classification, we employed a structured data collection methodology. We develop a highly detailed spreadsheet schema to record information spanning from reference terminology for PwVI to evaluation strategies (*e.g.*, presence of user studies), and from device type to communication method. Each of the 10 readers were asked to independently annotate and collect data for a calibration paper (Liu et al. [200]) to align their understanding and interpretations of the schema. We maintain that using a single calibration paper is sufficient, given that the selected paper exhibits notably wide category coverage relative to others. We argue that using a single calibration paper is sufficient, given its wide category coverage. Not only does this structured process enhance the reliability of our findings, but it also supports transparency: we publicly release the raw annotations in the form of sortable, filterable, and searchable spreadsheets in the ICPSR data repository [251], as discussed in the contribution stanzas in Sec. 1, and on our project website[9].

3 Findings and Analyses of the Guiding Questions

Below, we detail our findings in response to the research questions listed in Sec. 1. Specifically, in Sec. 3.1, we discuss trends in the field of robotic wayfinding, finding, among others, that handheld wayfinding robots have historically been and continue to be less desirable than other embodiments. We introduce a taxonomy of wayfinding robots in Sec. 3.2, discussing themes and designs across robot systems, wearables, augmented white canes, and handhelds in both academic and commercial settings. In Sec. 3.3 we detail popular sensing modalities and algorithms, as well as their involvement with specific wayfinding embodiments. Human-robot communication, both unidirectional and bidirectional, is of utmost importance for robot-assisted wayfinding; we provide discourse on a variety of communication mediums, including language and haptic interfaces, in Sec. 3.4. Finally, we consider evaluation methodologies and target communities in Secs. 3.5 and 3.6 respectively, with an overall conclusion that the standardization of experimentation and evaluation is imperative for scaling both future innovation and provisions of assistance to PwVI users.

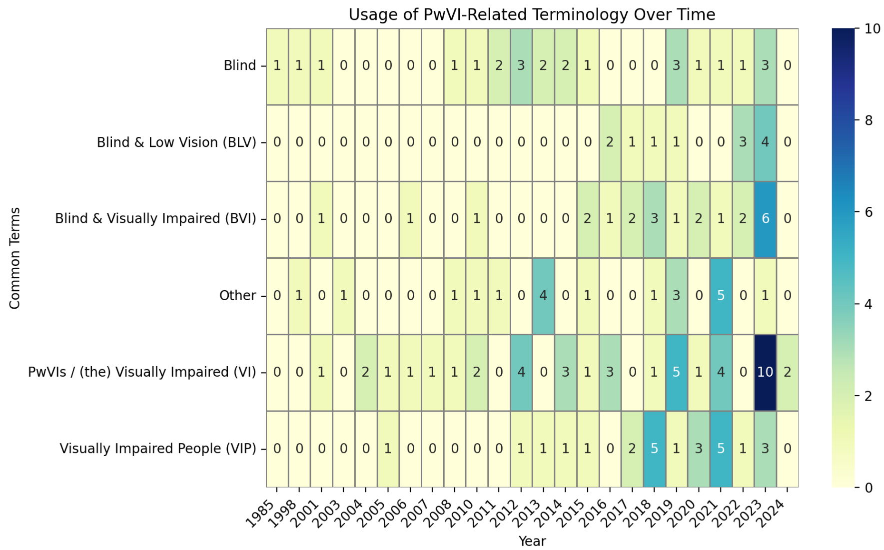

Figure 2: Heatmap demonstrating the flow of terminology for PwVI over time; Blind was the accepted term three or four decades ago, whereas recently common options are PwVI and BVI (the latter an acronym for blind and low vision). Note that some works do not adhere to the use of any particularly terminology; as such, these works are not counted in this figure (as opposed to including them in the Other row).

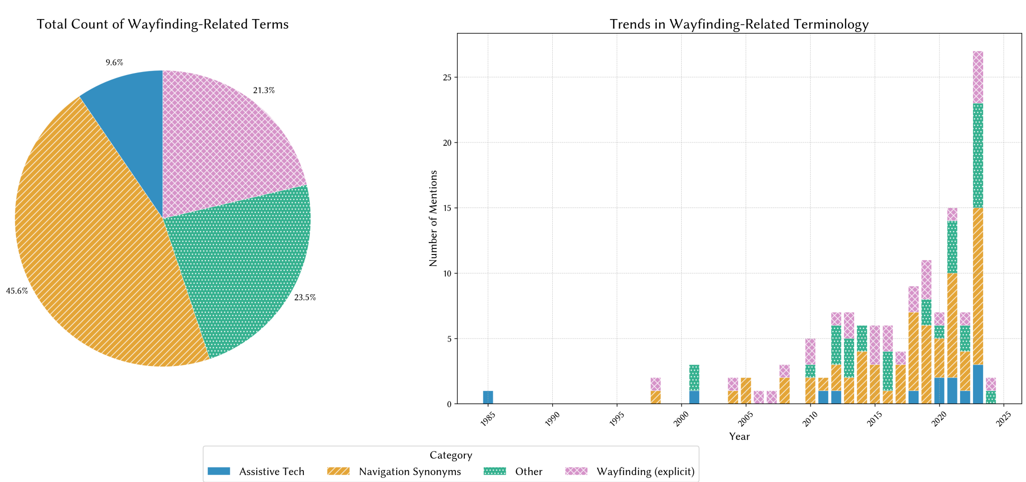

Figure 3: Visualization of the change in terminology used in place of *wayfinding*. Specifically, we can see that the most recent robotics works rely on phrases related to the task of navigation, such as traveling, guiding, or orienting. Years ago, the focus was on general terms of assistance and mobility. Note that our definition of wayfinding in Def. 1 unifies many of these concepts along.

3.1 RQ1: What are the historical and current trends in the area of wayfinding robotics?

Before addressing trends in robotic wayfinding, we briefly summarize the discussion in Sec. 1 regarding the terminology of wayfinding and PwVI. First, recall our note about the variety of terminology used to describe PwVI, including blind and low vision (BLV) and blind and visually impaired (BVI)[5]. In Fig. 2 we visualize the flow of terminology for PwVI over the past four decades.

Although the term blind was initially popular, the terms PwVI, BVI, and BLV have become the new norms. This heatmap of historical trends underscores the appropriateness of our choice of the PwVI terminology as well as buttresses our call for the term's wider adoption in the HRI field.

Although wayfinding (with robots) was first introduced under the theme of assistive technology, navigational keywords such as "orientation" and "guidance" have become more prevalent. We visualize these trends in terminology for the task of wayfinding in robotics in Fig. 3. Of particular note is that describing the task of wayfinding with the exact word "wayfinding" is still not common. Our proposed unifying definitions of wayfinding (Def. 1) and robotic wayfinding (Def. 2) for a human-robot dyad provides standardization to the field and helps to close this gap.

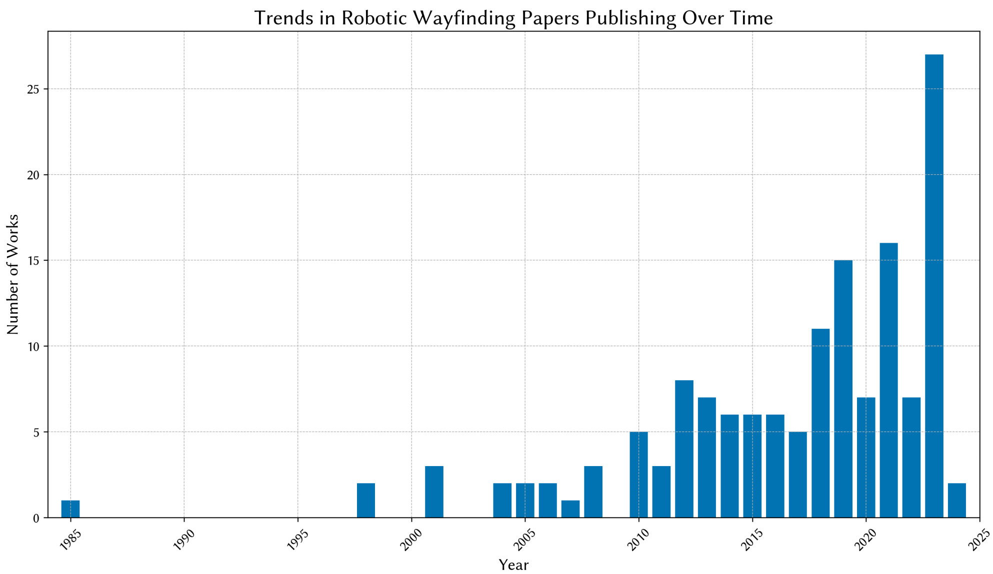

Figure 4: Number of papers published per year, from 1984 through February 2024. Note that the bar for 2024 on the plot is artificially small due to the search window as discussed in Sec. 2.

Robotic wayfinding research is becoming increasingly popular. Since around the turn of the millennium, as shown in Fig. 4, the trend has been one of significant growth. In the mid-2000s, the DARPA Challenges [48, 49] spurred innovations in autonomous navigation and planning for self-driving vehicles [228, 315]. Wayfinding robots, which are designed for the purpose, among others, of assisting with navigation, share a reliance upon many of the same mapping, planning, and perception pipelines used by self-driving cars; the boom in development of such algorithmic tools undoubtedly enabled a greater ease of development of such mobile robots, contributing to the uptick in around 2010 on the right-hand plot in Fig. 4. Starting in 2018, another competition, the annual VizWiz Grand Challenge [38, 119], sought to encourage the development of vision algorithms to assist PwVI with daily tasks; this, in part, contributed to the boost in upward trajectory during this time period, as shown in Fig. 4. An embodied VizWiz for robotics, as we discuss in Sec. 4.6, may push toward another development boom. Finally, a broad factor for the growth of wayfinding robots is both a decrease in costs and an increase in the availability of hardware in terms of compute, sensors, and robotics platforms. As will be discussed in depth in Sec. 3.2, we establish a taxonomy for wayfinding robots with four categories: (1) robot systems, (2) wearables, (3) augmented white canes, and (4) handhelds. The left side of Fig. 5 shows the overall counts of the top-level classification of wayfinding robots, whereas the right side of Fig. 5 shows the trends of wayfinding robot types over time. Of particular note is the explosion of developments in robot systems in recent years. We detail similar trends of robot system wayfinding robots in Fig. 6. In the right side of Fig. 6 we see that this aforementioned boom in development of robot systems can be specifically attributed to quadruped robots (in part due to increasing affordability, as discussed in Sec. 3.2). As seen in Fig. 7, wearable wayfinding robots are predominantly designed for wear above the waist, especially on the head of the user, such as a head-mounted camera [363] or smart glasses [100] for virtual and augmented reality applications [368]. In particular, above-the-waist formulations continue to be the most common wearable type, in part because of a general reliance of wearable wayfinding robots on vision-based sensing; intuitively, positioning a camera at a higher height can enable a more egocentric view with respect to what the PwVI would see, as well as a greater field of view of the surroundings. Furthermore, over the past decade and a half, there has been a motivation to improve the traditional solutions used by PwVI for wayfinding, such as white canes, via the use of sensors typically applied in the robotics domain [293, 322]. This trend is reflected on the right side of Fig. 8, where we can see a gradual increase in the development of augmented white canes in recent years. For example, inertial measurement units (IMUs) and ranging sensors, such as LiDAR, are most commonly added to white canes, as shown on the left side of Fig. 8 which can be used together to enhance localization and spatial awareness for PwVI. Finally, handheld wayfinding robots, (which are more atypical overall, as is evident from Fig. 5) are the lesser preferred embodiment of wayfinding robots [107] by PwVI. Often, handhelds rely on using a smartphone for, *e.g.*, its camera, as shown in Fig. 9 and discussed further in Sec. 3.2.5.

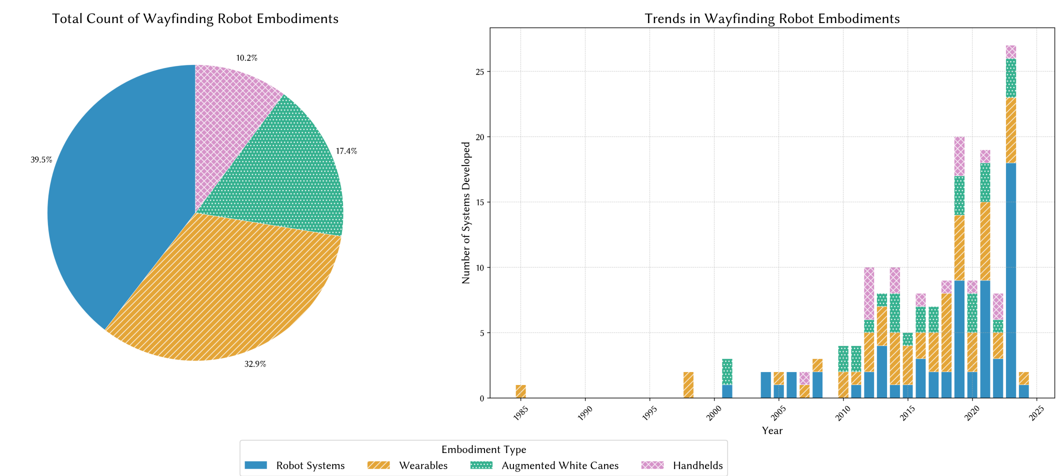

Figure 5: Distribution and frequency of development of different embodiments of wayfinding robots, in aggregate and year-by-year respectively. The left side of the figure shows the counts for the taxonomy elements of robot systems, wearables, augmented white canes, and handhelds. We can notice that robot systems have been broadly the most developed over the past four decades. The right side of the figure shows the counts for robot systems, wearables, augmented white canes, and handhelds over time. In particular, we see a recent large spike in robot systems. Refer to Tables 1, 2, 3, 4, and 5 for further specification. Note that the bar for 2024 on the right plot of the figure is artificially small due to the search window as discussed in Sec. 2.

3.2 RQ2: What robotic solutions exist to address the different components of wayfinding?

A wide range of embodiments for *wayfinding robots* (Def. 2) have been proposed in both academia and industry. We classify these embodiments into a taxonomy with four categories:

1. *robot systems*, what someone would think of colloquially as a robot, *e.g.* a mobile manipulator.
2. *wearables*, devices that can be worn or attached to a user, like a belt or a helmet.
3. *augmented white canes*, traditional white canes that have been modified (augmented) with new sensing capabilities, active guidance abilities, *etc*.
4. *handhelds*, not solely just *e.g.*, a smartphone (which would directly violate the definition of a wayfinding robot as listed in Def. 2), but also a novel device intended to be held in hand (for example, consider a wayfinding robot that uses a custom handheld tactile device to receive

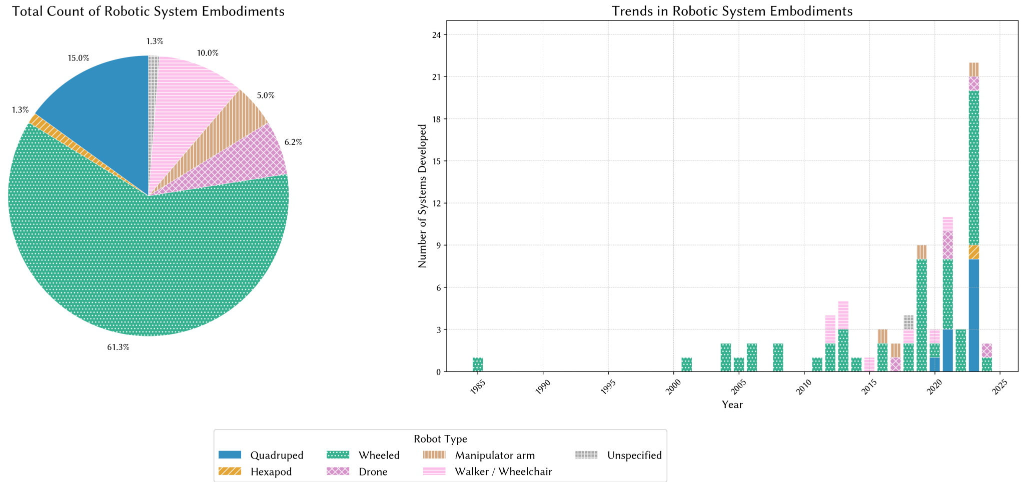

Figure 6: Distribution and frequency of development of different embodiments of robotic system wayfinding robots, in aggregate and year-by-year respectively. The left side of the figure shows the counts of different embodiments of robot systems, and the use of wheels is very common. The right side of the figure shows the number of different embodiments of robot systems over time. The recent explosion in the application of quadrupeds can, in part, be attributed to the increasing affordability of such robots from companies such as Unitree [323] for the synthesis of robot guide dogs (Sec. 3.2.1). Refer to Tables 1 and 2 for further specification. Note that the bar for 2024 on the right plot of the figure is artificially small due to the search window as discussed in Sec. 2.

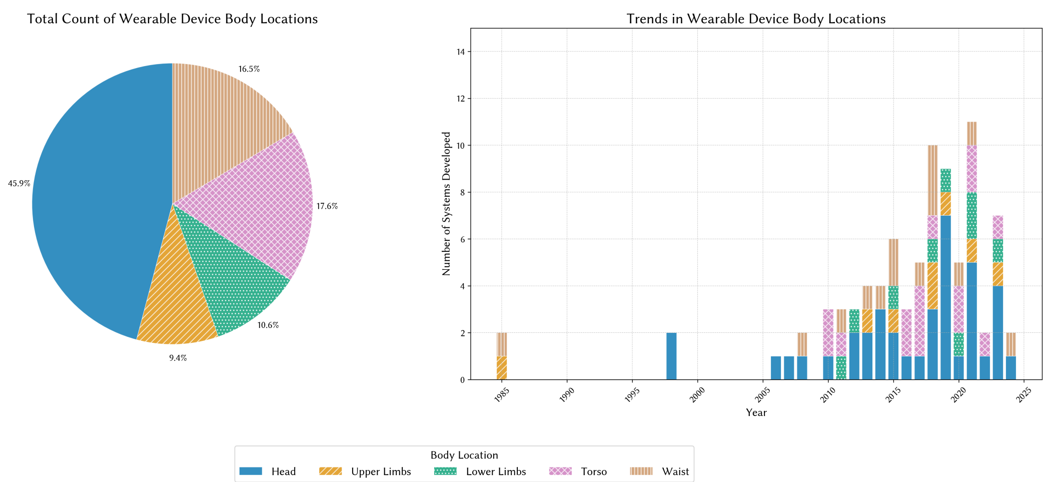

Figure 7: Distribution and frequency of development of different embodiments of wearable wayfinding robots, in aggregate and year-by-year respectively. The left part of the figure shows the counts of different wearable wayfinding robot subcategories; generally, there is a more uniform distribution of formulations compared to that of robot systems, aside from the overshadowing of head wearables, primarily because of headphones. The right part of the figure shows the trends over time for the various types of wearables. Specifically, we can see that head-wearables have been the dominate style of wearable for effectively the entire surveyed period (this is due to the common inclusion of headphones). Refer to Tables 1 and 3 for further specification. Note that the bar for 2024 on the right plot of the figure is artificially small due to the search window as discussed in Sec. 2.

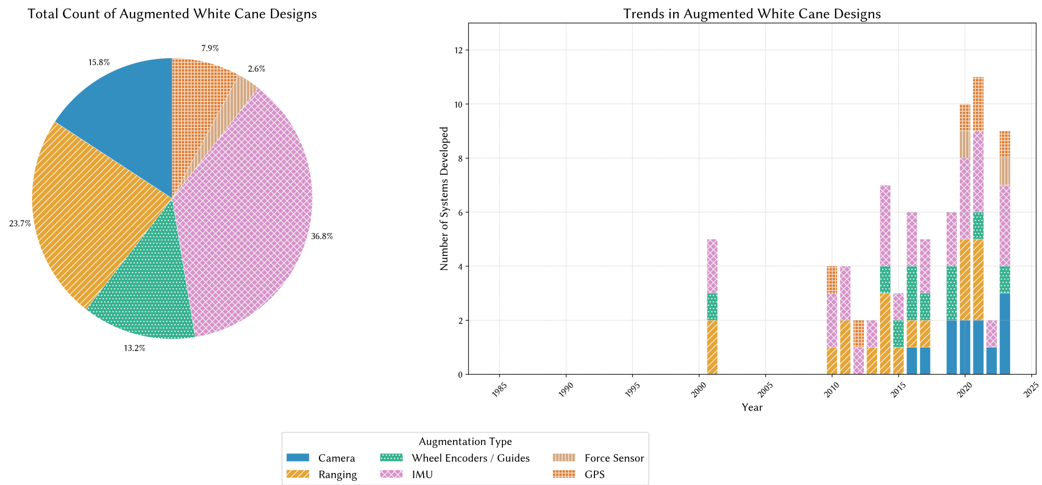

Figure 8: Distribution and frequency of development of different embodiments of augmented white cane wayfinding robots, in aggregate and year-by-year respectively. The left side of the figure shows the counts for the different augmented cane configurations. Note that most augmented cane formulations are very similar to that of traditional white canes; so, we highlight sensor diversity as a replacement for different embodiments. We can see that most augmented canes use an inertial measurement unit (IMU) alongside some perception unit like a camera or a LiDAR. The right side of the figure shows the trends over time for the various types of augmented white canes. We note that while there has been no recent surge in the use of robotic seeing-eye dogs (Fig. 6), there has been a steady increase in works investigating augmented canes as a wayfinding robot since 2001. Refer to Tables 1 and 4 for further specification. Note that the bar for 2024 on the rightside plot is artificially small due to the search window as discussed in Sec. 2.

input from the user [340]). This may or may not include a smartphone as a component of the overall system.

Recall from Sec. 1 that our Def. 2 excludes phone-based solutions and those that rely on static, environmentally pre-placed hardware. Although beyond the scope of this review, it is useful to briefly discuss several seminal non-robotic wayfinding works. GuideBeacon [63], CityGuide [62], and NavCog3 [4, 275] used Bluetooth beacons that have been previously installed in the environment to mark points of interest. A nearby wayfinding robot can then "see" the signal from these beacons, aiding in navigation and localization toward a specific goal, beyond what might be possible with GPS alone [62]. SeeWay [349] is an algorithm for indoor path planning based on a verbal instruction and images of landmarks. These studies were each developed for and deployed on smartphones. Finally, the VizWiz Grand Challenges [38, 119] have led to a surge in computer vision algorithms for varying aspects of visual question answering (VQA) [13] to help PwVI better perceive and understand their environment. For further discussion of such work for PwVI, we invite the reader to the existing reviews by Elgendy and Sik Lanyi [91] and Al-Razgan et al. [6], as well as the VizWiz project[10].

Table 1 provides a detailed categorical classification of taxonomy on a per-system basis. Based on their particular formulation, a wayfinding robot might not belong exclusively to one of these four categories but rather span two or more. Note that in Table 1, if a wayfinding robot *does* belong to more than one category, it is listed in each of the relevant categories (and subcategories). For further reference, we list these multi-class categorizations in Tables 2, 3, 4, and 5 for robot systems with varying additions, wearables with varying additions, augmented white canes with varying additions, and handheld devices with varying additions, respectively. Note that, for example, if a proposed wayfinding robot is a mixture of wearables and handhelds, it will be listed in both Tables 3 and 5 in the rows corresponding to wearable-handheld mixtures. We visualize these taxonomy tables via frequencies of embodiment occurrence both in total and over time at the top-level, robot system,

[10] https://vizwiz.org/

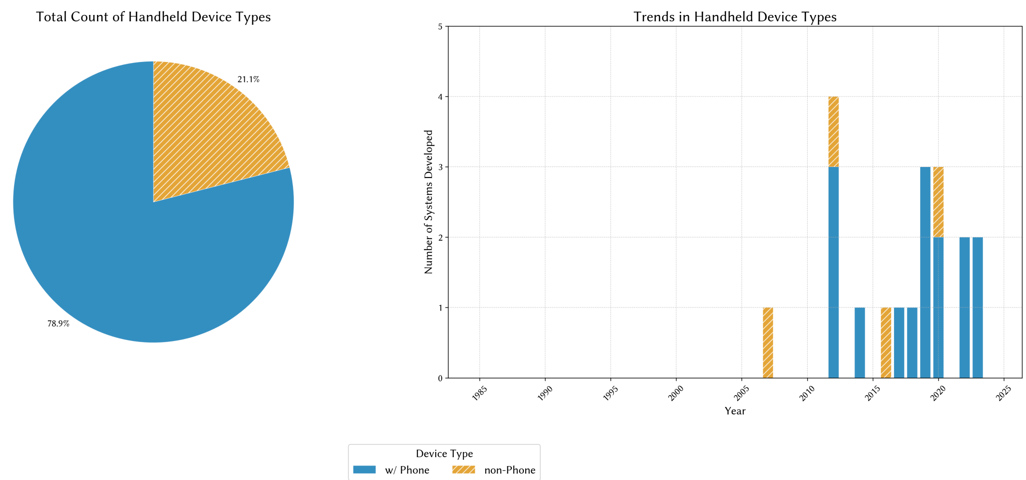

Figure 9: Distribution and frequency of development of different embodiments of handheld wayfinding robots, in aggregate and year-by-year respectively. The left side of the figure shows the counts for different handheld devices. The right side of the figure shows the trends over time for the various types of handhelds. Refer to Tables 1 and 5 for further specification. Note that the bar for 2024 on the right plot of the figure is artificially small due to the search window as discussed in Sec. 2.

wearable, augmented cane, and handhelds categorizations in Figs. 5, 6, 7, 8, and 9 respectively, and detail at length.

3.2.1 Robotic Guide Dogs

As seen in Fig. 6, legged robots are a recently common robot system embodiment utilized for robotic wayfinding. The vast majority of these legged robot morphologies are quadrupedal, although occasionally hexapedal [355], in the general formulation of what might be referred to colloquially as a "robot dog". Although quadrupedal robot dogs themselves are not a new system design, we attribute this recent surge in development and evaluation of robotic wayfinding to the increasing affordability of such robots from companies such as Unitree [323]. Notably, some of these robot dogs have a purchase price under $10,000 USD, which can significantly be cheaper than the cost of a real guide dog; canine guide dogs have associated costs that can reach as much as $42,000 USD or more for training, *etc*. [76, 293]. Although it may be too early for bipedal humanoid robots to be deployed for experimentation and evaluation in robotic wayfinding with PwVI, we anticipate that as production costs decrease and further innovation ensues, humanoid robots will become one of the common robot platforms developed for robotic wayfinding (though to act as a substitute for a human guide companion, rather than a guide dog). We discuss these ideas further in Sec. 4. Though many guide dog wayfinding robots are quadrupedal, there exists work that used aerial (*i.e.*, drone) [305, 364] or wheeled [200, 201, 332] wayfinding robots. Robotic guide dog wayfinding robots typically provide guidance by relying on some sort of physical coupling and force interplay between the wayfinding robot and the PwVI user, whether it be a leash [16, 61, 65, 76, 105, 122, 140, 144, 174–176, 180, 305, 322, 332, 334, 335, 342, 355, 364], or a harness [86, 168, 169, 331]. There are generally two formulations of leashes; slack-taut leashes (similar to a rope or string) [16, 61, 76, 105, 144, 174–176, 180, 305, 334, 335, 342, 364] and rigid leashes (not dissimilar from a white cane, but attached to the wayfinding robot) [65, 122, 140, 322, 332, 355]. Some of these rigid leashes have degrees of freedom for rotation, while others do not. Harnesses themselves are also rigid and are generally preferred among PwVI for guide dogs as opposed to solely leashes for reasons primarily rooted in safety [139]. We discuss the aspects of communication associated with such leash and harness designs as interactive forces in Sec. 3.4. However, not all quadruped robot systems were utilized for provisions of guidance; Sivacoumare et al. [292] used a quadruped robot as an agent to describe a user's surroundings (*e.g.*, enumerate objects present). There is little consensus as to the name of this

Table 1: High level device categories: colloquial robot systems, wearables, augmented whites canes, and handheld. If a solution falls within multiple categories, the reference will be put in both categories. *Note: (1) Wang et al. [331] contains two distinct systems; the reference in the robot systems→legged section refers to the first, whereas the reference in the robot systems→wheeled section refers to the second. (2) Kundu [182] contains two distinct system; the references in the wearable glasses and handheld phones sections refers to the first, whereas the reference in the cane→monocular camera section refers to the second. (3) Zhang et al. [365] contains two distinct systems; the reference in the wheeled robot section refers to the first, whereas the one in the canes section refers to the second.*

Device Type			Works
Robot Systems		Wheeled	[7, 21, 47, 51, 65, 105, 108, 110, 111, 115, 120, 133, 141, 148, 154, 155, 159, 160, 162, 173–176, 179, 180, 183, 194, 200, 201, 205, 221, 223, 233, 236, 239, 257, 260, 265, 285, 299, 304, 326, 331, 332, 334, 335, 356, 365, 372]
		Legged	[61, 76, 86, 122, 140, 168, 169, 215, 292, 331, 342, 355]
		Walker / Wheelchair	[51, 108, 120, 148, 221, 236, 265, 285, 326]
		Manipulator Arm	[21, 59, 306, 307]
		Drone	[16, 196, 197, 305, 364]
Wearables	Head	Headphones	[51, 52, 96, 110, 115, 116, 151, 179, 185, 200, 203, 214, 227, 236, 248, 252, 267, 281, 289, 290, 296, 305, 316, 340, 345, 347, 351, 358–361]
		Glasses	[11, 57, 100, 182, 267, 294, 316, 324, 347, 368]
		Helmet / Head-mounted	[83, 138, 185, 248, 296, 363]
	Upper limbs	Bracelet / Arm-band	[37, 116, 185, 248, 288, 304]
		Gloves / Fingers	[192, 211, 257]
	Lower limbs	Foot Attachment	[43, 151, 185, 192, 325]
		Leg-band	[122, 181, 196, 197, 325]
	Torso	Chest	[60, 83, 124, 191, 195, 211, 227, 252, 319, 330, 359]
		Shoulders	[43, 252]
		Necklace / Neck-hanging	[96, 360]
	Waist	Belt	[57, 83, 102, 131, 158, 236, 267, 289, 290, 304, 330, 364]
		Attached to belt	[43, 52, 94, 144, 325, 363, 364]
Augmented White Canes	Camera	Monocular	[57, 60, 138, 182, 284, 293, 351, 352]
		Time-of-Flight/ 3D	[351, 352, 359, 360]
		Stereo / RGB-D	[1–3, 358, 361]
		Tracking	[1–3]
	Ranging	(Ultra)Sonic	[37, 43, 96, 106, 138, 155, 214, 244, 255, 284, 290, 322, 327]
		Infrared	[57, 106, 255]
		LiDAR	[210, 293]
	Other	Wheel-like/ encoder tip	[155, 290, 293, 322, 351, 352, 358–361, 365]
		IMU	[2, 3, 60, 106, 155, 182, 210, 293, 351, 361]
		GPS	[10, 57, 138, 293, 365]
		Force Sensor	[57, 365]
Handhelds		w/ Phone	[14, 52, 94, 181, 182, 210, 216, 227, 257, 284, 345, 350, 368]
		non-Phone	[26, 144, 190, 283, 284, 330, 340, 350]

task of robotic guidance and navigation of a two-body system in this context; we propose the term *dyadic motion planning*, which we discuss further in Sec. 4.2.

Finally, we conclude with a note on designing a robotic guide dog as an instantiation of wayfinding robots. Most current such robotic guides are not designed with PwVI in mind; instead, they are constructed generally and then adapted to this particular task, usually only algorithmically (aside from creating and attaching a harness/leash). In other words, existing works typically utilize a Robots-as-a-Platform approach for the development of a specific algorithm. Furthermore, PwVI users with a guide dog often use a leash *and* a harness, where the latter is for primary communication and control and the former is for specific tasks, such as traversing stairs [139]; however, no studies detailed above integrate this dual design in their wayfinding robot (although recent work has begun to explore this [167]). Although wayfinding robots, such as quadrupeds, have great potential to act as robotic guide dogs, they often do not address user requirements, inducing stark disadvantages [139, 331]. It is imperative to incorporate the expectations of PwVI via, *e.g.*, participatory design, to move towards creating a purpose-built quadrupedal (or otherwise) robotic guide dog. We offer discussion on closing the gaps between expectations of PwVI and the current realities of robotic wayfinding in Sec. 4.6.

3.2.2 Wayfinding Robots on Wheels

Historically, wheeled robots have been the most common robotic system embodiment for wayfinding robots, as shown in Fig. 6; in fact, of the 71 wayfinding robots that utilize a robotic system formulation, 69% of them are wheeled. That said, we attribute part of this historical popularity of wheeled locomotion for wayfinding robots not to any sort of vast superiority, but rather to their wide availability and comparative ease of control. In fact, we see from Fig. 6 that, between 2020 (when the first legged wayfinding robot was proposed) and the end of data collection, wheeled robots account for only 55% of robot systems and legged wayfinding robots jump to 32% utility, again primarily due to the fact of increasing affordability of legged robots (Sec. 3.2.1). Some guide "dog" robots are built on wheeled bases rather than legged systems [200, 201, 332], as mentioned in Sec. 3.2.1. Compared to legged robots, wheeled robots can traverse large spaces more quickly and efficiently; however, they do not perform well when the terrain is not flat or non-deformable [39]. Stairs, for example, are a notable example of where a wheeled robot for wayfinding would not be able to assist PwVI (though other formulations, such as XR wearables, can; see Sec. 3.2.3).

Dragon [200, 201] is a highly representative work for a wheeled wayfinding robot. The objective is to help guide a PwVI user to a desired location or object, such as the kitchen or a chair, given a spoken command by the user. This goal-navigation is enabled by grounding visual language to the environment (*e.g.*, learning to assign natural language words and phrases to objects and locations in the robot's surroundings). Dragon supports dialogue (multi-turn, bi-directional conversation) to

Table 2: Papers reviewed that contain robot systems, as defined at the beginning of Sec. 3.2. The first partition contains works that are purely robot system solutions. The second partition contains works that use robot systems and wearables. The third partition contains systems that use robot systems with handhelds. The bottom partition contains works that use a robot system with (augmented) white canes. Note: Zhang et al. [365] proposed two distinct systems; the reference here refers to the first. Rahman et al. [257] belongs to both the second and third partitions.

Robot Systems	[7, 16, 21, 59, 61, 65, 76, 86, 105, 108, 111, 120, 133, 140, 141, 148, 154, 159, 160, 162, 168, 169, 173–176, 180, 183, 194, 201, 205, 215, 221, 223, 233, 239, 260, 265, 285, 299, 306, 331, 332, 334, 335, 342, 355, 356, 365, 372]
Robot Systems x Wearables Mixture	[51, 110, 115, 122, 179, 196, 197, 200, 236, 257, 304, 305, 364]
Robot System x Handheld Mixture	[257, 292]
Robot System x (Augmented) Cane Mixture	[155]

remove any potential ambiguity in the user's speech command. The grasp interface for the user is simple, resembling a traditional white cane. Other works attempted to emulate the overall white cane design as a grasp interface for PwVI but instead attached a small wheeled robot with sensors to the tip of the cane [155, 239].

Other wheeled robots have semi-anthropomorphic appearances with hands or arms. The Ballbot [194] has two simple 2-DOF arms that a user can grab onto; the motion of the arms and body induces a haptic communication interface, enabling PwVI to follow the wayfinding robot. However, this communication is only device-to-user; a speech dialogue interface, not dissimilar from Dragon [200, 201], is used to enable user-to-device communication. Balatti et al. [21] proposed a wheeled robot with a manipulator arm with an anthropomorphic dexterous hand to guide PwVI in unfamiliar environments. A user can grasp the robotic hand and be gently pulled along a safe path to a predefined goal. Notably, the pulling of the user is adaptive and varies according to the contrast between the current and ideal human poses. Their results showed that empirically, adaptive pulling reduced collisions between the user and environmental obstacles, as opposed to both no pulling and non-adaptive pulling. An interesting future paradigm for wayfinding robots is wheeled-legged robots, which combine the advantages of wheels and legs independently provide [39], allowing for a greater variety of environments and terrains that PwVI could utilize a wayfinding robot in.

A special subclass of wheeled wayfinding robots, in the form of walkers [51, 120, 148, 177, 224, 236, 265, 326] and wheelchairs [221, 285], are designed for PwVI and/or people with mobility challenges, such as older adults. Unlike many other robotic wayfinding systems, walker and wheelchair formulations can support some or all of a user's weight. This variant of wayfinding robot, not unlike augmented white canes (Sec. 3.2.4), typically has both active and passive guidance modes, which can be switched between manually by the user or automatically based on circumstances, such as avoiding an obstacle. Other walkers and wheelchairs are designed particularly for older adults, who are more prone to mobility challenges [177, 224]. A physically supportive, assistive robotic wayfinder has the potential to aid PwVI, older adults, and/or people with mobility challenges in daily tasks. The development of such wayfinding robots that can assist members of multiple demographics can allow for a wider impact and utilization. However, as PwVI often want to continue to use their traditional tools, such as a white cane, jointly with a wayfinding robot [30], it is important to consider how the interaction between PwVI and a load-bearing robotic wayfinder will facilitate the best user experience.

Although the previous works mentioned in this section can guide a user to the general desired location, they cannot assist with the last-few-meter or last-few-decimeter wayfinding problem of hand guidance to a specific intended object. At a much smaller physical scale is FingerRover [257], a small wheeled wayfinding robot worn on a user's finger to guide their hand to an object of interest (see Sec. 3.2.8).

Table 3: Papers reviewed that contain wearables, as defined at the beginning of Sec. 3.2. The first partition contains systems that use only wearables. The second partition contains systems that use wearables and (augmented) white canes. The third partition contains systems that use wearables and robot systems. The bottom partition contains systems that use both wearables and handhelds. Refer to Sec. 3.2.3 and Fig. 7 for further description. Note: Rahman et al. [257] belongs to both the third and fourth partitions.

Wearables	[11, 37, 83, 100, 102, 116, 124, 131, 151, 158, 185, 191, 192, 195, 203, 211, 248, 252, 267, 281, 282, 288, 289, 294, 316, 319, 324, 325, 347, 363]
Wearable x (Augmented) Cane Mixture	[43, 57, 60, 96, 138, 214, 290, 351, 358–361]
Wearable x Robot System Mixture	[51, 110, 115, 122, 179, 196, 197, 200, 236, 257, 304, 305, 364]
Wearable x Handheld Mixture	[52, 144, 181, 182, 227, 257, 330, 340, 345, 368]

3.2.3 Evolutions of Wearables

Wearable wayfinding robots are formulated in many different ways, as shown in Fig. 7 as well as Tables 1 and 3. Out of all wearables, we note that headphones are the most common, typically for purposes such as communication via the medium of audio (and often, speech). A subset of these audio wearables enables the delivery of spatial audio to the user, allowing PwVI to "follow" the direction in which the sound appears to come from [289]. Furthermore, we observed that head-mounted wearables or those that lie on the head, as well as chest-mounted devices and belts, were the most common wayfinding robot embodiments in the papers we surveyed. Head-mounted wearables encompass both the attachment of a camera to the head of user via *e.g*. a headband [363], as well as X-reality (XR) [11, 57, 294, 368] – which comprises virtual reality, augmented reality, and mixed reality [261]. For PwVI with low vision (rather than total blindness), XR can be used to overlay highlights on various objects in a user's surroundings (for example, stair drop-offs [368]). We discuss XR platforms as a communication interface further in Sec. 3.4. Refer to Kasowski et al. [157] for further details about the applications of XR for assisting PwVI.

Past work has shown that PwVI have a strong preference towards wearables that are body-mounted or head-mounted as opposed to gloves or other smaller handhelds [107], which aligns well with our empirical observations of commonality as a proxy. As is discussed in Sec. 3.4, there are a variety of communication interfaces used with wayfinding robots. In terms of wearables, one of the most consistently popular (device-to-user) communication interfaces is vibrotactile haptic feedback, often in the form of a haptic belt worn around the user's waist [83, 102, 131, 158, 236, 267, 304, 330, 364]. Built into these haptic belts are usually several vibratory motors that can be used to provide directional guidance (*e.g*., give a vibration in the direction the user should walk) [83, 131, 267], or give alerts indicating the relative orientation of some object (*e.g*., notify about an object 60 degrees to the left of the user). Although belts are popular means of disseminating information to users, they are also used to perceive the user's surroundings, such as with cameras [267] or an array of ultrasonic sensors [289, 290] on occasion. Regardless of function, belts are overall more discrete than some other embodiments of wearables [102]. More broadly, wearable wayfinding robots should be designed with ease of attachment in mind [102]. Some wearable systems utilize many sensors, each attached independently to different parts of the body [43]. Although this can provide a rich variety of data to better assist PwVI in wayfinding, it can come at the expense of usability in terms of ease of adornment, which can ultimately limit its adoption. Please refer to Secs. 3.2.9 and 4.3.2 for details and analysis respectively regarding the general lack of commercial adoption of wearable robotic wayfinding devices for PwVI, despite the continued growth in interest of researchers over the past two decades (Fig. 7).

3.2.4 Designs of Augmented White Canes

Unlike the other categories of robot systems, wearables, and handhelds, typical formulations of augmented white canes all have the same morphology. A typical design begins with either a traditional white cane or an object that resembles one, and then integrates various sensors to enhance perception beyond the standard $\sim$ 1m ground-level sensing radius of traditional white canes. Some works rely on ultrasonic sensors [322], whereas others rely on a fusion of LiDAR and camera vision [293]. Generally, an augmented white cane integrates a subset of various sensors, including RGB and stereo cameras, LiDAR and RADAR, IMU, GPS, and/or wheel-like encoder tips. Refer to row 3 of Table 1 for a fully enumerated list of frequently used sensor types. We leave discussion of sensing modalities themselves to Sec. 3.3, and instead focus here on the two main subcategories of augmented white cane wayfinding robots: (1) *active* augmented canes and (2) *passive* augmented canes.

Active augmented white canes have a mechanism that enables steering or otherwise physical guidance of the user. Some works utilize a grounded active rolling tip [351, 352, 358, 361], a motorized wheel-like tip attached to the end of the white cane, to steer the user as they follow a planned path. This rolling tip can be enabled or disabled by the user, allowing the PwVI user a sense of customization in toggling between active and passive guidance. While the grounded active rolling tip does provide information to the PwVI in the form of directionality, it does not provide more explicit forms of communication, such as force feedback, owing to the mechanical decoupling between the tip and the user's grip. Another approach proposes the utilization of grounded kinesthetic feedback in the augmented white cane design [293]. To clarify, kinesthetic haptic feedback involves applying physical force to induce certain motions of a person, which is in contrast to vibrotactile haptic feedback that simply uses a pattern of vibration on the user's skin to convey information (refer to Sec. 3.4 for further discussion on communication methods). In contrast to the rolling tip that is motorized only at the tip and does not directly apply force to the user, Slade et al. [293] used an omni-wheel to apply torque directly to the shaft of the cane, enabling real-time force feedback. Of particular note are the findings that grounded kinesthetic feedback tends to be more effective as a communication medium for navigation than audio or haptic feedback [293]. Similarly, other works considered the use of rotational torques [322] or centrifugal forces [10] to steer the user in a certain direction.

Passive augmented white canes can sense the user's environment with some sensor configuration, but cannot physically guide or steer the user. Such a formulation is more similar to a traditional white cane that has enhanced environmental perception due to, *e.g.*, the attachment of a camera to the cane [284]. While lesser in capability, passive augmented white canes are not necessarily defunct. Because their usage and form factor closely resemble those of traditional white canes, adaptation challenges should be minimal between traditional white canes and passive augmented white canes [170], as opposed to the slightly larger gap to active augmented white canes. It is worth noting that active augmented canes generally allow users to revert the cane into a passive mode [293, 351, 352, 358, 361].

A downside of augmented white cane wayfinding robots all sharing the same morphology is that they all share the same broad weaknesses. In particular, white canes are not very stable, resistant to interference, or able to provide any sort of physical support in terms of load-bearing part or all of a user's weight [365] (directly contrasting with the walkers and wheelchairs discussed in Sec 3.2.2).

Table 4: Papers reviewed that contain white canes augmented with various sensing capabilities, as defined at the beginning of Sec. 3.2. The first partition contains works that are purely based on integrating sensing technology with the white cane form factor. The second partition contains works that use an augmented white cane with a wearable(s). The third partition contains works that use an augmented white cane with a robot system. Refer to Sec. 3.2.4 and Fig. 8 for further description. Note: Kundu [182] and Zhang et al. [365] proposed two distinct systems; the reference here refers to the second.

Augmented Canes	[1–3, 10, 106, 182, 244, 255, 293, 322, 327, 352, 365]
Augmented Canes x Wearables Mixture	[43, 57, 60, 96, 138, 214, 290, 351, 358–361]
Augmented Cane x Handheld Mixture	[210, 284]
Augmented Cane x Robot System Mixture	[155]

Table 5: Papers reviewed that contain handhelds, including those that may make use of smart phones, as defined at the beginning of Sec. 3.2. The first partition contains works that use purely handhelds. The second partition contains works that used handhelds with wearables. The third partition contains works that used handhelds with an augmented white cane. Refer to Sec. 3.2.5 and Fig. 9 for further description. Note: Kundu [182] proposed two distinct systems; the reference here refers to the first. Rahman et al. [257] belongs to both the second and fourth partitions.

Handheld	[14, 26, 94, 190, 283, 350]
Handheld x Wearable Mixture	[52, 144, 181, 182, 227, 257, 330, 340, 345, 368]
Handheld x Augmented Cane Mixture	[210, 284]
Handheld x Robotic System Mixture	[257, 292]

3.2.5 A Word on Handhelds

As is seen in Fig. 9 and Tables 1 and 5, handheld wayfinding robots are not commonly developed compared to the other three categories of our wayfinding robot taxonomy. The majority of handheld systems counted in Fig. 9 rely on using a mobile phone's sensors, such as IMU or camera, often in conjunction with some other system, *e.g*. an augmented white cane [284]. Reliance on common sensors integrated with most mobile phones may be more realistic than the expectation for a PwVI user to buy a special wayfinding robot with unique proprietary sensors, as users likely already own a mobile phone. However, a few novel handhelds have been proposed, including a custom tactile user-to-device communication device equipped with buttons and a scroll wheel [340]. Wang et al. [330] utilized a handheld braille display that refreshes to convey obstacle distance information. However, prior work has found that PwVI strongly prefer wayfinding robots that are not gloves or handhelds [107]. Given these findings and the general desire of PwVI to continue to use their traditional tools, such as a traditional white cane, in addition to a wayfinding robot [30], we offer the conclusion that although further exploration of small handhelds may hold academic interest, such devices appear to have a lower likelihood of gaining real-world adoption with PwVI.

3.2.6 Immobile Guides

Recall that our definition of wayfinding (Def. 1) draws on Orientation & Mobility (O&M) themes from the social sciences. In O&M, a simple method for (temporarily) conveying information is the palm-drawing method [28, 306], whether it be for spatial and navigational information [28, 306] or rudimentary communication [310]. Here, a guide can trace a route on the palm of a PwVI with their finger to indicate directions. A subset of work has applied this idea to robotic manipulator arms as an immobile (and temporary) provider of physical guidance [59, 306, 307]. Such a system can facilitate a touch-based device-to-user communication medium by using the end effector to "draw" a route on the palm of a PwVI user to provide directions to a destination. The typical intended application and environment of this particular wayfinding assistant is often as a kiosk clerk at the entrance to semi-familiar or unfamiliar public spaces, such as a mall. Such a deployment is reasonable, as PwVI often report consistently high levels of confidence only when navigating familiar areas, such as their homes [130]. There are many connections between the formulation of manipulator arm wayfinding robots and communication interfaces at large; we refer the reader to Sec. 3.4 broadly for discussions on communication.

3.2.7 Aerial Guides

Beyond systems anchored to one position, such as the aforementioned robotic manipulator arms, there has been a recent interest in exploring the utility of drones as wayfinding robots [16, 196, 197, 305, 364]. Typically, these drones are connected to some sort of leash that is either held by or attached to the PwVI user [16, 305, 364], while others have proposed tracking the user untethered [196, 197] and communicating with a haptic wearable during dynamic activities such as running. Although drones may be desirable because of their high degree of maneuverability, the effects (if any) of the noise produced by the drone propellers on the aural environmental perception of PwVI (as discussed in Sec. 1, PwVI strongly rely on their sense of hearing to understand their surroundings) are not well explored. Furthermore, concepts such as privacy and discreetness have not been deeply investigated [18, 36, 130]. We invite future studies to investigate such concepts to help inform the future design of more agile wayfinding robots.

3.2.8 Hand-based Wayfinding in the Haptic Space

Although many wayfinding robot formulations have been discussed thus far in Sec. 3.2 can effectively assist PwVI in navigating to a general point of interest, there is typically still a final small distance to go, commonly referred to as the last-mile problem. The problem of last-mile navigation generally refers to navigating to a nearby (ideally visible) object after arriving at the correct general region [333]. In the context of robotic wayfinding, Saha et al. [272] termed this general navigation challenge as *last-few-meter wayfinding*. For example, wayfinding robots that rely on GPS for positioning are exposed to several meter errors commonly associated with GPS signals [272]. Although the use of a real-time kinematic (RTK) global positioning variant, as in some works [52], can limit this error to a few centimeters, wayfinding is generally not limited to only the overall body position in some coordinate frame, but depending on the specific goal, can also include physically grabbing the object. Even wayfinding robots that utilize mapping and localization methods [200, 360], such as SLAM [87], can achieve a lower position error than GPS in a sufficiently feature-dense (indoor or outdoor) environment [117] and still may not be sufficiently fine-grained for hand-level guidance and interaction. Some systems [3, 330] explore last-few-meters wayfinding with a camera, either as a wearable or on an augmented cane, to assist PwVI in reaching certain targets such as a chair. For example, Wang et al. [330] used a vibrotactile haptic (*e.g.*, vibrations; see Sec. 3.4) belt and refreshable braille display to guide the user, whereas Agrawal et al. [3] combined audio with vibrotactile haptic commands to provide directions.

This more local challenge of wayfinding in the haptic space (the space reachable by a person without taking a step [2, 110]) we term the *last-few-decimeter wayfinding problem*. Wayfinding robots designed for this task often involve the use of wearables. For instance, Shih et al. [288] developed a haptic wristband with a mounted vision system that can provide directional vibrotactile feedback cues to guide the hand to a target object. Similarly, Gui et al. [116] created a gesture-based system that can either verbally describe an object a user points to or guide the hand (again with a vibrotactile wristband) to an intended object. Viia-hand [248] adds a head-mounted camera and uses both speech and spatial audio (sounds manipulated to appear emanating from an object or direction) to direct hand motion. In a more specific context, ShelfHelp [1, 2] and Gharpure and Kulyukin [110] explore simplifying the everyday task of grocery shopping by helping guide the user to select particular products; these wayfinding robots use speech to guide the user's hand, though with varying levels of verbal instructions. Uniquely, FingerRover [257] is a small wheeled robot worn on a user's finger, with the purpose to "drive" the user's hand to the object of interest, around any obstacles on *e.g.*, a desk.

Despite this variety of works on this last-few-distance wayfinding problem, these methods are often designed to search for a finite ontology of objects (*e.g.*, 7 [116] or 10 [288] object categories). A promising future direction to overcome this hurdle is teachable AI [225, 338], which enables PwVI users to "teach" an AI model, personalizing it to recognize and more effectively search for a particular user's belongings (moving beyond predefined classes). Furthermore, most of these wayfinding robots detailed are wearable-based; an area ripe for exploration would include creating robotic system wayfinding robots that can assist with this last-few-decimeter wayfinding task in addition to other tasks that such a type of system already assists with today.

3.2.9 Commercially-available Robotic Wayfinding Products

The wayfinding robots discussed until now, including in the taxonomies Tables 1, 2, 3, 4, and 5, were sourced from academic venues as discussed in our methodology (Sec. 2). However, given that robotic wayfinding research is very user-facing, we found it important to touch on the potential for the commercialization of such devices. Although not a wayfinding robot, some of the products that have seen the most success thus far with the PwVI community have been mobile apps, such as BeMyEyes [31]. BeMyEyes is designed to perform visual question answering (VQA) [13] to describe a user's surroundings and connect with a sighted volunteer who can see through the mobile phone's camera to assist in the completion of tasks. Prandi et al. [253] found that such apps are generally versatile and work in varying environments. However, these apps cannot physically guide users, instead relying on instructions from sighted volunteers, which may be ambiguous to PwVI [44].

There exists several commercial robotic wayfinding products. One example is Glidance's Glide [142]. Glide is somewhat of a smart cane inspired by a guide dog; it is wheeled and can steer a user around static and dynamic obstacles with the capability to perform VQA, and exhibits a haptic handle to provide a non-language medium of communication. Glide is notable because, unlike many works in robotic wayfinding, it is designed in conjunction with PwVI. Another commercial wayfinding robot is NextGuide's augmented white cane [235]. This augmented cane can detect obstacles up to 10 meters away (in contrast to the $\sim$ 1m radius that a traditional white cane provides). It employs a tactile thumb-pointer that swings to point in the direction of a space free of obstacles to communicate with the user. However, this work is in its early stages and is not widely commercially available as of this writing. Another commercial solution is LUCI [206], an intelligent wheelchair designed for PwVI and/or individuals with mobility challenges. LUCI utilizes a full sensor array, including radar, camera, and ultrasonic sensors (refer to Sec. 3.3 for further discussion on typical sensing and algorithmic formulations). Instead of acting as a fully autonomous navigation platform, it emphasizes shared control to allow the user to have the desired amount of control while preserving safety in anomalous conditions. Finally, Guidi [204] is one of the few wearable robotic wayfinding products in the market; it is a belt-like wearable with cameras, haptic feedback, and GPS. As will be discussed with respect to haptic communication in Sec. 3.4, different vibration patterns can be utilized to guide users around hazards. A commonality observed across these commercial robotic wayfinding products is their integration of haptics as a communication medium; although language can contain rich information, it has the potential to be ambiguous and may take too long to disseminate [45] in real-time conditions, such as for hazard avoidance [159, 340].

We do not claim this product list to be complete, but rather a representative sampling of the current market space. However, there are not many products in the market designed for robotic wayfinding in general at the time of this writing. We discuss further barriers and trade-offs of commercialization and wider adoption by the PwVI community, as well as the market gap in Secs. 4.3 and 4.6 respectively.

3.3 RQ3: What methods of sensing/perception are commonly used in these robotic solutions?

3.3.1 Global and Local Perception

Any robotic solution for wayfinding requires a method that perceives the environment to guide the user effectively. Information from the environment that is useful for navigation can be considered from both global and local perspectives. Global navigation entails knowing one's location in relation to a goal, even if the goal is outside one's immediate vicinity. This information is useful for planning routes from start to goal and typically relies on information from a GPS or GIS system. Local navigation requires knowledge of the location of objects in the vicinity relative to oneself. This is important to avoid collisions with obstacles but can also be used with odometry methods to build a global frame of reference in the absence of GPS and can aid in route planning by distinguishing between occupied and free space. Of the 116 wayfinding robots that implemented obstacle detection, 72 used this information to avoid obstacles, 59 alerted users about obstacles, and 106 used information about obstacles (note that some were multifaceted). A wayfinding robot that treats objects as sources of information rather than solely as hazards could provide great benefits, as this is more closely related to the wayfinding skills currently used by PwVI [238].

3.3.2 Sensors for Perception

The most commonly employed sensors were cameras, which were used in 92 robotic wayfinding assistants. This is perhaps the most intuitive solution because the goal is to supplement the user's lack of visual information regarding the world. Cameras can be made small, relatively cheap, and are widely available in consumer devices such as smartphones. There are many different types of cameras suitable for different applications.

Monocular cameras were the most common camera included in sensor arrays, used in 53% of the 87 wayfinding robots that incorporated cameras. This encompasses any type of camera with a single lens, including most RGB cameras typically found in smartphones and other consumer devices. They are frequently used in conjunction with RFID tags or other visual beacons, either in the environment or on the user [110, 154, 179, 182, 233]. However, one limitation is the lack of depth information in the data. Depth can be extracted from an RGB image using machine learning or other computational methods [54, 259, 348], but not without some ambiguity (which may be tolerable depending on the application). The computational power required makes such solutions infeasible at scale [358], although recent work has made progress towards faster, on-device depth estimation [259] through training on large-scale unlabeled data [348]. Future wayfinding robot works could instead consider exploring applications of monocular depth estimation models [54, 259, 348] as a means to decrease both the cost and size of the hardware. Most wayfinding robots use monocular RGB cameras instead for object identification or scene description [65, 69, 105, 124, 140, 181, 185, 257, 283, 284, 293, 299, 317, 319, 324]. Obstacle detection from a monocular camera over a series of frames can be used with a visual odometry algorithm to provide user localization [319]. Frequently, however, processing data from a monocular camera requires connection to a separate computer or database system [47, 69, 181, 196, 197, 257, 283, 334, 335, 340, 345]. Devices that use machine learning models for object detection are typically trained on a separate device and can only run a reduced model on the device itself, particularly lightweight wearable devices [65, 69, 140, 227, 284, 288, 292, 293]. Another limitation is that monocular cameras typically have a relatively narrow field of view (FOV). To circumvent this limitation, potential solutions have included a monocular fisheye camera [288] or the placement of several cameras facing different directions to provide a larger FOV in the aggregate [65].

Stereo cameras use two lenses separated by a fixed baseline distance. The relative change in the location of the same object detected in each lens (disparity) can be used to estimate the distance of the object from the camera. Stereo cameras are the most commonly used solution for depth estimation. This can also be useful for tracking the location of a human user relative to a wayfinding robot [223, 342]. Depth information can be used to inform PwVI of the distance to a target object [116, 141]. More accurate depth information can be obtained when combined with LiDAR [355] or tracking cameras [2]. Additionally, they can achieve the same functionality as a monocular camera by considering only the information from one lens. They were used in 35 reviewed devices, with the Intel RealSense D435 and ZED being the most common stereo cameras. Other work used structured light for depth estimation with a sensor, such as an Xbox Kinect, which projects a known infrared pattern onto objects in the FOV [223, 236, 296, 347].

Tracking the position of the device while moving requires more than visual information; it requires an Inertial Measurement Unit (IMU), which is a sensor that combines an accelerometer, gyroscope, and magnetometer. 34 devices surveyed used an IMU. When integrated with stereo cameras, readings from an IMU can be used with algorithms such as Simultaneous Localization and Mapping (SLAM, described further in 3.3.3) to provide continuous estimates of the device location while moving through space [68]. Tracking cameras, such as the Intel RealSense T265, perform onboard processing to directly output the pose estimation of a device [2, 3] based on sensor readings from, for example, fisheye cameras and IMUs. However, they cannot provide depth information and as such, wayfinding robots that deploy tracking cameras are often utilized in conjunction with stereo depth cameras [2, 3, 168, 169, 252, 361].

Ranging was the second most common sensing paradigm used in 71 of the surveyed wayfinding robots. Ranging sensors directly estimate distance by emitting light (LiDAR, laser, and infrared sensors), sound (ultrasonic), or radio (radar) waves and measuring the time it takes for them to return. The combination of LiDAR and infrared sensors is the most common solution for this category of applications. Light Detection and Ranging (LiDAR) and infrared sensors, used in 21 devices surveyed, provided precise distances to a single point. LiDAR, which was used in 27 surveyed devices, extends this by sending out multiple beams of laser light in varying directions, allowing it to completely map a scene. Depending on the granularity desired in the current environment, a wayfinding robot can use LiDAR that is 3D (obtains a three-dimensional reconstruction of the surroundings), 2D (obtains a top-down view of the surroundings), or 1D (obtains the distance to the closest straight-ahead object), although adding sensing dimensions significantly increases the price of the sensor. Similarly, 3D time-of-flight cameras, such as the Swiss Ranger 4000 [351, 352, 360], pulse-modulated infrared light into an environment and measured the phase shift to obtain depth maps. Light-based sensors are generally limited by environmental lighting conditions, but others, such as ultrasonic and RADAR sensors, do not have this issue. Ultrasonic sensors were the second most common type of ranging sensors used in 29 wayfinding robots. They operate by emitting high-frequency sound waves well above the limits of human hearing [327]. Some devices use multiple devices facing different directions to ensure that the scene can be fully mapped [255]. RADAR (Radio Detection and Ranging) is a less common solution used in only two devices surveyed [205, 210].

Sensors can provide estimates of the position of objects relative to the robot; however, many devices rely on GPS or a beacon system to obtain global position estimates. Nineteen surveyed devices relied on connections to some kind of satellite-based positioning system (*e.g.*, Global Positioning System (GPS) or Global Navigation Satellite System (GNSS)). GPS is a well-established and widely available technology, but it often cannot provide position estimates to the level of specificity needed to navigate a pedestrian. GPS signals are also often unreachable indoors; therefore, indoor devices typically rely on beacons or markers. A beacon is any type of audible, visible, or otherwise perceivable (*e.g.*, via radio frequencies) landmark that is purposely embedded in an environment to be easily sensed by smart devices. Common types of beacons use technologies including Bluetooth Low Energy (BLE), Ultra-widebandwidth (UWB), and Radio Frequency Identification (RFID). All of these require very little power to operate and can be easily sensed by a device with the necessary capabilities. One major drawback of this method is that it requires installation in the environment prior to use by PwVI, which is not scalable. A less common sensor type is wheel-and-joint odometers. These sensors are prone to drift; however, fusing the readings from these sensors can improve the accuracy of odometry algorithms.

3.3.3 Algorithms

In addition to having sensors to perceive the environment, any collected sensor data are meaningless without effective algorithms to process and leverage them for decision-making. These algorithms have evolved over time to match the available hardware and required functionality. The main functions performed by the algorithms surveyed were object detection and recognition, localization and mapping, path planning, and control functions.

Perception algorithms receive raw data from sensors and convert them into other information, such as free-space paths, the presence of pedestrians, or the detection and identification of obstacles. Due to the popularity of cameras, vision algorithms are the most common algorithm type, explicitly mentioned in 36 of the 148 wayfinding robots.

Among computer vision algorithms, the You Only Look Once (YOLO) algorithm [263] is the most common. YOLO was introduced in 2015 and has since become the standard for object detection due to its low inference latency. YOLO achieves this by simultaneously classifying and localizing objects using a single Convolutional Neural Network (CNN). Although not as accurate as other vision algorithms, its speed makes it ideal for a variety of uses, including assistive navigation devices [263]. Nine devices surveyed used some version of the YOLO algorithm [47, 69, 115, 124, 133, 159, 160, 293].

Another common algorithm is RANdom Sampling And Consensus (RANSAC) [101]. RANSAC is a method for fitting a model to noisy data that automatically filters out outliers, which is particularly important when working with noisy sensors, such as cameras. It does this by starting with a model using as few data points as possible and then iteratively enlarging the set with compatible points. It was used by several wayfinding robots [83, 105, 352, 358, 359], three of which incorporate it to aid in estimating pose during visual odometry (described in the next paragraph below) [352, 358, 359]. One device uses RANSAC to aid in finding paths to follow by locating the vanishing point of the lines in an image [105]. Another device uses RANSAC to segment a floor and identify free space [83].

Once information about the environment is extracted from the sensors, it can be used to create a map (a representation of the environment) and the user's location within that environment. Odometry algorithms can provide an estimation of the position and orientation of a device at each time step. Although many sensors can be used for this task, visual odometry methods are the most common owing to the wide availability of camera devices [15]. Eight devices surveyed used some form of visual odometry [69, 252, 288, 352, 358–360, 363]. One device relied solely on a fisheye lens camera and used a deep learning network to extract pose information [288]. Two other wayfinding robots relied on stereoscopic cameras to obtain depth information directly [252, 363]. Pose estimation can be improved by adding other sensors. The most common combination is to use a Visual Range Odometry (VRO) algorithm with readings from a time-of-flight camera, such as the SR4000 [352, 359, 360]. One device used Visual Inertial odometry algorithms to combine readings from a camera and an IMU [69]. Another device combined all these modes of sensing, IMU, camera, and depth, to create a depth-enhanced visual inertial odometry (DVIO) algorithm [358].

Points obtained from an odometry algorithm, in addition to LiDAR point clouds and/or a series of egocentric images, can be used to update Monte Carlo Localization (MCL) (*i.e.*, particle filtering) [78], used in 70% of the 20 wayfinding robots that explicitly describe their respective localization algorithms. Particle filtering is a Bayesian filtering method. A Bayesian filtering algorithm maintains a "belief" about its location. The MCL stores this 'belief' as a sampling of points from a probability distribution, where each point represents a probable location on a map. At set time intervals, this belief is updated based on previous beliefs and the differences between the previous and current sensor measurements. As more measurements are obtained, the distribution of points gradually becomes narrower until it converges to a small area of likely positions. Adaptive MCL (AMCL) [103] adapts the number of particles used to keep localization error under some bound, enabling a faster rate of converge than MCL, at the cost of increased memory usage. MCL and AMCL are quite common filtering methods, used in 11 of the 14 wayfinding robots that localize via particle filtering.

Another localization method based on Bayesian filtering is Kalman filtering [152]. Similar to the MCL, Kalman filters (KF) store beliefs as samples of particles; however, these particles are assumed to come from a Gaussian distribution. This renders KFs less computationally expensive. However, the probability distribution for localizing a mobile robot is often multimodal and cannot be accurately represented by the single (unimodal) Gaussian distribution used in the standard Kalman filter. Six devices surveyed used some type of KF: [52, 61, 151, 192, 216, 332]. For further insights into the many variants of KFs, see Khodarahmi and Maihami [165].

For mapping the environment, Simultaneous Localization and Mapping (SLAM) [87] is the most common solution, used in 34 of the 36 wayfinding robots included that employ mapping techniques. SLAM allows a robotic device to jointly localize and construct a map as it navigates, even if it has never entered that space before, making it a valuable tool for a wayfinding robot to guide a user through a space unfamiliar to both the robot and user. For future discussions on localization and mapping methods for assisting PwVI, we refer the reader to the survey by Bamdad et al. [23]. Once a map has been constructed, and the user's position within it determined, a wayfinding robot requires a path-planning algorithm to navigate from its current location to the goal of the user.

Search-based planners such as A* [125], Dijkstra [84], RRT* [156] and others are explicitly described in 14 of 149 devices surveyed. These algorithms can be applied to an existing map of a space to efficiently determine the optimal path between the robot's current position and goal. Although they did not design a wayfinding robot, Mohammadi et al. [219] proposed a path-planning algorithm utilizing GANs [112] to generate paths for use by any wayfinding robot to guide PwVI. Other work, also using an A* variant, considered how to first navigate the robot to PwVI for subsequent assistive wayfinding use [198]. Future work in robotic wayfinding could investigate the applications of recent state-of-the-art planning algorithms such as Neural Informed RRT* [134] or LLM-A* [217]; we refer the reader to the surveys by Zhang et al. [362] and Nahavandi et al. [228] for more details on the navigation algorithms. In Sec. 4.2 we argue for concretizing a new motion planning paradigm for probabilistic dyadic systems, *e.g.*, a robot and a person moving jointly together while physically connected, where, for example, the robot acts as a guide [233].

Preventing collisions between the dyad (the wayfinding robot and user) and various objects along a planned path is important for enabling safe guidance of PwVI. Dynamic Window Approach [104], a trajectory planning method, is especially suited to collision avoidance in the presence of dynamic obstacles, such as pedestrians or vehicles, by planning over short time intervals. It was used in six works surveyed, typically for handling local navigation [76, 108, 115, 183, 200, 201]. Other collision avoidance algorithms sometimes used aboard wayfinding robots include Vector Field Histograms [41] and Artificial Potential Fields [164].

For mobile robots, once the environment has been perceived and a path has been planned, the exact control commands required to execute the actions must be computed. Algorithms for control use information on the device's current state and previous actions in an environment to compute the best future action to maximize a reward. The two main types of algorithms that emerged in the literature are Model Predictive Control (MPC) [279] and Reinforcement Learning (RL) [291], described in seven of the 148 wayfinding robots covered in this study. RL has the advantage of not requiring a system model, which is particularly useful if the system is complex or the model is unknown. However, it requires time to train, and not relying on a model means that RL algorithms are sensitive to changes in the system. MPC can fully exploit the dynamics of a model; however, for complex systems, it can be much more computationally expensive. One device surveyed used MPC [332] to better model both humans and robots in a guiding scenario. Six of the seven devices used some variant of RL [1, 108, 168, 169, 205, 223]. One variant of RL, Decentralized Distributed Proximal Policy Optimization (DD-PPO) [339], was used in two devices surveyed [168, 169]. This method makes learning a model more feasible for resource-intensive systems, such as small wearable devices. Q-Learning [318] is another RL variant used in one device [108] to model intent of a user. An interesting future direction of intent modeling could entail investigations of intent prediction for the purposes of collaboration[135, 136] or proactive provision of assistance [64, 137] to PwVI in, *e.g.*, a table-top environment (see Sec. 3.2.8) or mobility scenarios.

Current systems must balance providing all the information and accuracy necessary to guide the user while remaining lightweight, power-efficient, and cost-efficient. Older systems rely on bulkier sensors; advances in sensor hardware design and machine learning have enabled the production and amplification of capabilities of smaller sensors. Further advancements in technology are likely to benefit what can be done in this area.

3.4 RQ4: What methods of communication are commonly used in these robotic solutions

Effective communication across a human-machine interface typically requires efficient bidirectional information transfer: (1) device-to-user (Sec. 3.4.1), and (2) user-to-device (Sec. 3.4.2). However, both directions are not often considered simultaneously in the development of wayfinding robots. Tables 6 and 7 classify the works according to the various methods of communication employed in the device-to-user and user-to-device directions, respectively. Of the 148 devices wayfinding robots surveyed, 62 did not implement or describe user-to-device communication, and 9 did not implement or describe device-to-user communication. For user-to-device communication, we do not consider implicit cues, such as walking around with the device or moving the device in an ordinary manner (*e.g.*, normal white cane usage) to constitute user feedback. It is unlikely that a device that is fully capable of navigation or obstacle avoidance will be used in practice if communication with that device is not intuitive or efficient. The type of information that needs to be transferred depends on who the active agent is and how tasks are shared between the human and the device. We observed three main paradigms in our review: robot-active solutions, human-active solutions, and shared autonomy solutions. These paradigms have also been noted by other authors [232, 365].

In *robot-active systems*, the robot drives the motion with the human following. In this context, "robot" refers more generally to any device with actuation abilities that give it mobility, and not only devices that fall under our definition of a *wayfinding robot* in Def. 2. Devices that can mobilize themselves are often much more expensive and complex to develop than those that cannot. However, this paradigm is applicable to several mobile robotics solutions [183, 200, 257, 322]. From that point, the only communication that needs to occur between the user and device is the movement of the robot itself, indicating where the user should follow. The burden of communication is predominantly on the user rather than the device. An advantage of these systems is that they can be useful for PwVI with additional mobility challenges. For example, autonomous wheelchairs (Sec. 3.2.2) can drive the movement of a wheelchair-bound user [221]. However, a disadvantage of these systems is that the designers often do not provide many opportunities for the user to provide feedback throughout the guidance [86, 169, 305, 331]. Consequently, although these devices may be useful for navigating to a specified location, it may be difficult for a user to explore a space where there is no specific intended destination. Furthermore, many designers do not consider any information that the robot might provide to the user, beyond its movement.

In *human-active systems*, the human user drives the motion with the robot, either worn or carried. Because human-active systems do not require mobile actuation, they are significantly cheaper to develop. This category includes wearables, sensors integrated with white canes, and some mobile robotic solutions. These devices mostly support obstacle avoidance, although some can perform higher-level navigation. For a human-active system, the user does not necessarily need to communicate a destination unless the device provides navigational assistance. However, the device must communicate either (1) obstacle and hazard locations or (2) areas of free space. Here, the communication medium is something other than independent movement; therefore, the burden of communication is predominantly on the device, not the user. The advantages of these systems are that they give the user more freedom to explore a space because a specific destination does not need to be provided. The main disadvantage of this style of system is that users with mobility challenges may be unable to use them, as these systems are often heavy and bulky, and the burden of movement is on the user.

In *shared-autonomy systems*, the movement is shared between the user and the device. The degree to which movement is shared varies widely across devices. The earliest example of this paradigm was a robotic walker by Rentschler et al. [265] in 2008, which allowed the user to be in control until an obstacle was detected. Upon detecting an obstacle, the autonomous mode is activated until the user is safely guided around the obstacle. Several devices [351, 352, 358] have been developed for (active) augmented white canes (Sec. 3.2.4) with wheels added to the end, where the user pushes the cane, but the steering mechanisms in the wheel allow the device to indicate the direction of travel to avoid obstacles. Another example embeds partial autonomy in cane-like and car-like guidance robots [365]; the partial autonomy mode is used to give users the ability to set the speed by pushing and pulling the robot while the robot autonomously steers. Shared autonomy is a newer and less common paradigm, but it has been steadily increasing, with three devices reported in 3 devices from 2023 alone [76, 260, 355]. Because motion is shared between the robot and user, the burden of communication in such formulations is shared. This could allow for greater customization of the wayfinding robot subject to the user's needs and preferences whilst being guided.

The content of communications between the user and device can be defined by both the paradigms described above and the general context, which is the purpose of wayfinding robots. However, *how* this content is communicated must still be considered.

3.4.1 Device to User Communication

As listed in Table 6, audio (whether spoken or not) and haptic interfaces are by far the two most common mediums to facilitate communication *to* the user. In particular, the distribution of devices incorporating haptic and speech interfaces has not seen too much change as the number of devices has grown, as visualized in Fig. 10. Although the way in which information is communicated to PwVI is important, neither audio nor haptics is universally better than the other; each medium poses challenges as well as favorable benefits, which may depend on both user preference and the current environment the user is inhabiting.

Speech audio is utilized by many of the wayfinding robots in Table 6 for providing directional guidance, whether it be at the granularity of *e.g.*, "Turn left" [100, 319] or "Turn X-degrees left" [293]; others also provide semantic feedback to enable environmental awareness [115, 200, 205, 359]. Spatial audio, regardless of whether it contains speech, simulates binaural hearing to create the illusion of a sound originating from a particular direction. This audio variant can be used as an aid for spatial awareness and, broadly, navigation. It is worth noting that typically, only non-speech audio is conveyed binaurally (since spoken language already can contain spatial information as in the example of directional guidance in the previous sentence); of all papers surveyed, only Loomis et al. [203] utilizes spatial speech audio. Although language-based communication can be rich in detail, it is partial to unintentionally induced ambiguities [44, 178]. For example, a wayfinding robot that provides verbose spoken directions whilst containing little sensory information may be challenging for PwVI to accurately follow [44]; more broadly, PwVI may struggle more with spoken directions provided by a person with sight as opposed to another PwVI [44]. Early audio feedback devices using natural language relied on scripted dialogue or finite vocabularies. Newer works, although ultimately still reliant on a fixed ontology, utilize multi-turn conversation (dialogue) [194, 200, 201] between the wayfinding robot and user as a means to remove possible perceived ambiguities in the user's request within the context of a prebuilt map with visual-language grounding [200, 201]. Recent developments in Large Language Models (discussed further in Sec. 4.1) and broadly open vocabulary systems are growing in possibility for inclusion in the designs of wayfinding robots for more dynamic provisions of support and assistance to PwVI.

Non-speech audio, on the other hand, is simply sound that does not include spoken language. For example, BBeep [159] is a luggage-shaped wayfinding robot that emits a beep-like tone to alert nearby people to move out of the path of PwVI. Non-speech audio is often used to communicate information that must be given frequently, such as heading of travel or obstacle direction [51, 52, 96, 100, 191, 195, 227, 248, 289, 296, 319, 340], or to communicate urgent information that would take too long

Table 6: Communication methods for *device-to-user* interfacing: haptics, audio, and visual feedback. If a work falls within multiple categories, the reference will be put in each category.

Communication Method (Device to User)		Works
Haptics	Manipulator arm	[59, 306]
	Map	[190]
	Interactive forces	[7, 10, 16, 21, 47, 61, 65, 76, 86, 105, 106, 108, 110, 111, 115, 120, 122, 140, 141, 144, 148, 155, 160, 162, 168, 169, 173–176, 179, 180, 183, 194, 200, 201, 205, 221, 223, 233, 239, 257, 260, 265, 290, 293, 299, 305–307, 322, 331, 332, 334, 335, 342, 351, 352, 355, 356, 358, 364]
	Vibrotactile	[1, 3, 26, 37, 43, 57, 60, 83, 94, 102, 106, 115, 116, 131, 148, 158, 185, 192, 196, 197, 211, 214, 236, 244, 252, 255, 260, 267, 284, 288, 325, 326, 330, 350, 364]
	Grounded kinesthetic	[293]
	Electric shock	[106, 154, 304]
	Braille Displays	[111, 330]
Non-speech audio	Beeps / Discrete alerts	[37, 51, 52, 96, 100, 106, 138, 159, 191, 192, 195, 234, 255, 284, 285, 289, 290, 319, 368]
	Earcons	[340]
	Auditory icons	[174–176]
	Continuous sounds	[16, 100, 110, 227, 289, 290, 296, 340]
	Spatial sounds	[52, 96, 248, 289, 290, 296, 319, 340]
Speech Audio	Natural language	[1–3, 14, 43, 51, 57, 59, 60, 94, 100, 110, 115, 116, 120, 124, 133, 138, 141, 150, 151, 154, 160, 162, 173–176, 179, 181, 183, 185, 191, 194, 195, 200, 201, 203, 205, 210, 214, 215, 236, 248, 265, 267, 281–284, 293, 294, 305–307, 316, 317, 319, 324, 327, 340, 345, 350–352, 356, 358–361, 363, 368, 372]
	Spatial	[203]
	Dialogue	[120, 194, 200, 201]
Visual Feedback	(Touch) Screens	[47, 120, 162, 284]
	Indicator lights	[255, 285]

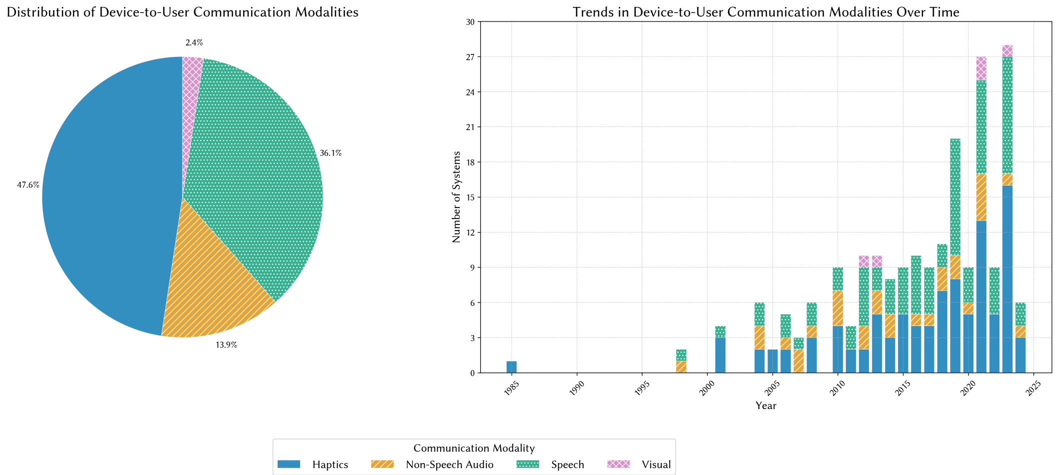

Figure 10: Distribution and frequency of use of mediums of communication *from* the wayfinding robot (device) *to* PwVI (users), in aggregate and year-by-year respectively. The left side of the figure shows the counts of different mediums of device-to-user communication, with haptics and speech being the two most common. The right side of the figure shows the counts of different mediums of device-to-user communication over time; the proportion that each modality of device-to-user communication is employed has not seen much shift over the last 4 decades.

to convey in speech [45, 106, 176, 255, 340, 368]. Auditory icons, sometimes called sound icons, are everyday sounds that can be easily associated with an object or action, whereas earcons are often abstract, tonal sounds [45, 296] (these are not strictly diametrically opposed foes, but rather the two abutting ends of a spectrum [45]). We note that although some works claim the use of auditory icons or earcons, in actuality they are beeps or discrete alerts due to a lack of immediate associative and musical qualities. Sonification, the act of converting data into an audio representation, can be viewed as an umbrella term for auditory icons and earcons [72, 296]. Interfaces that produce continuous sound often vary properties like pitch [37, 227, 289] or tempo [100, 340] to communicate how close or far an object is (this is an example of parameter-mapping sonification [72, 296]). Uniquely, Spagnol et al. [296] developed a sensory substitution algorithm that continuously creates natural-sounding yet synthetic liquid noises with physical meaning, where properties such as the quantity or timbrel attenuation of bubbles embedded in the liquid are directly mapped to features of the inputted depth images; in principle, this can be thought of as a hybrid of auditory icons and parameter-mapping sonification (though to be exact, this is an example of model-based sonification [296]). Figure 10 shows that, despite its potential, non-speech audio has not been commonly explored as a device-to-user communication interface. For further reading on the taxonomies and designs of auditory representations (beyond the scope of use by PwVI), we encourage readers to explore the works of Csapó and Wersényi [72] and Brewster [45].

Haptic interfaces for PwVI have been explored as early as 1985 (Tachi et al. [304]) and are commonly divided into two categories: (1) tactile feedback and (2) proprioceptive feedback [278]. Tactile feedback generally comprises sensations that can be felt through the skin [278]. Tactile haptic device-to-human communication interfaces include palm-drawing robotic manipulator arms (Sec. 3.2.6), tactile maps, vibrotactile haptic feedback, electric shocks and braille displays, as listed in Table 6. On the other hand, proprioceptive feedback comprises the sense of the body's pose and any applied forces; this notably encompasses kinesthetic haptic feedback, which governs the use of motion and force to guide the movement of a person [278, 293]. Proprioceptive haptic device-to-human communication interfaces would include grounded kinesthetics and interactive forces, as listed in Table 6. Early haptic feedback mechanisms utilized weak electric shocks for communication [154, 304], but such a medium has not been used by any wayfinding robots covered in this survey since 2001. The compact size and accessible price of vibrotactile motors have resulted in vibration becoming a more common method of feedback in embodiments such as haptic belts and augmented white canes (Sec. 3.2). The most popular method of haptic feedback, however, were interactive forces implicit when holding onto a handle or leash attached to a moving robot. Several studies have investigated algorithms and handle designs to make such interaction forces more clearly felt and understood by the user [140, 332, 342]. Balatti et al. [21] used a dexterous robotic hand on a wheeled base to pull the user, implicitly communicating the safe path through these interactive forces; they found that adaptively pulling the user reduces collisions between the user and environmental obstacles. Others focused on providing information in ways that PwVI are already familiar with, such as Braille and tactile maps [330]. Specifically, Braille displays have been used to provide longer-form information, but these are not common (primarily due to their expense and low literacy rates). Studies suggest that as few as 10% of the legally blind population in the United States is Braille literate [286]. Additionally, refreshable Braille displays, smart Braille devices, and Braille note takers typically cost between $500 to $6000 USD [249]. Tactile maps are not commonly used because their size makes it difficult to embed them into an existing device. However, there have been preliminary investigations towards resolving this problem via building interactive tactile maps, allowing users to zoom in and scroll across sections for higher detail [190]. Koustriava et al. [172] found that audio-tactile maps can be more effective than spoken descriptions for route following due in part to the aforementioned ambiguities of natural language. More creative methods of haptic feedback include using a robotic manipulator arm to draw paths on the user's hand [306] (as discussed in Sec. 3.2.6), and providing vibration feedback to the knee to indicate directions while running [196]. For further in-depth analysis of how haptic interfaces can broadly assist PwVI (*e.g.*, beyond the scope of robotic wayfinding), we refer the reader to the recent literature review by Jiang et al. [147]; those interested in understanding further the overall design of haptic communications and experiences should explore the comprehensive work by Schneider et al. [278].

Touchscreen devices have been used in several newer works owing to their wide availability and familiarity, such as in tablets, smartphones, or laptops as a user interface [120, 162, 182, 226]. Accessibility measures for these screens (*e.g.*, screen readers) are already widely implemented and commonly used by PwVI [45]. As a result, these devices can use existing screen reader technology to make the interface accessible [162]. A screen itself can be utilized to display a speaking face such that users with low vision and hearing impairments can lip-read and still understand spoken information [120]. However, not all content, such as detailed visuals, can easily be transformed into speech [45, 313]. Furthermore, an inherent limitation of touchscreen devices is their flat and featureless surfaces (although recent work has attempted to convey features haptically [367]); PwVI often determine the shape or texture of a physical object solely with their hands but lose out on more visual-based information, such as color [100]. Recently, some progress has been made towards addressing this loss of non-tactile information, such as for identifying and differentiating materials [371].

Finally, virtual reality (VR), augmented reality (AR), and mixed reality (MR) — collectively, X-reality (XR) [261] — are recently being used to assist PwVI with low vision in wayfinding and interaction activities. Colors can be superimposed into a user's surroundings to communicate spatial awareness, such as highlighting stair drop-offs [368] or street cross-walks [57] to decrease safety risks, visualize depth and segmentation information of various objects [11], and overlay arrows for directional guidance [294]. One interesting future direction would be to expand these visual overlays to include pseudo-haptics , to give the illusion of perception of physical properties such as material or texture [278], going a step beyond recent work on material recognition [371]. We encourage future works to further investigate the use of XR for potential improvements in both robotic wayfinding formulations and the experiences of PwVI.

3.4.2 User to Device Communication

Often, the exact mechanism through which the user can communicate with the wayfinding robot is a problem left for future work, as was seen in many of the works reviewed. However, there are various methods for devices that did consider communication from the user to the device. We detail the various modalities of communication utilized to enable the user to communicate, for example,

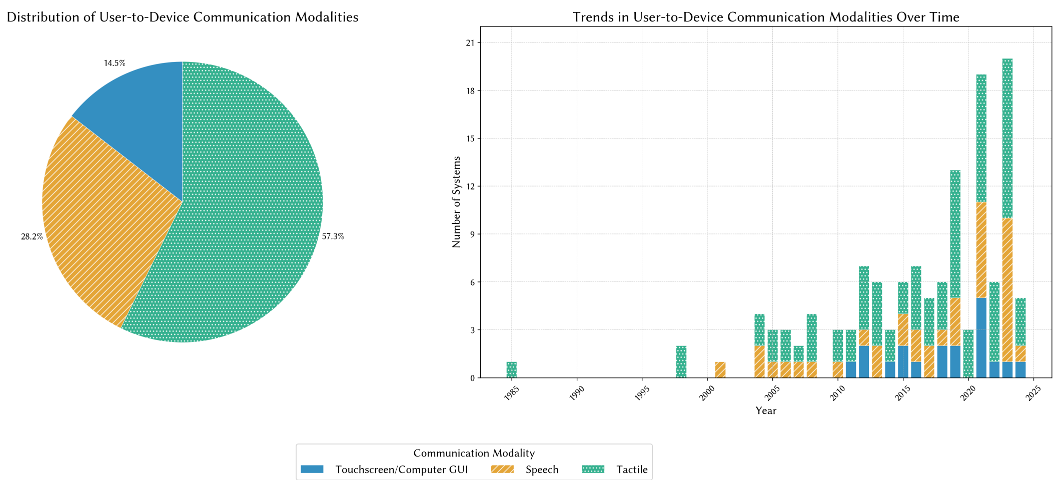

Figure 11: Distribution and frequency of use of mediums of communication *to* the wayfinding robot (device) *from* PwVI (users), in aggregate and year-by-year respectively. The left side of the figure shows the counts of different mediums of user-to-device communication; tactile inputs (*e.g.*, buttons) have been used 57% of the time. The right side of the figure shows the counts of different mediums of user-to-device communication over time; though speech and tactile interfaces remain the most common, touchscreens and other GUIs for low vision users have been slowly increasing in use since the early 2010s.

feedback with the wayfinding robot in Table 7. There is a need for future work in robotic wayfinding to explicitly deal with the aspect of user-to-device communication in order to allow for feedback and a general support for sustainment of bidirectional communication.

Table 7: Communication methods for *user-to-device* interfacing: tactile, audio, touchscreens. If a work falls within multiple categories, the reference will be put in each category.

Communication Method (User to Device)		Works
Haptics and Tactile	Interactive forces	[1, 21, 61, 76, 106, 108, 111, 120, 148, 223, 236, 244, 260, 265, 293, 307, 334, 335, 352, 355, 358, 359, 364]
	Input Devices (*e.g.*, buttons, joysticks)	[14, 43, 60, 110, 115, 138, 140, 158, 173–176, 179, 180, 183, 203, 205, 210, 255, 265, 284, 285, 289, 290, 293, 304, 306, 340, 351]
	Moving the device	[2, 3, 7, 11, 57, 69, 83, 144, 159, 181, 196, 216, 226, 255, 283, 292, 324, 327, 330, 368]
	Barcode Scanners	[110]
	Body Movement	[100, 191, 192, 252, 288, 363]
	Hand Gestures	[116, 227, 306]
Speech Audio	Natural language	[7, 10, 51, 60, 110, 120, 124, 154, 162, 168, 174–176, 180, 191, 194, 200, 201, 210, 215, 236, 248, 257, 284, 288, 292, 294, 316, 340, 356, 359–361, 363, 372]
	Dialogue	[138, 194, 200, 201, 294]
Touchscreens/Laptops	Phone / Tablet	[94, 96, 120, 120, 138, 150, 173, 181, 182, 210, 227, 292, 325, 345, 350]
	Laptop GUI / Web Interface	[52, 105, 210]

The most common and oldest method is tactile feedback in the form of buttons, joysticks, levers, and keypads. Figure 11 shows the historical primacy of tactile input for facilitating user-to-device communication. Although perhaps familiar, it can be difficult for a user to remember what each lever, joystick, and/or button is supposed to do, and it requires the addition of extra hardware to the device. Body movements, such as hand gestures, can be a more intuitive way to communicate [116, 227, 306]. Interactive forces (*i.e.*, pushing and pulling between the device and user) are another common method, particularly relevant for shared-autonomy devices [106, 265, 334, 335].

Algorithms for natural language processing, particularly automatic speech recognition, have expanded the abilities and hence adoption of speech input devices. Earlier attempts to use speech inputs struggled with low accuracy, particularly in noisy environments [176], but speech recognition systems have since improved significantly and can accommodate a wide variety of phrasing of a user's goals through, *e.g.*, disambiguation techniques [200]. As seen in the right half of Fig. 11, the 2020s have seen a rapid rise in using speech for user-to-device communication. Sec. 4.1 presents a discussion on the potential of Large Language Models to further buttress speech interfaces for PwVI and beyond.

Closed-loop communication, involving both device-to-user and user-to-device communication, is frequently overlooked. User-to-device communication is often not addressed, relegating the role of PwVI to that of only followers, rather than active participants. In addition, the use of speech for feedback was particularly prevalent, despite the fact that it is less discreet and may interfere with a sensing capability that PwVI do not want obstructed [18, 36, 130]. This challenge highlights the need for devices to consider the communication needs of the device and its user, especially because users can be distracted and potentially overloaded with information. In other fields of HRI, recent efforts have been made to utilize tactile feedback beyond typing on a keyboard or similar devices. For example, fabric-like sensors can recognize social gestures such as taps or pokes to enable a person to communicate with the robot [71], and skin-like sensors can allow for safer physical human-robot collaboration [246]. The addition of such features to the communication interface of a wayfinding robot is undoubtedly an intriguing direction. We provide further insights into the future of communication methods and the rise of haptic interfaces in Sec. 4.4.

3.5 RQ5: How are the different robotic solutions evaluated for real-world use? What type of metrics do they use?

The proper evaluation of a robotic wayfinding solution is paramount for its future adoption. We compare works along three main axes of evaluation: (1) methodology, (2) participant demographics, and (3) environment. In other words, we sought to learn how solutions were benchmarked and with whom and under what conditions the benchmarking was conducted. While Sec. 3.6 discusses the latter two axes listed above, this section focuses on the methodology of evaluation experiments, specifically what components of the wayfinding robot systems are evaluated and how.

3.5.1 Systemic Evaluation

As outlined in Def. 2, wayfinding robots should perform a variety of functions. Sections 3.3 and 3.4 focus on the technical makeup of the subsystems that individually contribute towards such functionalities. Not all existing wayfinding robots address *all* functions from Def. 2. Therefore, all robotics solutions need not evaluate their various technical subsystems or holistically evaluate the entire system. Moreover, some systems are designed only to address one technical aspect of a robot wayfinder, and in such cases, the singular contribution is evaluated. Therefore, the evaluation approaches of the works cited in this review can be categorized as: (1) Isolated subsystem evaluation, where subsystems are tested on individual performance [76, 195, 304]. The metrics and techniques used to evaluate each wayfinding subsystem are detailed in Table 10, and (2) Holistic system evaluation, where all subsystems are evaluated in unison as a singular user-facing product [161, 356]. Some works have tested both independent subsystems and the entire system [115]. Many works chose to evaluate their subsystems in isolation to support their individual advancements.

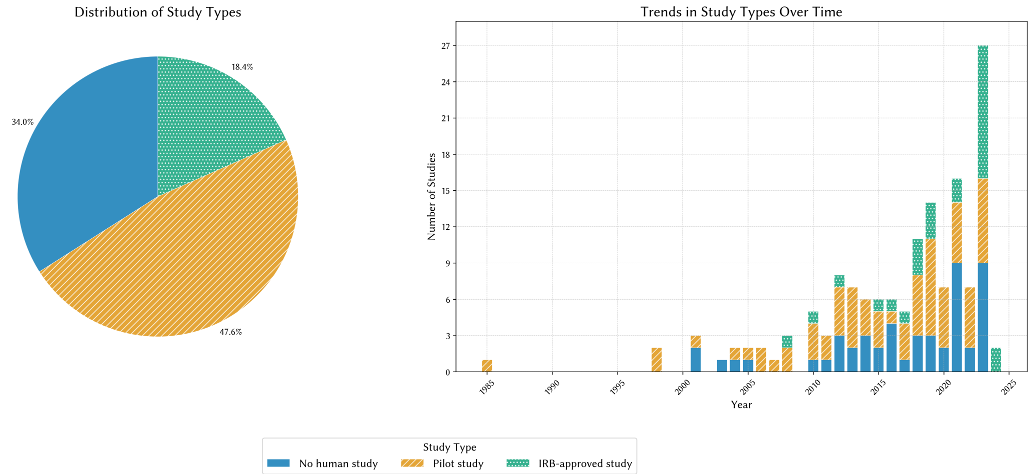

Figure 12: Frequency of different user study formulations of robotic wayfinding works over the past 4 decades. Per year, the order of the stacked bar is no human study on the bottom, pilot study in the middle, and IRB-approved study on the top. We see that in the past few years, many more works have sought IRB approval to conduct formal user studies. Refer to Table 8 for further specification.

3.5.2 User Studies

There are many differing evaluation methodologies employed by authors. Some authors conducted human-in-the-loop user studies with formal recruitment procedures, often approved by the Institutional Review Board (IRB) (see Row 1 of Table 8). Many pilot studies had no formal recruitment, which generally implies that the participants were known to the authors (see Row 2 of Table 8). Other authors did not report any human-in-the-loop testing (see Row 3 of Table 8), opting only for individual component benchmarking, as discussed in Section 3.5.1. In particular, of the 97 works that conducted a user study, only 28 obtained IRB approval; the final 52 works reported no study at all. Wayfinding robots are designed with an explicit primary purpose of interacting with people; therefore, we stress the importance of formally evaluating these systems to determine their practical functionalities in HRI scenarios. These classifications in the aggregate and over time are visualized in the left and right sides of Fig. 12 respectively. Of particular note is that most IRB-approved studies were conducted within the last couple of years.

Table 8: Prevalence of types of User Studies. We can note that historically, IRB-approval has often not been sought out for studies; however, as visualized in Fig. 12, it is recently becoming more popular.

IRB-approved studies	[2, 10, 11, 69, 102, 115, 158, 159, 162, 183, 200, 205, 248, 257, 260, 265, 285, 293, 296, 325, 331, 359, 360, 364, 365]
Pilot studies	[1, 3, 14, 16, 21, 26, 43, 47, 51, 52, 60, 65, 83, 94, 96, 100, 106, 108, 110, 116, 122, 124, 131, 141, 144, 148, 150, 160, 168, 174, 175, 179, 194, 196, 197, 203, 211, 221, 223, 233, 236, 244, 252, 255, 282, 284, 288, 289, 294, 304–306, 316, 319, 322, 326, 327, 330, 334, 340, 342, 345, 350, 352, 355, 356, 358, 361, 363, 368]
No human studies	[7, 37, 52, 59, 76, 93, 105, 111, 120, 140, 151, 154, 155, 169, 173, 176, 180–182, 185, 191, 195, 201, 210, 214–216, 226, 227, 234, 239, 267, 281, 283, 290, 292, 299, 303, 307, 317, 324, 332, 347, 351, 372]

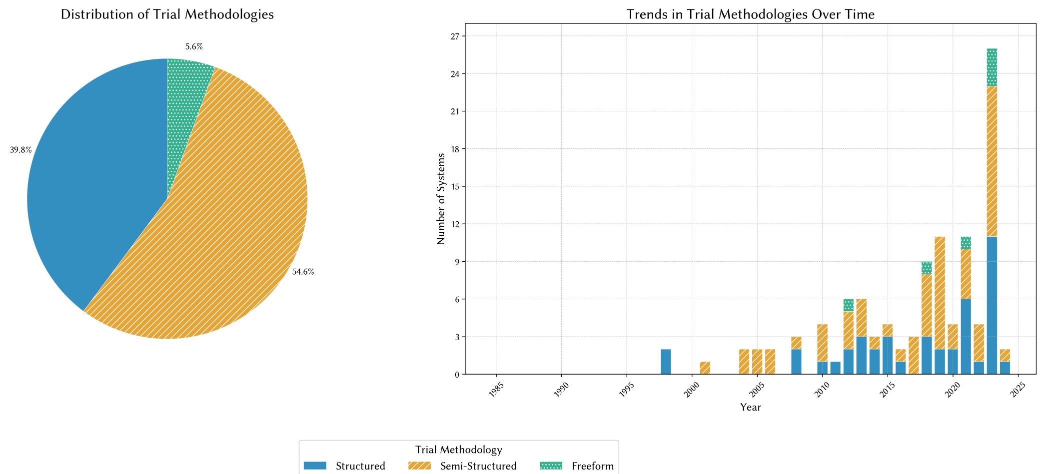

Figure 13: Frequency of different trial methodologies of robotic wayfinding works over the past 4 decades. Per year, the order of the stacked bar is structured on bottom, semi-structured in middle, and structured on top. We note that freeform-style methodologies are almost entirely avoided, in favor of majority semi-structured formulations. Refer to Table 9 for further specification.

3.5.3 Methodologies

System trials are conducted to evaluate the wayfinding robot holistically at varying degrees of freedom. Structured and semi-structured evaluations, as defined below, account for the vast majority of system trials, with 29% and 40% of 148 works including a portion of evaluation that is structured and semi-structured, respectively; only 4% of works utilized unstructured (freeform) paradigms as part of their evaluation. We note that some works have multiple evaluation phases and/or use a mix of evaluation strategies. For example, having one component of evaluation be structured and another be semi-structured [244, 255]. These three different methodologies have their own pros and cons, which are highlighted below, and their adoption is dependent on the use case and goals of the researchers. Table 9 details the exact trial methodologies used in the works analyzed in this review. The three categories of study methodologies that were commonly employed during system trials, ordered from most to least restrictive, are:

1. *Structured:* Users are given strict instructions to adhere to on how they use the system. For example, trial participants might be provided with a script to follow when engaging with the robot and cannot deviate from the provided script [65]. In such a methodology, all participants will follow exactly the same path with no variability in robot interactions. These trials are the most restrictive but allow researchers to control for variability and rigorously test systems.

2. *Semi-structured:* Participants in these types of trials are provided with guidelines on using the system but are afforded some freedom in their usage [200, 211, 368]. For example, participants might be told that they are required to reach a set of checkpoints, such as particular environmental landmarks, but their mode of interaction, exact command, communication, or path is left unconstrained. Such methodologies aid researchers in learning how participants might naturally interact with the system while maintaining some structure in comparing events with different participants. Such a method may also help authors highlight the versatility of their systems in handling variable user inputs.

3. *Freeform:* Users are given access to the wayfinding robot and allowed to use it as they please, as if users were using the system in the real world [162]. Participants are given very little to no information on how to use the system. Researchers monitor the usage of the system and make observations on the human-robot interactions. Such methodologies allow researchers

to study naturalistic interactions with the robot and enable them to cater the system's design to such naturalistic behaviors.

Table 9: Types of methodologies for system trials. Usually, some amount of structure is imposed on the participants of the study. Refer to Fig. 13 for usage trends of these different methodologies over time.

Structured	[7, 10, 26, 43, 51, 65, 83, 94, 96, 102, 115, 116, 131, 140, 148, 158, 190, 196, 197, 203, 205, 210, 221, 244, 248, 255, 257, 265, 282, 289, 294, 305, 325, 331, 335, 345, 351, 355, 356, 364, 365]
Semi-structured	[2, 3, 11, 14, 16, 61, 69, 76, 86, 100, 106, 108, 110, 116, 141, 144, 150, 159, 160, 168, 169, 174–176, 179, 180, 183, 192, 194, 200, 201, 211, 223, 233, 236, 244, 252, 255, 260, 285, 288, 293, 296, 306, 319, 322, 326, 330–332, 334, 342, 350, 358–361, 368]
Freeform	[83, 162, 257, 260, 296, 350]

3.5.4 Metrics

Various metrics can be used to evaluate the different subsystems that comprise a wayfinding robot. The metrics chosen depend on both the goals of the study and background of the authors. Table 10 lists the common evaluation methods for different subsystems. For example, a robot's navigation capabilities are popularly evaluated using tests to verify whether the robot can reach a particular destination from a starting position [115, 200, 293, 361]. Some works interpret this accuracy as a simple percentage of times that the robot successfully reaches its end goal from the start goal. Others include information on the speed and efficiency of the navigational path of the robot [158, 293, 326, 359, 365]. This time-to-completion metric (first row of the navigation subsystem in Table 10) is useful when averaged across multiple study participants, but is subject to individual PwVI participants mobility in addition to their comfort in using the wayfinding robot. Path length and walking/running speed are the primary factors for determining time-to-completion.

The evaluation of obstacle avoidance subsystems has an implicit dependency on a robustly functioning obstacle detection subsystem. Typically, obstacle avoidance is evaluated simply through a rate of success (*e.g.*, averaging the results from multiple trials of whether or not there was a collision) and/or counting the number of collisions that occurred [11, 158, 293, 296]. Obstacle detection is often evaluated using typical computer vision metrics, such as precision and recall. Some works, especially those focusing on last-few-decimeter hand guidance wayfinding (Sec. 3.2.8), also judge their detection subsystem on the error between the predicted and distance to an object of interest [288].

Given that a wayfinding robot must be able to assist and respond to the user, it is important to evaluate the performance of the communication subsystem. However, more so than other subsystems, the efficacy of the communication module is tied to the experience of the user (due to its purpose as the primary interface for HRI); for example, the perceived clarity of communication can differ, within reason, between different users.

All evaluation metrics discussed thus far inform the evaluation of the technological abilities of the robot. Evaluating the human experience is another important factor in testing the robot's performance. Such user experience is evaluated both objectively and subjectively. Questionnaires like the NASA Task Load Index (NASA-TLX) [126], Quebec User Evaluation of Satisfaction with assistive Technology (QUEST) [80, 81], and System Usability Scale (SUS) [46] are often employed for objective evaluation, rating the workload, satisfaction, and usability respectively of a wayfinding robot [9, 16, 110, 115, 160, 243, 260, 285, 293, 305, 331, 365, 369]. Such questionnaires are ubiquitous in human factor research and are standardized to extract and compare how human users perceive and, more broadly, "feel" about systems. Studies have found that these three questionnaires have both high internal consistency (measured by Cronbach's Alpha [70, 309]) and high test-retest reliability (measured by the Interclass Correlation Coefficient [27, 337]), indicating that the collected results are consistent and stable over time and use [8, 25, 79, 82, 343]. Pre-, in-between, and post-trial interviews are commonly used as tools for subjectively evaluating user experiences [3, 350, 368]. As with trial freedoms (Table 9, Fig. 13), interviews are also conducted at varying levels of structure. Particularly, some interviews follow a strict question-answer format, while others ranged from semi-structured interviews to full open conversations [368] about the participants experience using the wayfinding system. Such evaluation of the user experience is particularly helpful for evaluating the communication subsystem, enabling comprehension of its perceived quality and usability.

3.6 RQ6: For whom are the robotic solutions designed, and who was involved in the evaluation?

As noted in Section 3.5, not all solutions address all the different functions of *robotic wayfinding*. Similarly, not all solutions need to address *all* user demographics or usage environments. Therefore, the design and evaluation of wayfinding solutions depend on their intended and tested demographics and environments. In this section, we first distinguish between the intended participant demographics and the actual test demographics considered in the curated works. We then expand on a similar distinction between the intended and test environments.

3.6.1 Participant Demographics

The intended demographic target for a wayfinding solution heavily impacts the design and thus evaluation of a solution. Visual impairments are not isolated in their occurrence, often appearing alongside other mobility challenges (*e.g.*, the likelihood of visual impairments, alongside other medical conditions, increases with age). Thus, wayfinding systems designed for visual impairments also seek to alleviate the issues caused by other ailments. Such designs lead to multi-faceted systems that give rise to unique methods of wayfinding. We discuss some of these additional design considerations and how they influence the design of the wayfinding robot below.

Table 11 details the intended user demographics of all surveyed works. Note that we only categorized works that explicitly stated their intended target demographics. While 92% of existing solutions were built to address people with visual impairments only, notable solutions arise when focusing on the intersection of different target demographics.

Consider the 5 solutions that were intended for use by people with visual impairments and additional mobility challenges [148, 210, 221, 248, 285]. These solutions capitalize on the unique nature of mobility challenges to add additional functionalities to wayfinding solutions. For example, Peng et al. [248] proposed a prosthetic that includes intelligent object grasping in addition to wayfinding, thereby vastly improving users' local mobility. Similarly, Sharma et al. [285] created a wheelchair assistant. This design eases the guidance constraints faced by other solutions that must consider the added complexities of multiple communication interfaces. This wheelchair design can also lead to a more comfortable and safer experience for users, as discussed in Sec. 3.2.2.

Similarly, two wayfinding solutions were built for older adults with visual impairments [265, 283]. Therefore, the safety of the user and movement pace were more important considerations in the design of these wayfinding robots. We note that there are four solutions intended for older PwVI with mobility challenges [108, 120, 194, 326]. As expected, these works inherit the joint advantages of each of the designs independently, as discussed above (and in Sec. 3.2).

Table 11 bundles all visual impairments into one category (in row 1, specifically); however, visual impairments, by definition, have variable visual acuities and thus include multiple nuanced lived experiences, as discussed in-depth in Sec. 1. Thus, different acuities give rise to varying solutions as well. For example, Guerreiro et al. [115] aimed to build a solution for those who are completely blind, whereas Garrote et al. [108] sought to improve the lives of (even sighted) people who might have difficulty navigating complex or unknown environments.

Some solutions that are designed solely for people with partial visual impairments capitalize on newer technologies such as Virtual and Augmented Reality (VR/AR) [368], as discussed in Secs. 3.2 and 3.4.1. Meanwhile, other solutions are intended for use by sighted people experiencing visually complex environments (*e.g.*, bus drivers [267]) or people who are temporarily vision impaired (*e.g.*, firefighters [340]), in addition to users who are visually impaired.

Although the intended demographics inform the design of wayfinding solutions, they are not always aligned with their test demographics, as listed in Table 12 (and through the disparity with Table 11). Notably, 50% of the works that conduct user studies of wayfinding systems with a human user (only 67% of all works, even less with Institutional Review Board (IRB) approval; see Sec. 3.5.2) do so with sighted individuals with/without some form of visual obstruction (*e.g.*, blindfolds, closed eyes). Table 12 provides the particulars of the test demographics used by each surveyed paper. We note that 42 studies conducted their system evaluation with only PwVI (as defined by the respective authors), 41 studies chose only sighted individuals, and 15 works tested their systems with both populations. Note also that some studies are evaluated solely by the authors or a single individual known to authors [51, 169, 201, 332, 351, 355]

Multiple factors influence the decision to test wayfinding robots with sighted individuals:

1. *Scarce Availability of the target population*: Though it is ideal to test wayfinding robots with the demographic they are designed to assist (*e.g.*, older PwVI with mobility challenges), it may not always be possible due to logistical infeasibilities [110]. Because PwVI wayfind differently than sighted individuals [300], this population distribution shift can bias the results of the evaluative study and, more broadly, researchers' understanding of the true efficacy of their proposed robotic wayfinder [232, 247].
2. *Unique Needs*: As PwVI have unique needs, researchers must go through extensive, yet important, checks to be able to conduct user studies. This aspect particularly affects solutions designed to assist PwVI with additional mobility challenges or are older adults. Most notably, only Rentschler et al. [265] evaluated their system with older participants. None of the reviewed papers evaluated their system with people with mobility challenges.
3. *Convenience Sampling*: Wayfinding robots are currently in their experimental development; consequently, many researchers choose to retain individuals in their target demographic for tests once their system has matured to preserve the novelty of their system with their test participants. In contrast, others choose to involve their target demographic in the continuous development of their system [30].

Another notable testing strategy used in previous works was to conduct multiple (often iterative) phases [110, 257, 326]. In such a strategy, a preliminary study is first conducted to verify critical factors of the system (*e.g.*, basic functionality and safety) with a non-target population (*e.g.*, sighted individuals). Insights from these studies are used to improve the system before conducting a final study with the target population. Such evaluation strategies not only aid in ensuring the safety of the target population but also in evaluating the best version of the system.

3.6.2 Evaluation Environments

As with demographics, the intended usage environment also impacts the design and subsequent evaluation of robotic *wayfinders*. As wayfinding has universal applications, it must be performed in both indoor and outdoor environments. These environments can be further bisected into structured and unstructured environments. Examples of each of these environments are as follows: (1) Outdoor Structured: sidewalks; (2) Outdoor Unstructured: a national park; (3) Indoor Structured: airports; and (4) Indoor Unstructured: large hotel lobbies. As discussed in Sec. 3.3, outdoor navigation is a significantly harder task than indoor navigation. Thus, unsurprisingly, 47% of the systems reviewed in this survey were designed only for indoor spaces, 14% for only outdoor spaces, and 27% for both indoor and outdoor spaces — 11% of works did not specify an intended environment. Some works have even tackled the challenging task of navigating in multi-story buildings and therefore accounted for, *e.g.*, the presence of stairs as an obstacle [368]; Kacorri et al. [150] evaluated NavCog3 [275] in this exact scenario.

Given that efficient navigation requires robust handling of environmental obstacles, wayfinding robots can be designed to detect and thus avoid both static obstacles (*e.g.*, chairs and pillars) and dynamic obstacles (*e.g.*, humans and animals). Recall from Sec. 3.3, that the temporal challenges offered by dynamic obstacles renders them a remarkable challenge. Therefore, more systems incorporate static obstacle handling than dynamic obstacle handling. In particular, 67% of systems designed for outdoor navigation aim to tackle obstacles in the environment — with 54% and 60% intending to account for dynamic and static obstacles, respectively. In contrast, 75% of systems geared towards indoor navigation are designed to tackle obstacles — with 40% and 73% accounting for dynamic and static obstacles, respectively.

As observed with demographics, although systems may be designed to perform well in their respective environments, they are not always tested in these environments. Once again, outdoor environments are challenging to test in due to the inherent dangers that they pose to users and the increase in difficulty in variable control. Thus, only 42% of systems designed for outdoor use were actually evaluated outdoors (*e.g.*, sidewalks [208]), with only 43% of the capable systems testing any obstacle handling. In contrast, 74% of *robotic wayfinding* systems were evaluated in indoor settings — with 61% of capable systems also evaluating obstacle handling. Supermarkets [110, 179], airports [183], and office spaces including hallways [60, 200, 330, 332, 358] are common examples of indoor testing environments. Researchers have utilized hallways with obstacles in the form of boxes or furniture to test their systems [76, 169, 293]. Evaluation in simulation is also popular because of the scarce human participant availability and risks associated with human user testing, as noted in Sec. 3.6.1. Several of the works reviewed in this survey evaluated at least one component of their system in a simulated environment [65, 111, 155, 211, 215, 233, 284, 289, 306, 332, 340, 350].

4 Thoughts, Open Challenges, and Future Directions

As discussed in Sec. 3, despite the progress made towards realizing wayfinding robots, numerous unresolved problems remain. We provide insights into and reflections on the possible benefits and challenges of large language models (Sec. 4.1), two-body planning (Sec. 4.2), adoption and commercialization of wayfinding robots (Sec. 4.3), expanding communication interfaces (Sec. 4.4), standardizing experimentation *and* evaluation (Sec. 4.5), and the alignment (or lack thereof) between the expectations of PwVI and the current reality of wayfinding robots (Sec. 4.6).

4.1 Large Language Models for Wayfinding and Beyond

Over the past half-decade, there has been an explosion in the research of autoregressive language modeling in the form of Large Language Models (LLMs) and their multimodal counterparts (MLLMs). As in many other fields, these generative models have begun to percolate into the field of wayfinding and, more broadly, means of assistance for PwVI. LLMs and MLLMs have the potential to unlock a new wave of technologies that automate and supercharge assistance to PwVI [145, 199, 295]. For example, some MLLMs have demonstrated the potential to provide last-few-decimeter (Sec. 3.2.8) instructions on where to find a specific object in space based on (egocentric) images once the PwVI has navigated themselves to the correct position without any fine-tuning [370]. Other applications may include replacing communication methods that use a fixed ontology to interact with the user [200, 201] with interfaces that support open-ended dialogue and intelligent mapping of communicated requests to actions that a wayfinding robot can perform.

However, the adoption of LLMs/MLLMs is not without its problems. For example, the broad issue of hallucinations[11] [55] creates questions about the reliability and robustness of a system, such as a wayfinding robot, that might integrate such models. Hallucinations can diminish the

[11]Hallucinations are generated outputs of a model (*e.g.* an LLM) that may sound plausible, but somehow deviate from user-desired behavior or violate some set of constraints [55].

trust users have in intelligent systems [321], although there have been recent efforts to detect when hallucinations occur [56, 209, 245]. Recent work has shown that CLIP [256] (a typical foundation model integrated into many MLLMs) struggles to provide useful information when given images and videos taken by PwVI due to both (1) the limited disability-related content present in training and (2) image quality issues such as poor lighting, blur, or occlusions [212]. The curation of a large-scale image and video dataset created by PwVI may help overcome this challenge [20, 213]. Alternatively, other studies propose the use of MLLMs to provide instructions to PwVI on how to capture a more optimal image [346]. Some recent studies argue that there is limited viability in using static images as a means of explaining dynamic environments and instead explore the use of real-time video LLMs [366]. Rigorous experiments have highlighted the struggle of current MLLMs to perform spatial reasoning [258], although recent efforts have begun to improve this, especially for use by PwVI [123]. We encourage the exploration of further LLMs/MLLMs and their lightweight counterparts, Small Language Models (SLMs), on edge devices such as wearables to imbue abilities of stronger temporal 3D understanding, as well as investigations into the use of sensing modalities in language models beyond camera and video.

Beyond the issues of hallucinations, there are broader practical limitations of deployment, including inference latencies and network dependencies, as well as computational, memory, and storage constraints [344]. For example, an LLM with 7 billion 4-byte parameters would require around 28 GB of GPU VRAM, which is beyond the memory specifications of most typical robots systems, wearables, *etc*. Furthermore, such powerful GPUs are not only expensive to purchase but also incur high energy and water costs [121, 193], making them potentially cost-prohibitive for many user and consumer applications (let alone the physical size of such GPUs). Other solutions such as connecting to more powerful remote environments (*e.g.*, cloud computing) rely on the presumption of quick and stable network access (which is not a given at every moment in daily life), as well as a willingness to relinquish digital privacy by sharing large quantities of personal data. However, recent work has made steps towards processing in a "private cloud" [118]. Although recent efforts to reduce the memory footprint of LLMs by shrinking the number of bits per parameter [118, 329] (creating SLMs) and increase inference speed by optimizing attention computations [73, 74] are promising, more work is required to address these challenges. We proffer that language models will *not* be generally suitable for wide-scale adoption in robotic wayfinding until they can run predominantly on-device with power efficiency and low inference latency while maintaining user trust (future variants of SLMs will likely help to shrink these gaps [32]).

4.2 Dyadic Motion Planning and Physical Human Robot Interaction

A subset of the field of HRI focuses on the idea of dyadic collaborative manipulation to address planning for two agents to manipulate a shared object [136, 297]. In formulations where a wayfinding robot provides physical guidance for a PwVI, the navigation and planning stack should consider the presence of the user and the physical coupling between the human and robot [233]. We define *dyadic motion planning* as the coordination and synchronization of a physically, potentially loosely, coupled human-robot team that considers the non-deterministic motion of a user[12] and relies on some type of sustained bidirectional communication (here, we use loose coupling to refer to the nonrigid, variable physical connection between a user and robot). Furthermore, in some cases, the wayfinding robot in the human-robot dyad may need to intelligently disobey [13] the user to *e.g.*, prevent a collision [169, 218]. For example, consider harness or leash-tension dynamics between a mobile guide robot and a PwVI user [76, 122, 168, 233, 234, 305, 342] or a user holding onto the wayfinding robot itself [194, 200] who may change grip or extension of their arm during movement; Balatti

[12]This is as opposed to a rigid connection, such as that of a coupled truck and trailer system whose dynamics are rather well-defined [35, 233]; Kim et al. [168] proposed a delayed harness model to address some of the limiting assumptions of the rigid coupling paradigm.

[13]In Sec. 1, we propose a unifying definition for wayfinding robots (Def. 2) built from a set of "tools" that wayfinding robots can and should use. Mirsky and Stone [218] proposed a set of requirements to enable building intelligent disobedience into wayfinding robots to keep PwVI safe. Creating a robust wayfinding robot for use by everyday individuals in dynamic, real-world scenarios will likely necessitate satisfying both sets of criteria.

et al. [21] mounted a manipulator arm on a mobile base and designed an adaptive pulling function to both physically guide and maintain safety of PwVI during travel. We note that the task of dyadic motion planning may be referred to by various other names, including assistive [200, 240], cooperative [222, 277] or coupled [234] navigation, human-aware motion planning [187], physical human-robot interaction (pHRI) [194, 342], or even just navigational guidance [200]. We can dually view dyadic motion planning through a cognitive psychology lens as a combination of task sharing and action coordination [280], in which the individuals of the human-robot pair both try to adjust their actions with respect to the other, and in which both have a general understanding of what the other may do under some conditions. In robotic tasks, it is important to consider how a (wayfinding) robot's current actions may influence the subsequent behavior of the user, including eliciting specific and desired responses [58, 270, 271]. However, most works within this review have not explicitly considered the induced dyadic nature of adding a human user into the wayfinding robot's motion planning, or have done so by simply dilating the robot's collision boundary to include all space in which the human should reside [200], which may be overly conservative [233]. We encourage future work to give more explicit consideration to human-robot dyad systems, specifically to how the user reacts to the robot's motion and how the robot should react to the user's motion. Personalization options [240] would add further fluidity to HRI.

4.3 (Inhibitors of) Commercialization and Wider Adoption

There is a burgeoning interest among PwVI in the concept of a robotic wayfinding assistant [130]. Given the myriad solutions and approaches detailed in Sec. 3, a reasonable question to ask is why we do not see more applications and adoption of wayfinding robots by PwVI worldwide.

4.3.1 Commercializing high-tech wayfinding devices

Among the most successful and popular high-tech wayfinding products is BeMyEyes [31], a mobile app designed to describe and answer questions about images sent by users, as well as connect them to (sighted) volunteers who can help PwVI accomplish tasks by seeing through the device's camera. By virtue of being an app that is downloadable onto most people's devices (with low cost of use), it is an attractive option; mobile apps are fairly versatile across different environments [253]. However, this solution does not qualify as a wayfinding robot (Def 2) and cannot physically guide the user, among other tasks. Initial work has already been done toward adopting the premise of BeMyEyes' remote assistance to mixed reality (MR) devices [294]. That said, an interesting future evolution of this paradigm could include a volunteer remotely teleoperating a wayfinding robot to provide an added level of assistance to PwVI users. Some new commercial products that are more closely aligned with this definition include Glidance's Glide [142] and NextGuide's smart cane [235], as well as the open-source 3D printable work by Slade et al. [293]. Such wayfinding robots are relatively new and have a higher associated price tag than, for example, a traditional white cane. However, the costs of training, *etc*., real seeing-eye dogs are quite high (as much as $\$42,000 - 50,000$ USD or more [76, 293]), and with falling costs of quadruped robots (some models priced at $\$10,000$ USD [323]), it is not unreasonable to expect the beginning of adoption of robotic quadrupeds in the next few years. One major caveat in the face of possible monetary savings is that real dogs offer a sense of companionship that is often cherished by PwVI. To broaden interest in quadruped robots as a substitute, there will need to be considerations about how to handle the "robotic-ness" of the robot [30, 139] in design processes. Furthermore, with the increasing research on and affordability of bipedal (*i.e*., humanoid) robots, we encourage future work to investigate how such a robot may serve as a partial replacement for a human guide companion for a PwVI, similar to how quadrupedal robotic guide dogs have the potential to partially replace seeing-eye guide dogs.

PwVI particularly require wayfinding assistance in semi-unfamiliar and unfamiliar spaces (*e.g*., grocery stores or libraries), as many report feeling confident only when navigating familiar areas (*e.g*.,a home) [130]; further, PwVI may desire different levels of assistive guidance and autonomy in these different spaces [365]. One approach is to market wayfinding robot products towards these high-foot-traffic, unfamiliar spaces (such as malls and assisted living facilities) as an additional service to provide their patrons, just as some already do with motorized carts. Such a model would help distribute costs over many people and increase the daily usability. Alternatively, allowing PwVI a free trial period to integrate a wayfinding robot into their life before purchasing could assist in boosting adoption [107].

4.3.2 On the topic of wearable wayfinding robots

Wearable wayfinding robots have the potential to be cost-effective, given their smaller size. However, many wearable systems are unwieldy or uncomfortable to attach or use. For example, some systems involve attaching various small sensors and devices in different places on the user [43, 192, 288, 363]. One concern of wearables in particular is a disdain for having many separate sensors and devices to attach, each with one dedicated purpose; as such, multi-purpose wearable wayfinding robots may find more success with PwVI users [107]. Regardless of the specific embodiment, PwVI usually need to be trained, sometimes extensively, before they can adequately interact with and use a wayfinding robot. Some studies involve training PwVI before performing user studies [331], connecting back to Sec. 3.5. We encourage a focus on designing intuitive interactions, dynamics, and communication interfaces such that PwVI who already have experience with traditional tools such as white canes or guide dogs can directly transfer to use of a wayfinding robot.

4.3.3 In pursuit of customization and social acceptance

Finally, another side of this challenge is how to satisfy the differing desires of PwVI with respect to utility, discreetness, and privacy concerns in the context of a wayfinding robot [18, 36, 130]. This is partly complicated by the ubiquity of cameras (Sec. 3.3.2) which induce shared ethical concerns: nearby (sighted) individuals may feel that being continuously recorded violates their privacy, and PwVI may wish to avoid receiving information that they consider intrusive [5]. Recall that some works disguise the wayfinding robot as an everyday object [330], whereas others utilize overtly noticeable quadruped [168] or wheeled [200] robots. Alternatively, this can be thought of as how much or how little to conform to some set of governing social norms that exist within a given environment [18, 161] (for example, seating preferences [3], or acceptable types or levels of noise [16, 159]). Customizability is paramount feature to consider in designing a wayfinding robot [18, 98, 301], and many PwVI expect to be able to customize commands just as guide dog owners may want to augment their guide dog's training to be adapted to them [139]. A correlation exists between the involvement of PwVI in the design process of a wayfinding robot and perceptions of usefulness and utility [139]. Beyond customization by form and function, consideration of the level of vision impairment of a user is important for design, as discussed in Sec. 3.6.1. It is an open challenge to find a one-shoe (or few-shoe) fits-all solution, and we expect that many successful future solutions will incorporate participatory design to include PwVI in the research process to achieve this. We further discuss the divergence between expectations of PwVI and the reality of the current state of wayfinding robots in the following section (Sec. 4.6); such a gap can in part explain limitations to widespread adoption and commercialization, too.

4.4 Broadening Mediums of Communication

As discussed in Sec 3.4, there are a variety of mediums used to facilitate (bi)directional communication between a wayfinding robot and the user. We observe that a majority of these works typically utilize audio, both with and without speech. However, audio connected to headphones can obstruct the hearing pathways that PwVI rely on to perceive their environment [30, 149]. Furthermore, PwVI struggle with following verbal directions given by sighted individuals, especially when there is little sensory information provided [44]. Then, it stands to reason that non-speech audio such as beeps [159] or bubble noises [175] have the potential to be unintuitive or ambiguous without the necessary training or context. When using a loudspeaker or headphones, audio (speech or non-speech) may be frustrating or annoying to a user, and may additionally draw unwanted attention to them [30]. However, this is not to say that audio as a method of communication is inherently bad; different communication mediums are best suited for different scenarios. Combining speech and auditory icons could enable a wayfinding robot to communicate more information to PwVI than would be possible with either individually; however, users could be overwhelmed if too much information is provided [45].

Separately, haptics have a bright future as an alternative communication method. A main challenge in haptic interfacing is that most existing commercial haptic designs, such as those in iPhones and laptop trackpads, are very limited in the effects they can provide [278]. In other words, their limited customizability with commonly predefined effects causes poor user experience [166, 278]. An interesting avenue of potential work for new haptic interfaces as a communication medium for wayfinding robots and PwVI is the application and integration of fluid-based haptics, such as the work by Shen et al. [287], who created gloves with electroosmotic pump arrays. We envision that such novel haptic interfaces may allow for greater variability of a "haptic language" between a wayfinding robot and a PwVI user by simulating different shapes and sensations in new ways that typical actuators and their predefined effects cannot, in both user-to-device communication and device-to-user communication. In part, this could enable easier exploration of augmenting a user's *haptic space* — the space within which a person can interact without moving, as opposed to tasks of navigation and route planning [2, 110] (see Sec. 3.2.8 for details on wayfinding in the haptic space).

4.5 Standardization of Experimentation and Evaluation

As discussed previously in Secs. 3.5 and 3.6, there are many styles in which to conduct evaluation and testing of wayfinding robots; clearly, there is a lack of consensus on a set of criteria to test as well as environments to test in. This lack of standardization holds true in the broader field of assistive robotics for people with a range of disabilities as well [232]. This is in direct contrast to other fields such as computer vision (CV). CV, in particular, has flourished with the introduction of standardized benchmarks and associated challenges, such as the seminal ImageNet Challenge [269]. Such challenges provide well-curated data and healthy competition, which allow researchers to focus more on conceptual contributions to the field rather than building their own datasets and infrastructure [66]. Corke et al. [66] argues that the field of robotics as a whole tends to be driven by experimentation more so than evaluation as in the sense of CV (where experiment implies a discovery, whereas evaluation implies systematic testing against a set of standards).

However, calling for the standardization of experimentation (and evaluation) is easier said than done. Evaluation in robotics, and especially HRI, is difficult, in part because it is very difficult to standardize hardware, software, and environments across laboratories worldwide [77]. Such constraints do not constitute as much of a significant hurdle in other fields, such as CV. In the context of robotic wayfinding, there is no agreed-upon standard for the environments in which to perform user studies and evaluations of a wayfinding robot. Furthermore, there is no standard for the selection of users for participation in evaluation studies; as discussed in Sec. 3.6.1, some works test with PwVI, whereas others simulated visual impairment with sighted individuals wearing blindfolds. This is particularly problematic as PwVI often learn to navigate the world differently than people with sight [300], which can create the potential for divergence between user study results and real-world experiences of PwVI [232, 247] (though, for evaluation of interfaces for product selection tasks, *e.g.*, grabbing a certain item off of a shelf at the supermarket, Gharpure and Kulyukin [110] found no meaningful difference in performance between PwVI and blindfolded, sighted participants). However, curating a test group for a user study on robotic wayfinding made up entirely of PwVI may not always be logistically feasible [110].

Recent work by Stratton et al. [298] in the related area of social crowd navigation noted a similar issue with a lack of established, effective benchmarks and proposed a unifying definition of complexity to help move the field towards a consensus on standards. Similarly, we hope that our proposed definitions of wayfinding (Def. 1) and wayfinding robots (Def. 2) will similarly push the fields of Robotic Wayfinding for PwVI, and broadly HRI, towards establishing of standards. We further hypothesize that the development of HRI simulators, such as Habitat [254, 276, 302] or RCare World [353], with tailoring towards robotic wayfinding, may allow for both faster design iterations and the democratization of repeatability and evaluation. We note the annual VizWiz[10] Challenges

[38, 119] as a driver of innovation in the field of CV for pushing the envelope of useful algorithms for assisting PwVI broadly in the area of visual question answering (VQA) [13]. A future series of challenges, an "embodied VizWiz" (not too dissimilar from the proposed Seeing-Eye Robot Grand Challenge [218]), as noted in Sec. 3.1, may help achieve similar gains in robotic wayfinding goals.

4.6 Aligning User Needs and State-of-the-Art Technologies

As discussed in Sec. 3.3, although many different types of sensors are utilized in the pursuit of enabling perception of wayfinding robots, reliance on vision sensors (*e.g.*, cameras and LiDAR) is significant. However, it is important to move beyond vision-based sensing due in part to blind spots, to include other sensing modalities such as environmental audio (for example, guide dogs use both their sight and hearing to detect obstacles and hazards [139]). Furthermore, wayfinding robots are typically powered electrically by rechargeable batteries (as opposed to hydraulics); PwVI users may have concerns about the battery life of such devices (especially in cases where a higher quantity of sensors is active for longer). If the robot runs out of power, it is often very difficult for a PwVI to locate it [36, 139].

Furthermore, a common issue for PwVI with guide dogs and canes is detecting head-level hazards, such as truck mirrors or low-hanging tree branches [50, 139, 255]. Some wayfinding robots do not explicitly address this issue [200, 293], whereas others that mount vision sensors on a user's head and shoulders are more promising [61, 115, 139, 252, 255, 342]. Relatedly, PwVI often use both a leash *and* harness with their guide dog [139]; however, no studies surveyed in this review have investigated this dual inclusion in the formulations of a wayfinding robot (although contemporaneous work by Kim et al. [167] has begun to explore this duality).

As discussed in Sec. 3.4.1, natural language is a popular medium of communication from device to user. Given that aural perception is a primary avenue through which PwVI experience their surroundings, the common design of utilizing earbuds or headphones, which obstruct the hearing of environmental cues, to convey audio commands may often not be desirable [30, 149]. Unlike wayfinding robots that can physically guide the user [21, 169, 194, 200, 293, 359], language-only based guidance is subject to more ambiguity and potential bias [44, 178]. For example, PwVI given verbal instructions by sighted individuals have a harder time following routes and reaching goals compared to when they are given verbal instructions by other PwVI [44]. In particular, verbal directions that include more sensory information and less text are more useful and less frustrating for PwVI [44]. Other work has found that wayfinding robots incorporating some form of physical collaboration, rather than just verbal feedback, can help PwVI perform certain tasks more successfully [40]. Thus, when designing a wayfinding robot, it is important to include PwVI in the design process, especially for crucial areas, *e.g.*, instruction generation and following. We encourage future studies to incorporate more feedback from PwVI in their research and product-making. For deeper discussions on the philosophies and trade-offs of including the target demography (*e.g.*, PwVI) in design processes, we refer the reader to Nanavati et al. [231].

Just as recent studies have shown that reliance on the generative models discussed in Sec. 4.1 have the potential to be detrimental to the critical thinking abilities of users [171, 189], reliance on navigation tools may negatively impact the long-term spatial awareness of PwVI [143]. Thus, it is worthwhile to consider designs of wayfinding robots that can vary levels of navigational assistance [365], returning to the idea of desired customizability [18, 98] (Sec. 4.3.3).

5 Limitations

Despite the breadth and depth of the review provided in this survey, we acknowledge several limitations of our work. First, as discussed in Sec. 2, we cover all works on robotic wayfinding spanning from 1984 to early 2024 (when the literature search was conducted). Thus, works on robotic wayfinding released in March through December of that year were omitted. Due to this limitation, the data for the year of 2024 appears artificially lower in various figures and plots in this article than otherwise as it includes only several months of the year. Furthermore, our search was limited to articles written in English. As such, it is possible that there are robotic wayfinding works within the surveyed time window that we did not collect nor discuss. Future reviews could cover multilingual works to potentially provide a more diverse perspective on the state of robotic wayfinding. However, we believe that our coverage of various international venues, albeit written in English, positions us relatively well in this regard.

6 Conclusion

In this survey, we provide a comprehensive review of the current state-of-the-art of Robotic Wayfinding for People with Visual Impairments. We proposed unifying definitions for both *wayfinding* (Def. 1) and *robotic wayfinding* (Def. 2), noting various historical connections across fields in Sec. 1. We provided a comprehensive analysis of wayfinding robot embodiments, sensing modalities, communication interfaces, evaluation methods, and target communities in Sec. 3. Furthermore, we argue the importance of both supporting customization and standardizing experimentation and evaluation for robotic wayfinding, providing some initial thoughts on how the field can be brought together. Finally, we proposed to concretize the probabilistic planning and guidance problem of a human-robot team as *dyadic motion planning* to enable wayfinding robots to exhibit more nuanced behavior. Recent developments in areas including LLMs and new communication interfaces hold exciting potential for evolving wayfinding robots, and such technologies, alongside cooperative design practices, may help push the adoption and commercialization of robotic wayfinding products. We hope to see a continuing and expanding interest in robotic wayfinding in the years to come. Future work will help usher in the next generation of robotic wayfinding and, more broadly, systems and algorithms that enhance human-robot interaction — designed for and usable by people of all ability.

Table 10: Popular evaluation metrics of different subsystems within the wayfinding robots surveyed in this review. Note that the metrics listed here might not encompass every possible metric, but is rather intended to be representative of the most common evaluation methods of said subsystems.

Subsystem	Metrics	Meaning
Localization	Localization error	Accuracy between predicted and actual position and orientation of the wayfinding robot and/or user
	Convergence statistics	Comprises both the time and distance traveled necessary to achieve an acceptable (small) localization error.
Navigation	Time-to-completion	How long it takes study participants to reach a goal or complete a navigation task (in effect, combines metrics of pace and path length)
	Deviation from intended path	Includes counting number of deviations (*e.g.*, count how many times a participant walks in wrong directions) as well as trajectory variability or distance deviated
	Goal reached	Typically binary classification of whether the wayfinding robot can guide the user to the goal within some tolerance, aggregated into an overall success rate
Obstacle detection	Precision	How many detections that are actually correct, out of all detections made
	Recall	How many objects detected, out of all possible objects in the environment
	Distance error	Accuracy between predicted and actual distance to a detected object
Obstacle avoidance	Success Rate	Typically binary classification of whether the wayfinding robot can guide the user to the goal without any collisions, aggregated into an overall success rate
	Collision count	How many collisions occur during one particular navigation trial (or the average over many trials)

Table 11: Intended evaluation demographics covered. Note that if a proposed work is designed with multiple demographics in mind, it will be cited in each applicable row. The intended evaluation demographics often differ from the tested demographics.

Target Demographic	Works
Visually Impaired	[1–3, 7, 10, 11, 14, 16, 21, 26, 37, 43, 47, 51, 52, 57, 59–61, 65, 76, 83, 86, 94, 96, 100, 102, 105, 106, 108, 110, 111, 115, 116, 120, 124, 133, 138, 140, 141, 144, 148, 151, 154, 155, 158–160, 162, 168, 169, 173–176, 179–183, 185, 190–192, 194–197, 200, 201, 203, 205, 210, 211, 214–216, 221, 223, 226, 227, 233, 234, 236, 239, 244, 248, 252, 255, 257, 260, 265, 267, 281–285, 288, 289, 292–294, 296, 299, 304–306, 316, 317, 319, 322, 324–327, 330–332, 334, 335, 340, 342, 345, 347, 350–352, 355, 356, 358–361, 363–365, 368, 372]
Older Adults	[108, 120, 194, 265, 283, 326]
Mobility challenged	[108, 120, 148, 194, 210, 221, 248, 285, 326]
Did not mention	[69, 122, 131, 132, 150, 238, 290, 307]

Table 12: Test evaluation demographics. Note that if a proposed study includes people from multiple demographics, it will be cited in each applicable row. An example of a visual obstruction for simulating visual impairment with sighted individuals is a blindfold.

Study Participant Demographic	Works
PwVI	[10, 11, 14, 16, 26, 43, 47, 52, 65, 69, 83, 86, 94, 96, 100, 102, 110, 111, 115, 141, 144, 150, 158–160, 162, 168, 174–176, 179, 183, 190, 203, 205, 257, 260, 265, 284, 288, 293, 294, 306, 316, 322, 325, 330, 331, 340, 345, 350, 360, 365, 368]
Sighted Individuals with visual obstructions	[1–3, 11, 14, 21, 60, 61, 69, 76, 83, 110, 116, 140, 144, 148, 168, 169, 194, 196, 197, 200, 201, 223, 236, 248, 252, 255, 282, 285, 289, 293, 296, 305, 319, 322, 325, 326, 331, 332, 334, 342, 345, 355, 356, 358–361, 363, 364]
Sighted Individuals without visual obstruction	[51, 131, 252, 294, 340, 352]
Not Specified	[106, 192, 233, 307, 327]

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