

A REVIEW OF ASSISTIVE NAVIGATION SYSTEMS FOR VISUALLY IMPAIRED PEOPLE: TRENDS, CHALLENGES, AND FUTURE SCOPE

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Abstract: Visual impairment is a global issue affecting more than 2.2 billion individuals, significantly limiting independent mobility and safe navigation. Over recent years, numerous assistive technologies have been proposed, including IoT-enabled mobility aids, wearable devices, deep learning-based perception systems, and physiological monitoring approaches. Despite these advancements, current solutions remain fragmented and fail to address real-world navigation comprehensively. This paper reviews a set of representative studies covering diverse approaches such as smart sticks, embedded systems, computer vision-based detection models, and emotion-aware warning mechanisms. A critical analysis reveals seven major research challenges: lack of end-to-end navigation systems, insufficient real-world validation, limited user-centric design, incomplete obstacle detection, absence of adaptive feedback, weak sensor integration, and unresolved ethical concerns. Based on these findings, this paper outlines key research directions for developing robust, scalable, and user-focused assistive navigation systems.

Keywords: accessibility, assistive navigation, deep learning, EEG emotion recognition, IoT, obstacle detection, smart blind stick

I. INTRODUCTION

According to the World Health Organization, at least 2.2 billion people worldwide live with some form of vision impairment, with approximately 36–39 million experiencing complete blindness [1]. This disability profoundly affects daily life activities, particularly independent mobility and outdoor navigation. The inability to perceive the environment visually creates constant risks of collision with obstacles, difficulty in crossing roads, challenges in using public

transportation, and a general loss of independence that severely impacts quality of life.

Assistive technology for visually impaired people (VIP) has evolved significantly over the past two decades. Traditional aids such as the white cane and guide dogs remain widely used, but each carries notable limitations. The cane provides only limited haptic feedback about the immediate ground-level environment, while guide dogs require extensive and expensive training, and may not perform reliably in all environments [2]. These limitations have driven an extensive research effort to develop electronic travel aids (ETAs) and smart navigation systems.

Recent years have witnessed a rapid diversification of assistive navigation technologies. IoT-enabled smart sticks equipped with ultrasonic sensors and rain detectors offer obstacle detection and emergency alerting capabilities [3]. YOLO-based camera systems running on laptops or smartphones can recognize pedestrian crossings, vehicles, and obstacles in real time [4]. Lightweight multitask neural networks such as SPVINet simultaneously classify outdoor scenes and detect walking paths [5]. EEG-based emotional recognition models detect when a visually impaired person is in distress on a blocked blind road [6]. Hardware wearables embedded in shoes or sticks leverage Arduino microcontrollers and gyroscopes for orientation-aware obstacle detection [7], [8]. Accessible pedestrian signal (APS) systems use audio and vibrotactile cues to guide crossing at traffic intersections [9].

Despite the breadth of this research, a comprehensive survey of the literature reveals that no single existing system addresses the full spectrum of navigation needs identified by VIP themselves. A user-needs study conducted with 49 visually impaired participants in Ireland found that over 63% had been injured during outdoor navigation at some point, that current journey apps fail to provide adequate information about traffic lights, crossroads, and physical obstacles, and that 42.9% of participants still rely on sighted guides for outdoor travel [1]. This persistent gap between technological capability and real-world user needs motivates a critical synthesis of recent work.

This paper provides a systematic gap analysis of eight representative studies spanning the breadth of current assistive navigation research. Our contributions are: (1) a structured taxonomy of current assistive navigation approaches; (2) identification and categorization of seven major research gaps; (3) a comparative analysis of methodological and coverage limitations; and (4) a proposed road map for future research. The remainder of this paper is organized as follows: Section II reviews the surveyed studies; Section III presents the gap analysis; Section IV proposes future research directions; and Section V concludes.

II. REVIEW OF SURVEYED STUDIES

A. User Needs Survey and Navigation Framework

El-Taher et al. [1] conducted a questionnaire-based study with 49 visually impaired participants in collaboration with the National Council for the Blind of Ireland (NCBI). The study covered six dimensions: outdoor navigation activity, navigation support usage, hazards, journey preparation, street crossing, and surrounding visual features. Key findings included that 73.5% of participants walk alone to familiar places on a daily or weekly basis, but only 22.5% do so to

unfamiliar destinations—demonstrating a strong dependence on environmental familiarity. Most critically, 63.2% of participants reported having been injured at least once during outdoor navigation. The most frequently cited hazards were uneven pavements, poles, and hanging branches—obstacles that current systems largely fail to detect.

The study also proposed a four-phase navigation framework encompassing: (Phase 1) Building a static map through machine learning-based detection of intersections, pavements, traffic lights, and public transportation infrastructure; (Phase 2) Pre-journey planning including temporary changes and human density estimation; (Phase 3) Real-time navigation with obstacle avoidance, public transport usage, and road crossing assistance; and (Phase 4) Post-journey feedback collection. This framework represents perhaps the most holistic vision for an integrated assistive navigation system in the literature, but it remains a conceptual proposal without experimental validation.

B. IoT Smart Stick with Emergency Alerting

Singh et al. [3] presented an IoT-based smart walking stick incorporating an HC-SR04 ultrasonic sensor for obstacle detection and a rain sensor for wet-surface warning. The system uses a NodeMCU (ESP8266) Wi-Fi microcontroller to connect to the IFTTT (If This Then That) web service, enabling automatic email alert dispatch to emergency contacts when the user presses a panic button. Obstacle proximity is communicated through a buzzer with distance-varying patterns (1-second delay for objects under 20 cm, 0.5-second delay for under 15 cm).

The system was tested by blindfolding a participant and measuring detection performance in indoor room and stair environments. While the prototype demonstrates reliable obstacle detection and an effective emergency communication channel, its validation is narrow in scope. The rain sensor provides a novel environmental awareness capability, but the system offers no information about obstacle type, no GPS-based localization, and no outdoor navigation assistance beyond local proximity alerts.

C. Smart Shoe for Obstacle Detection

Burugari et al. [7] proposed a smart shoe integrating an Arduino Uno, ultrasonic sensor, gyroscope, and vibration motor. The shoe-embedded form factor represents a user-friendly, hands-free wearable approach. The gyroscope provides orientation data, while the ultrasonic sensor estimates obstacle distance and triggers vibration alerts. Notifications are also sent via a Telegram Android application.

The proposed system demonstrates the viability of foot-worn electronics as an assistive platform, with advantages in compactness and unobtrusiveness. However, the system's evaluation is limited, the gyroscope integration for navigation is underdeveloped, and the form factor raises practical concerns about battery life, durability, and waterproofing for outdoor use.

D. Accessible Pedestrian Signal Assistance

Usha Rani et al. [9] proposed a hardware-based Accessible Pedestrian Signal (APS) system using an Arduino UNO, relay, SD card module, audio amplifier, speaker, and DC motor. Activated by a pedestrian push button, the system temporarily halts traffic by switching signals to red, plays an audio countdown from an SD card, and uses a vibrating DC motor to guide visually

impaired pedestrians. The system operates for a timed crossing window before resetting.

This system addresses one of the most critical and dangerous moments in outdoor navigation—road crossing at intersections. However, the system requires pedestrians to locate and press a physical button, has no autonomous detection capability, and depends entirely on fixed infrastructure installation. The authors acknowledge that the system does not collect location or landmark information, limiting its utility to pre-instrumented crossings.

E. YOLO-Based Real-Time Camera Navigation

Kania et al. [4] implemented a scenario-recognized navigation system using the YOLOv8 object detection model to process live webcam video and provide audio feedback via Google Text-to-Speech (gTTS). The system detects vehicles, obstacles, crosswalks, and staircases, providing real-time spoken navigation guidance. The system achieved a mean average precision (mAP@50) of 85–60% with an inference time of 3.1 ms, running on a laptop with a standard webcam.

The approach is notable for its use of commercially available hardware (webcam/smartphone) and offline processing capability in areas with poor connectivity. However, the system was evaluated in controlled environments, and the custom training dataset was modest in scale. Objects such as e-scooters, overhanging branches, uneven pavements—the most frequently cited hazards by VIP—were not included in the detection scope.

F. TinyML Object Detection on Embedded Smart Stick

Widayaka et al. [8] implemented a TinyML-based object detection system on a smart blind stick using the XIAO ESP32S3 Sense microcontroller with an OV2640 camera. The FOMO (Faster Objects, More Objects) model, trained via the Edge Impulse platform, detected cars, motorcycles, road separators, and tactile guides with an F1 score of 78.1%. The system achieved an inference time of 1,368 ms with 119.4 KB peak RAM usage and 90.2 KB flash usage, demonstrating the feasibility of deep learning object detection on extremely resource-constrained hardware.

TinyML's key advantage is enabling on-device inference without cloud connectivity, preserving user privacy and enabling deployment in connectivity-poor environments. However, the small training dataset (283 images, ~50 per class) limits generalizability, the 1,368 ms latency is potentially too slow for fast-moving obstacles, and the grayscale image processing reduces detection accuracy compared to RGB inputs.

G. SPVINet: Multitask Lightweight Scene Perception

Hong et al. [5] proposed SPVINet, a lightweight multitask neural network for IoT camera-based navigation assistance. SPVINet simultaneously performs scene classification (sidewalk vs. intersection, with traffic light status recognition) and path detection (blind road and crosswalk direction and endpoint estimation). The network integrates Enhanced Inverted Residuals (EIR) blocks and a Lightweight Vision Transformer (LWVIT) block, achieving 91.7% scene classification accuracy with only 0.993 M parameters—the smallest among all compared models.

SPVINet represents a significant technical advance in lightweight multitask perception. The ablation study confirms the contribution of each architectural component. However, the dataset used is relatively small (3,730 images), geographically specific to Chinese urban scenes, and does not include pedestrian-

level hazards such as overhanging objects or uneven surfaces. The system also does not address obstacle avoidance or public transportation assistance.

H. EEG-Based Emotional Warning Model

Yu and Hu [6] proposed a novel approach to detecting when visually impaired people are in distress on blocked blind roads using EEG (electroencephalogram) signals. A Wavelet Scattering Network (WSN) classifies emotional states into normal, nervous, and extremely nervous with 95.11% accuracy on a custom dataset and 86.14% on the public SEED-IV benchmark. The warning system demonstrated a significant reduction in time-to-assistance compared to no-warning conditions in field tests with 10 visually impaired volunteers.

The EEG-based approach is innovative in passively detecting distress without requiring explicit user input. However, the Emotiv EEG acquisition device is expensive (estimated at several hundred to over a thousand USD), limiting accessibility for low-income users. The experiment involved only 10 participants walking on a real blind road, raising questions about scalability and ecological validity. Signal acquisition quality may also be severely degraded in noisy outdoor environments.

III. GAP ANALYSIS

Gap 1: Absence of Integrated Multi-Phase Navigation Systems

Perhaps the most fundamental gap across all reviewed studies is the absence of any system that addresses the complete navigation journey of a visually impaired person. As illustrated in Table I, each study addresses only one or two phases of the navigation cycle. The IoT smart stick [3] and smart shoe [7] provide only local obstacle proximity alerts without route planning or environment mapping. The APS system [9] assists only at pre-instrumented intersections. YOLO-based systems [4] and TinyML sticks [8] focus exclusively on real-time detection without pre-journey information. SPVINet [5] provides scene classification and path detection but not obstacle avoidance or public transportation assistance.

The four-phase framework proposed by El-Taher et al. [1] articulates what an integrated system would require: offline map construction using satellite and street-view imagery, dynamic pre-journey planning with temporary obstacle checking and human density estimation, real-time multimodal navigation assistance, and post-journey feedback. No existing system comes close to implementing more than one of these phases. This is not merely a technical gap but a research prioritization problem—most studies optimize a single component without considering interoperability with other phases.

TABLE I
Navigation Phase Coverage of Reviewed Studies

Study	Env. Mapping	Journey Planning	Real-Time Nav.	Post-Journey
El-Taher et al. [1]	Proposed	Proposed	Partial	Proposed
Singh et al. [3]	No	No	Partial	No
Burugari et al. [7]	No	No	Partial	No
Usha Rani et al. [9]	No	No	Partial (crossing)	No
Kania et al. [4]	No	No	Yes (detection)	No
Widayaka et al. [8]	No	No	Yes (detection)	No
Hong et al. [5]	No	No	Yes (scene+path)	No
Yu & Hu [6]	No	No	Yes (emotion)	No

Gap 2: Insufficient Real-World Robustness and Validation

A critical concern across all reviewed studies is the limited scope of real-world validation. The smart stick prototype by Singh et al. [3] was tested by blindfolding a non-visually-impaired participant in indoor rooms and stairs. The APS system [9] was demonstrated in a laboratory setup. The YOLO-based system [4] was primarily evaluated on controlled video streams. Even SPVINet [5], the most rigorously evaluated system, was trained and tested on a dataset of only 3,730 images collected in Chinese urban environments.

The EEG warning system [6] stands out for its real-environment field testing with actual visually impaired participants on real blind roads, but involved only 10 subjects. The user-needs survey [1] provides the most ecologically valid insight into real-world challenges through its 49-participant questionnaire, but this is descriptive rather than evaluative. The absence of longitudinal user studies, standardized benchmarking environments, and evaluation with diverse VIP populations across varying weather conditions, lighting, and geographical contexts represents a fundamental weakness of the field.

Gap 3: Limited User-Centered Design and Technology Adoption

The user-needs survey reveals a striking paradox: 61.2% of VIP already use assistive technology, yet 42.9% still depend on sighted guides, and 20.4% would like to use technology but have not received adequate training [1]. This suggests that the problem of VIP navigation is not purely technical—it is substantially about usability, accessibility, and training. Yet none of the hardware or software systems reviewed in this survey conducted user studies with actual visually impaired participants during the design and iteration phase.

The APS system [9] acknowledges that the user must press a physical button, which requires prior knowledge of its location—a significant barrier for

users navigating unfamiliar intersections. The TinyML stick [8] emits different buzzer tones for different object types, requiring users to memorize a tonal vocabulary without evidence that this cognitive load is manageable in real-world, high-stress navigation scenarios. SPVINet [5] provides scene and path output but does not specify how this information would be communicated to users with different levels of residual vision or hearing impairment.

Gap 4: Limited Detection Scope and Obstacle Coverage

El-Taher et al.'s survey [1] identifies the most common hazards reported by VIP as uneven pavements/ground (24%), poles (24%), and hanging trees/branches (24%)—all at different heights and requiring detection at varying distances. Yet across all reviewed detection systems, none addresses the full range of these hazards. The IoT smart stick and smart shoe use ultrasonic sensors with a single detection axis, unable to detect overhead objects such as hanging branches that pose a high injury risk [3], [7]. The YOLO-based system [4] detects vehicles and crosswalks but not ground-level hazards like uneven pavements or small curbs. The TinyML system [8] detects only four object categories.

Furthermore, dynamic obstacles—moving pedestrians, cyclists, and e-scooters—are particularly challenging. The survey found that 73.5% of VIP report that bicycles and 61.2% report that e-scooters have reduced their confidence in outdoor navigation [1]. These fast-moving, irregular obstacles are absent from the training sets and detection scopes of all reviewed embedded systems. This represents both a safety gap and a research opportunity in multi-class, multi-height dynamic obstacle detection.

Gap 5: Absence of Context-Aware and Adaptive Feedback

Navigation assistance is inherently context-dependent. The appropriate response to detecting a vehicle differs depending on whether the user is on a sidewalk, attempting to cross a road, or exiting a building. None of the reviewed systems maintains contextual awareness across navigation events. The YOLO system [4] provides object-level audio labels ('vehicle detected', 'crosswalk ahead') without integrating these into a coherent navigation strategy. The smart stick [3] beeps at different rates based on proximity but does not adapt behavior based on whether the user is indoors or outdoors, in a familiar or unfamiliar environment, or near a road crossing.

SPVINet [5] represents the closest attempt at context-awareness by simultaneously classifying the scene (sidewalk vs. intersection) and detecting paths. However, the system does not integrate this scene context with real-time obstacle information or user-specific navigation preferences. The EEG system [6] detects emotional distress but is siloed from any navigation information—it cannot, for example, detect distress and automatically trigger a more cautious routing algorithm. Truly adaptive navigation requires sensor fusion, multi-level situational awareness, and personalized user models that adapt to individual skill levels, preferences, and mobility patterns.

Gap 6: Poor Sensor Integration and System Interoperability

All reviewed systems rely on a single primary sensing modality: ultrasonic sensors for proximity detection [3], [7]; cameras for visual perception [4], [5], [8]; EEG for emotional state [6]; or microphone-based APS for crossing assistance [9]. There is minimal cross-system integration or sensor fusion across these

modalities. Ultrasonic sensors provide reliable distance information in low-light conditions but cannot identify obstacle type. Cameras provide rich semantic information but are sensitive to lighting conditions, occlusion, and field of view limitations. EEG signals are highly informative about user state but require expensive, uncomfortable headgear.

The theoretical ideal would be a fused system combining ultrasonic proximity detection (for immediate obstacle alerts), camera-based semantic recognition (for environmental awareness), GPS/IMU for localization and routing, and physiological monitoring for user state assessment. The practical challenge is integration within a wearable form factor that is lightweight, affordable, has adequate battery life, and does not impose unacceptable cognitive or physical burden on the user. No reviewed study addresses this integration challenge, and the field lacks standardized interfaces or APIs that would enable modular combination of existing components.

Gap 7: Ethical, Privacy, and Societal Considerations

Assistive navigation systems increasingly involve continuous environmental sensing—cameras, microphones, GPS tracking, and biometric data collection. None of the reviewed studies addresses the ethical implications of deploying such systems. Camera-based systems [4], [5], [8] necessarily capture images of third parties in public spaces, raising privacy concerns in jurisdictions with strict data protection regulations. The EEG system [6] collects intimate neurological data whose storage, transmission, and potential misuse present significant privacy risks.

The IoT emergency alerting system [3] transmits location and distress signals to third-party servers (IFTTT), but the study does not discuss data retention, server-side privacy protections, or user consent frameworks. The user survey [1] was approved by the TU Dublin Research Ethics Committee and implemented anonymous data collection, representing best practice that is absent from hardware-focused studies. As assistive systems become more pervasive and data-intensive, addressing ethical frameworks, informed consent, and regulatory compliance becomes essential.

IV. FUTURE RESEARCH DIRECTIONS

A. Integrated Multi-Phase Navigation Architecture

Future work should prioritize the development of modular, interoperable navigation architectures that span all four phases identified by El-Taher et al. [1]. A promising approach would be a cloud-edge hybrid architecture in which computationally intensive map construction and route optimization are performed in the cloud, while real-time obstacle detection and feedback generation run on edge devices for low-latency, privacy-preserving operation. Research into standardized APIs and data formats for navigation assistance components would accelerate modular integration.

B. Multi-Modal Sensor Fusion

Addressing detection completeness requires fusing complementary sensor modalities. A promising research direction is the combination of stereo vision cameras (for depth-aware obstacle detection at multiple heights), ultrasonic or LiDAR sensors (for reliable close-range detection under adverse lighting), and IMU/GPS (for localization and orientation). Lightweight sensor fusion algorithms suitable for deployment on microcontroller-class hardware represent an

underexplored research area. The TinyML paradigm demonstrated by Widayaka et al. [8] provides a foundation that could be extended to multi-sensor inference.

C. Comprehensive Dataset Development

A significant barrier to progress is the absence of large-scale, diverse, annotated datasets representing the full range of navigation challenges faced by VIP. Such datasets should include: multi-height obstacle categories (ground-level, waist-level, head-level); dynamic obstacles (cyclists, e-scooters, pedestrians); adverse environmental conditions (rain, night, glare); geographically diverse urban and suburban environments; and tactile paving, crosswalks, and intersection types. Standardized benchmark datasets would also enable meaningful comparison across detection systems, which is currently impossible given the diversity of evaluation protocols.

D. Participatory User-Centered Design

Future systems must be co-designed with visually impaired users through iterative participatory design processes. This includes formative studies to identify unmet needs (as demonstrated by [1]), iterative prototyping with VIP feedback, longitudinal field studies measuring real-world impact on independence and safety, and accessibility audits of interfaces. Collaboration with disability organizations (as modeled by El-Taher et al. [1] with NCBI) should be standard practice rather than the exception.

E. Adaptive and Context-Aware Intelligence

Future navigation systems should incorporate machine learning models that adapt to individual users over time, learning their preferred routes, commonly encountered obstacles, and comfort levels with different navigation challenges. Context-aware reasoning—combining scene classification (as in SPVINet [5]) with obstacle detection, GPS location, time of day, and user physiological state (as in [6])—would enable far more nuanced and useful navigation guidance than any single-modality system.

V. CONCLUSION

This paper has synthesized findings from eight representative studies in assistive navigation for visually impaired people, spanning user-needs surveys, IoT hardware prototypes, deep learning-based detection systems, and EEG-based warning models. Our gap analysis identifies seven major research deficiencies: the absence of integrated multi-phase navigation systems; insufficient real-world validation; limited user-centered design; incomplete obstacle detection scope; absence of context-aware feedback; poor sensor integration; and neglect of ethical and privacy considerations.

The field has made remarkable progress in individual components—TinyML enabling on-device deep learning inference [8], multitask neural networks enabling simultaneous scene and path perception [5], and EEG-based emotional monitoring enabling passive distress detection [6]. Yet the persistent finding from the user-needs survey [1] that over 63% of visually impaired people have been injured during outdoor navigation, and 42.9% still rely on sighted guides, underscores that technological progress has not yet translated into meaningful real-world independence gains for the majority of VIP.

Future research must shift from isolated component development toward integrated, user-validated, ethically grounded navigation systems. This requires interdisciplinary collaboration among computer scientists, electrical engineers,

rehabilitation specialists, ethicists, and—most importantly—the visually impaired community itself. Only through such collaboration can assistive navigation technology fulfill its transformative potential.

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