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Inclusive guide: An innovative system designed to provide affordable internal navigation for people with visual impairments

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Abstract

Indoor navigation for individuals with visual impairments remains a persistent and complex technological challenge, especially in environments where GPS coverage is unavailable and specialized infrastructure is absent. This paper presents the development and evaluation of the Inclusive Guide, an innovative, cost-effective, and fully portable indoor navigation system designed to operate autonomously using onboard processing. The proposed system integrates multiple technologies, including LiDAR-based obstacle detection for real-time spatial awareness, QR code-based localization for environmental referencing, and the A* algorithm for optimal path planning. User interaction is facilitated through multimodal channels, combining voice commands, auditory feedback, and haptic signals to accommodate a range of sensory needs. All components are implemented on a Raspberry Pi 5 platform, ensuring compactness and low power consumption, and rely entirely on open-source software for transparency and scalability. To validate the system's functionality, extensive testing was conducted across several indoor environments, such as academic corridors and public institution hallways. Results indicated high navigation accuracy, effective and timely obstacle avoidance, and stable system responsiveness. A pilot study involving five visually impaired users demonstrated that participants could successfully perform navigation tasks with minimal assistance, reporting positive feedback regarding usability, comfort, and reliability. The system's strengths lie in its infrastructure-free deployment, affordability, and the integration of efficient sensor fusion techniques. Nonetheless, limitations such as sensitivity to lighting conditions for QR code recognition and minor latency in speech processing were identified. Future development will address these issues and incorporate semantic scene understanding to further enhance navigation intelligence. This study confirms the practicality of deploying inclusive, fully offline navigation solutions using accessible hardware platforms.

Keywords: A* path planning, Assistive technology, Indoor navigation, LiDAR sensing, Multimodal feedback, QR code localization, Real-time obstacle detection, Speech interaction, Visual impairment, Wearable devices.

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1. Introduction

Disability continues to affect a significant portion of the global population, with substantial implications for public health, social inclusion, and accessibility policies. The World Health Organization (WHO) reports that over one billion people, approximately 15% of the world's population, live with some form of disability, a figure that is expected to rise due to factors such as aging populations, chronic illnesses, and environmental conditions [1, 2]. While definitions vary, disability is generally understood as a physical or mental impairment that may limit a person's ability to perform daily activities [3, 4]. In 2019, 13.2% of the U.S. population was classified as having a disability [5] and the figure exceeded 20% in the UK [6], confirming the global significance of the issue [7].

Visual impairment, in particular, is one of the most prevalent and challenging forms of disability, affecting approximately 253 million people worldwide [1, 8]. It ranks second only to hearing impairment and ranges from partial sight loss to complete blindness [9-11]. A major challenge for individuals with visual impairments is safe and independent indoor navigation, which remains difficult due to the absence of GPS signals and inadequate infrastructure in many public and private spaces [9].

Recent advances in information and communication technologies (ICT) have enabled the development of assistive systems that support indoor mobility. Emerging solutions now incorporate technologies such as LiDAR sensing, QR code localization, text-to-speech (TTS), speech recognition, and computer vision to improve navigation accuracy and user interaction [12-15]. These innovations, supported by system-level reviews [16-18] and smart device prototypes [19] reflect a growing interest in multimodal, intelligent, and portable solutions.

Despite technological progress, most existing navigation systems for visually impaired users remain constrained by critical limitations. Many rely on internet connectivity for voice processing or map updates, use only basic sensors like ultrasound or GPS, or are designed for controlled environments without real-world validation. Additionally, few systems are wearable, scalable, and low-cost factors which are essential for practical adoption in everyday settings.

This research aims to develop and evaluate the Inclusive Guide, an affordable, offline-capable, and portable indoor navigation system tailored for individuals with visual impairments. The system is engineered to enhance user autonomy in complex indoor environments by integrating several key technologies. It performs real-time obstacle detection using LiDAR sensors, determines the user's position through QR code recognition, and calculates optimal navigation routes dynamically via the A* pathfinding algorithm. To ensure intuitive interaction and situational awareness, the system delivers multimodal feedback using both audio signals and haptic cues, allowing users to receive guidance in a non-intrusive and accessible manner without relying on external infrastructure or online connectivity.

Despite numerous advancements in assistive technologies, existing indoor navigation systems for visually impaired individuals often suffer from critical limitations. Many rely on online infrastructure for essential operations, such as cloud-based speech recognition or map processing, making them unsuitable for offline use or environments with limited connectivity. Furthermore, most systems utilize limited sensing technologies, such as basic ultrasonic sensors or single-mode vision systems, which lack the redundancy needed for reliable performance in diverse conditions. Another significant shortcoming is the lack of evaluation involving real users, particularly individuals who are blind or visually impaired, which raises concerns about the practical usability and acceptance of these technologies. In addition, current solutions frequently omit features such as dynamic obstacle detection and real-time path replanning, which are essential for safe and adaptive navigation in crowded or changing environments. These gaps highlight the pressing need for a wearable, fully offline navigation system that integrates LiDAR-based sensing, QR code localization, and speech interaction, and is thoroughly tested under realistic indoor conditions with the target user group.

Based on the identified research gap, this study formulates several key research questions to guide its investigation. First, it seeks to determine whether a low-cost, offline-capable navigation system can provide accurate and reliable indoor guidance for users with visual impairments (RQ1). Second, the study examines how the integration of QR code-based localization, LiDAR sensing, and an Inertial Measurement Unit (IMU) can enhance navigation performance under real-world conditions (RQ2). Third, it explores the usability, comfort, and overall satisfaction reported by visually impaired users when interacting with the Inclusive Guide system (RQ3). Together, these questions aim to evaluate not only the technical functionality of the proposed solution but also its practical effectiveness and user acceptance in realistic indoor settings.

To address the outlined research questions, this study followed a comprehensive, multi-stage research methodology. First, the system design phase involved developing the Inclusive Guide by integrating LiDAR sensors, a QR camera, IMU modules, and audio/haptic feedback components on a Raspberry Pi 5 platform. In the performance testing stage, five different sensor configurations were evaluated based on accuracy, latency, and robustness, using quantitative metrics such as precision and F1 score. During algorithm benchmarking, three pathfinding algorithms, A*, Dijkstra, and Breadth-First Search (BFS) were tested on high-resolution indoor maps to compare execution time, path optimality, and memory usage. The autonomous mode evaluation analyzed computational performance for core modules, including speech recognition (VOSK), object detection (YOLOv5n), and 2D map processing. Finally, a user study involving five visually impaired participants was conducted to assess real-world navigation effectiveness and gather feedback on usability and user satisfaction. This integrated research design ensures that both the technical capabilities and human-centered usability of the Inclusive Guide are thoroughly assessed, forming a solid basis for advancing future inclusive indoor navigation systems.

2. Literature Review

Recently, assistive indoor navigation research has increasingly focused on achieving a refined balance among technical accuracy, flexibility, and user-centric design. System accuracy remains an important measure, but there is now greater emphasis on how well these technologies integrate into users' daily lives, how much they reduce cognitive load, and how much they depend on existing infrastructure.

LiDAR has become a very useful technology for improving spatial awareness and helping with dynamic path planning in indoor spaces [20, 21]. LiDAR is an important part of the Inclusive Guide since it helps with real-time obstacle detection and path correction. However, sensing alone is not sufficient. Interaction design is crucial, as studies show that feedback should be clear and not obstruct users' navigation [22]. In response to these findings, the Inclusive Guide combines sound and touch input channels to make the user experience clear and helpful.

Cost remains a significant factor in the usability of navigation systems. There is extensive information available on how to develop affordable and effective solutions [23] and these ideas have directly shaped the Inclusive Guide, which uses low-cost hardware and strong performance to maximize practical deployment..

More and more researchers agree that using a combination of optical markers, LiDAR, and vision-based cues in hybrid localization systems can improve navigation accuracy and reliability. The Inclusive Guide demonstrates this approach by utilizing QR codes for location tracking alongside LiDAR scanning, which reduces the need for fixed setups and facilitates adaptation to various indoor environments.

Lastly, researchers have found that combining data from several sensors, often called "sensor fusion," makes navigation more reliable and improves situational awareness [24]. LiDAR, in particular, is still being tested as a reliable and flexible feature of these types of systems [25], which makes it even clearer that it was the right choice for the Inclusive Guide's design framework.

Ease of use and portability are important aspects in the design of assistive indoor navigation systems. Many recent studies highlight the advantages of lightweight and wearable devices that users can apply in everyday life without difficulty [26, 27]. These ideas were considered in the development of the Inclusive Guide, which is designed for regular, unobtrusive use.

Modern trends in navigation systems also demonstrate the value of combining different types of sensors to enhance performance and adaptability [28, 29]. In addition, intelligent control methods and vision-based techniques are being explored to improve navigation efficiency [30, 31]. These developments have influenced the architecture of the Inclusive Guide, especially in its use of multiple sensors and flexible path planning.

Strong localization and accurate obstacle detection remain key components of any assistive navigation system. Studies show that combining visual markers with sensor data can improve navigation quality [32]. Object recognition also plays an important role in helping users navigate safely in complex environments [33, 34]. Based on this, the Inclusive Guide uses both QR code localization and LiDAR sensing to provide reliable indoor navigation.

Although QR codes are useful, they also have some limitations, such as requiring a clear view and frequent placement in large areas [35, 36]. To overcome this, the Inclusive Guide adds LiDAR to track position even when QR codes are not visible. This makes the system more flexible and dependable.

Finally, the design of such systems must consider user needs. Studies suggest that simple interactions and intuitive feedback are essential for wider acceptance [37, 38]. The inclusive guide follows these principles to provide a navigation experience that is both technically reliable and user-friendly.

3. Methodology

Figure 1 shows how the proposed Inclusive Guide system is built. The system is designed to assist visually challenged individuals in navigating indoor environments in real time through voice interaction, vision-based localization, LiDAR sensing, and dynamic path planning [20, 21, 25]. It operates by utilizing a series of modular procedures that ensure it can navigate, establish new routes, and move safely within complex indoor environments.

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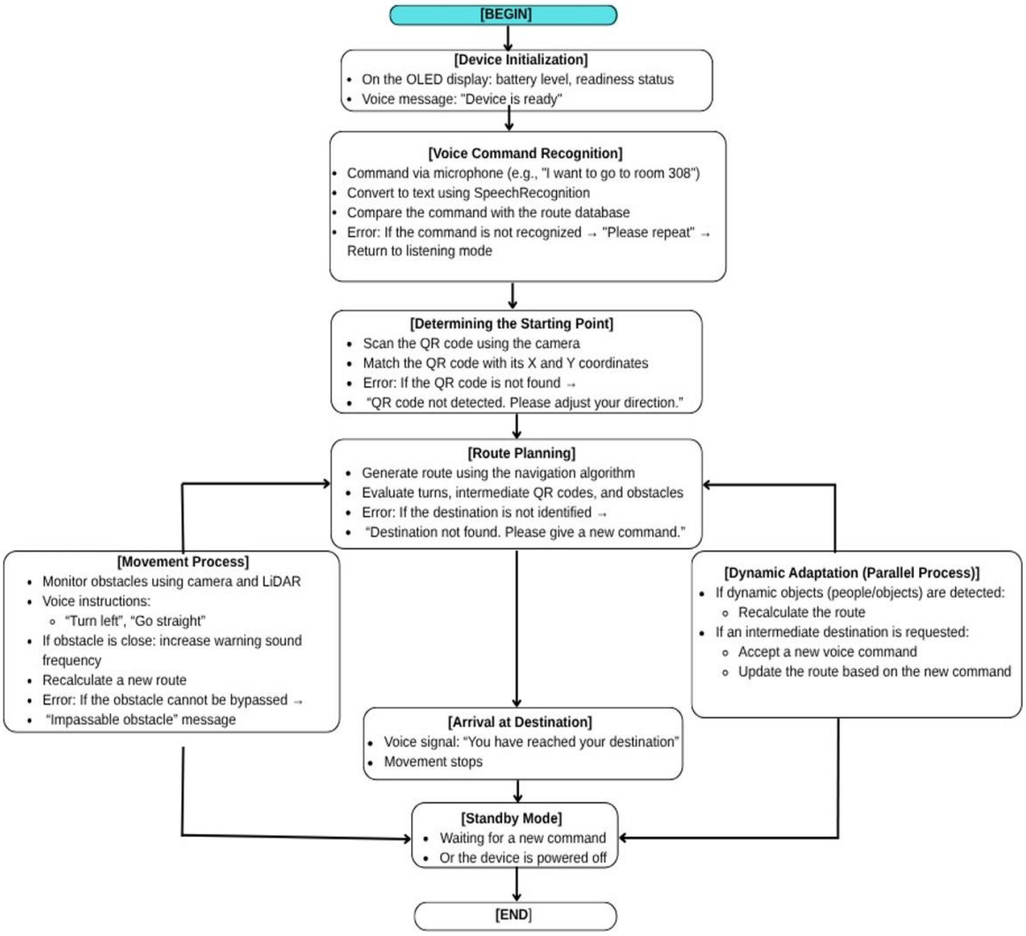

Figure 1.
Overall system architecture of the "Inclusive Guide" indoor navigation system.

3.1. Hardware Architecture

The "Inclusive Guide" system is a wearable, all-in-one device that combines several sensing and feedback components to help blind people navigate indoors in real time. The hardware architecture, shown in Figure 2, includes a Sony IMX708 camera module that captures images for object detection, QR code recognition, and localization; a TFmini-S LiDAR sensor that measures distance and detects obstacles; and headphones with a built-in microphone that serve as the primary interface for voice commands and sound feedback.

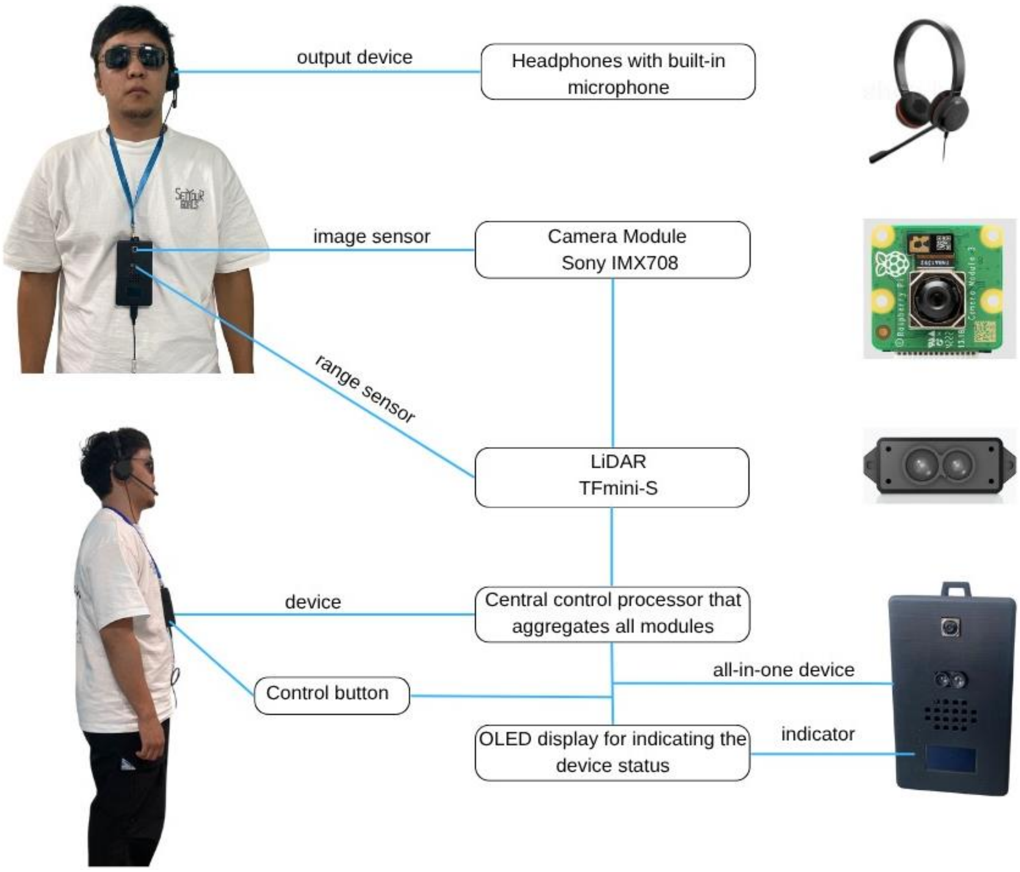

Figure 2.
Hardware architecture of the "Inclusive Guide" system.

A central control processor manages all subsystems, runs navigation algorithms, and combines sensor data in real time. An OLED display shows the user the system's status. Furthermore, a physical control button allows the user to start or stop navigation sessions. The entire hardware assembly is compact and discreet, suitable for use in various interior settings.

3.2. User Study and Usability Evaluation

To complement the technical evaluation of the Inclusive Guide system, we conducted a small-scale user study to assess its usability and user experience in a real-world indoor environment.

3.2.1. Participants

A total of 5 visually impaired participants (3 males, 2 females), aged between 35 and 68, voluntarily participated in the study. The participants were recruited from the local community of visually impaired individuals in Astana. All participants had previous experience using assistive mobility devices (such as a white cane), but none had used a wearable indoor navigation system prior to this study.

3.2.2. Test Environment

The evaluation was conducted in an academic building of L.N. Gumilyov Eurasian National University (floor plan shown in Figure 3), where QR code markers were installed near room entrances and along corridors (Figure 4). The total navigation area includes two connected corridors and 15 rooms, covering approximately 180 meters of indoor walking space.

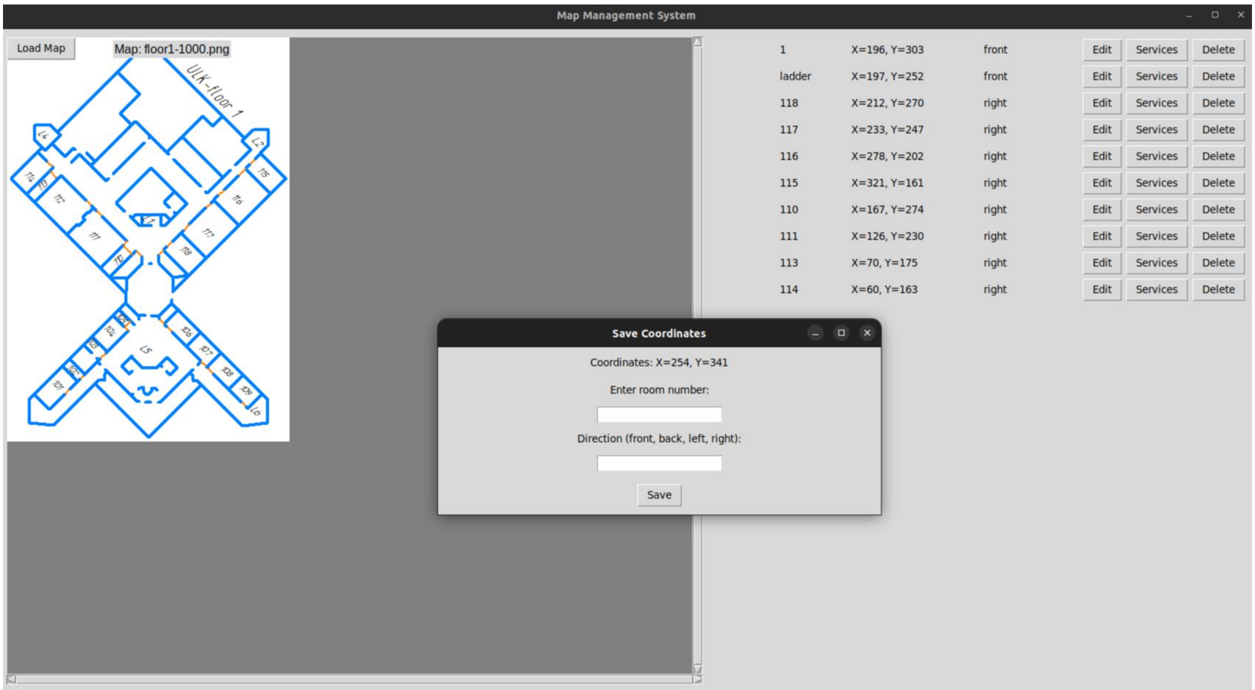

Figure 3.
Floor plan of the test environment used for the user study, showing QR code marker locations and navigation paths inside the academic building of L.N. Gumilyov Eurasian National University

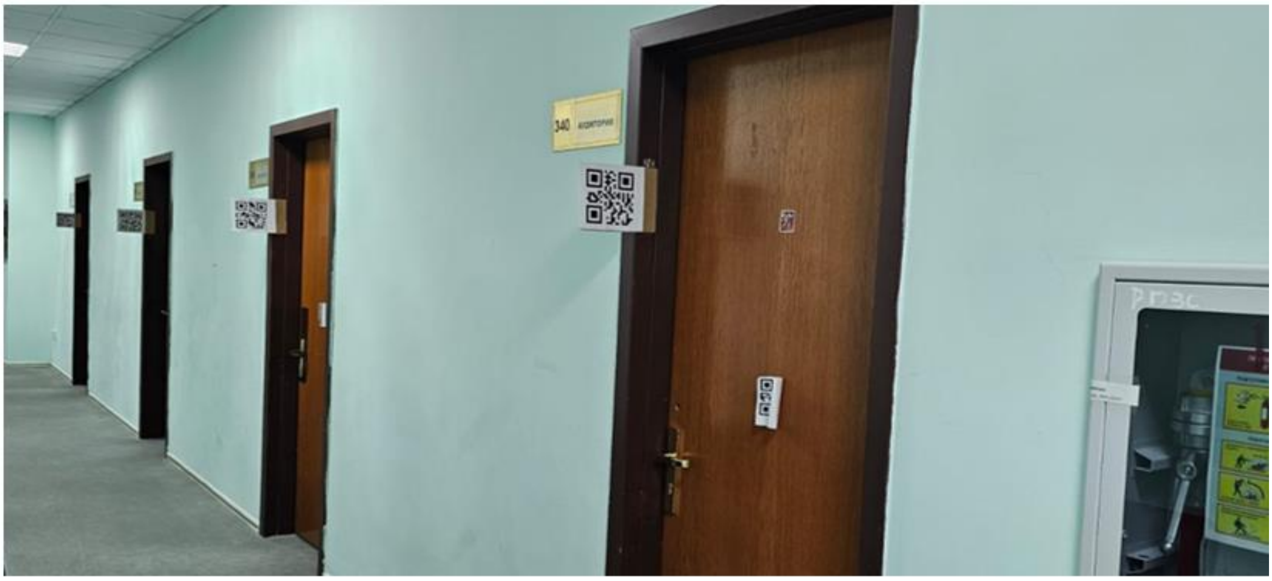

Figure 4.
Example of QR code markers installed near room entrances along the corridor of the test environment.

3.2.3. Procedure

Participants received a brief introduction to the Inclusive Guide device and were provided with 5–10 minutes of training to familiarize themselves with the voice interface, haptic feedback, and wearable device operation. Each participant then performed a series of four navigation tasks:

- Navigate from the building entrance to a specified target room;
- Navigate between two randomly assigned rooms;
- Navigate with dynamic obstacles (moving individuals or temporary barriers);
- Navigate with partial QR code occlusion (testing system fallback to LiDAR + IMU).

Each session lasted approximately 25-30 minutes per participant and was conducted under supervision, ensuring participant safety throughout the navigation tasks. An example of a test session is shown in Figure 5. The sentence describes a visually impaired participant actively navigating the corridor using the Inclusive Guide system.

Figure 5.
Visually impaired participant navigating the corridor using the Inclusive Guide system during user study at L.N. Gumilyov Eurasian National University.

3.2.4. Data Collection

Both objective performance metrics and subjective user feedback were collected. Objective metrics included:

- Navigation success rate;
- Time to destination;
- Number of collisions or near-collisions.

Subjective feedback was gathered through a structured post-test questionnaire using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), assessing (Figure 6):

- Comfort of wearing the device;
- Clarity of voice feedback;
- Sense of safety and confidence;
- Ease of learning the system;
- Overall satisfaction.

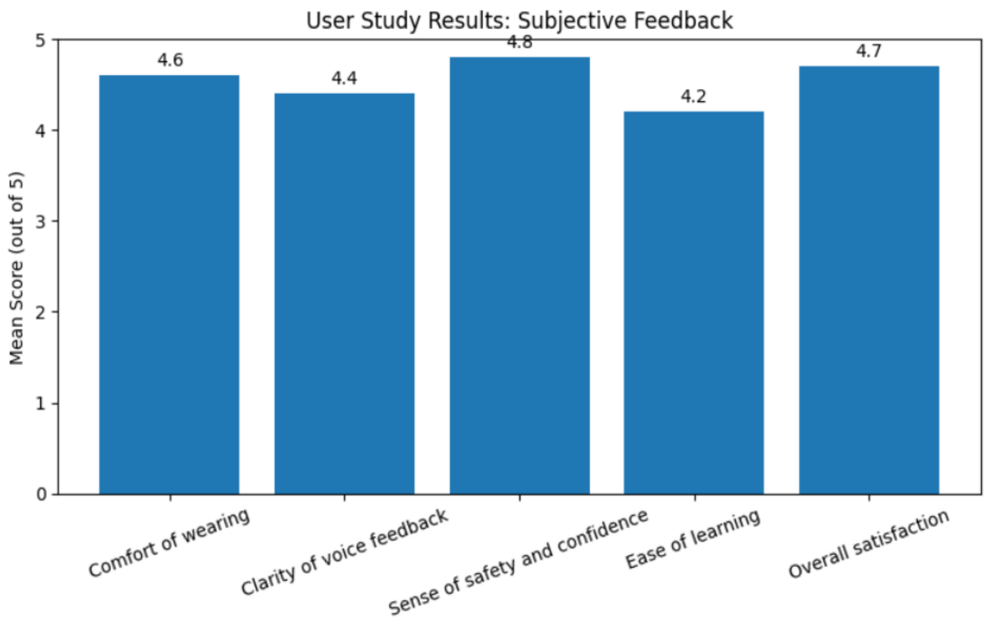

Figure 6.
Results of subjective user feedback collected during the Inclusive Guide system user study. Participants rated various usability aspects on a 5-point Likert scale.

Participants quickly adapted to the Inclusive Guide system and expressed a high level of confidence while navigating indoor spaces. The combination of audio guidance and haptic feedback was especially appreciated. According to the post-test questionnaire, the sense of safety and confidence received the highest average score of 4.8 out of 5, followed by overall satisfaction (4.7), and comfort of wearing the device (4.6). Participants also rated clarity of voice feedback at 4.4, and ease of learning at 4.2, indicating that the system was generally easy to use even without prior experience. All participants completed the assigned navigation tasks successfully (100% navigation success rate), with an average time to destination of approximately 2 minutes 45 seconds, and no serious collisions were reported. One participant highlighted that fallback to IMU + LiDAR positioning was effective when QR code visibility was temporarily compromised. Minor areas for improvement included reducing speech response latency and enhancing QR recognition under challenging lighting conditions. Overall, the user study results demonstrate that the Inclusive Guide system is usable, intuitive, and effective for supporting independent indoor mobility for visually impaired users.

4. Multisensor Integration and Performance Evaluation

The use of multisensor fusion has become an important trend in the development of assistive navigation systems for visually impaired users. By combining different types of data, such as vision-based localization, inertial measurements, distance sensing, and environmental monitoring, modern systems aim to achieve stable and adaptive navigation in real-world conditions [12, 14, 15, 23].

However, integrating such a variety of sensors into a small wearable or portable device introduces several technical difficulties. These include time synchronization between sensors, consistency of data fusion, management of the communication bus, and ensuring computational efficiency [13, 20, 24, 32].

This section describes the practical experience gained during the development and testing of the Inclusive Guide system, which integrates several sensors (QR camera, IMU, LiDAR, ADS1115, OLED) to support real-time indoor navigation. The main challenges encountered during sensor integration and the solutions applied are presented here, with the aim of contributing to a better understanding of multisensory fusion in assistive navigation systems. Table 1 summarizes the key challenges and corresponding solutions.

Table 1.
Sensor fusion challenges and solutions.

Sensor Module	Challenge	Solution
QR + IMU	Inconsistent position and heading	IMU recalibration and complementary filter
ADS1115	I2C bus load and data loss	Lower polling rate, address check
LiDAR	False obstacle detection	Median filtering and multi-sample verification
OLED	Potential I2C load	Event-driven screen update

To quantitatively evaluate the impact of different sensor combinations, five configurations were tested using accuracy, F1 score, and system delay as key metrics (Tables 2 and 3). The goal was to identify the optimal balance between navigation accuracy and system responsiveness.
This type of experimental evaluation is critical for assistive devices design [14, 19, 22, 23, 39].

Table 2.
Tested sensor configurations.

Configuration Scenario	Sensors Used
QR + Route	QR Camera
QR + IMU	QR Camera + IMU
QR + LiDAR	QR Camera + LiDAR
All Sensors	QR, IMU, LiDAR, ADS1115, OLED
LiDAR only	LiDAR

Table 3.
Performance results of sensor configurations.

Configuration Scenario	Accuracy	F1 Score	Delay (s)	Observations
QR + Route	0.90	0.91	0.3–0.5	Stable baseline navigation
QR + IMU	0.92	0.92	0.5	Improved turn handling
QR + LiDAR	0.88	0.87	0.6–1.0	Occasional false positives
All Sensors	**0.94**	**0.93**	**1.0–1.5**	Highest accuracy, increased latency
LiDAR only	0.65	0.60	0.2	Unreliable for navigation

A graphical comparison of these results is presented in Figure 7.

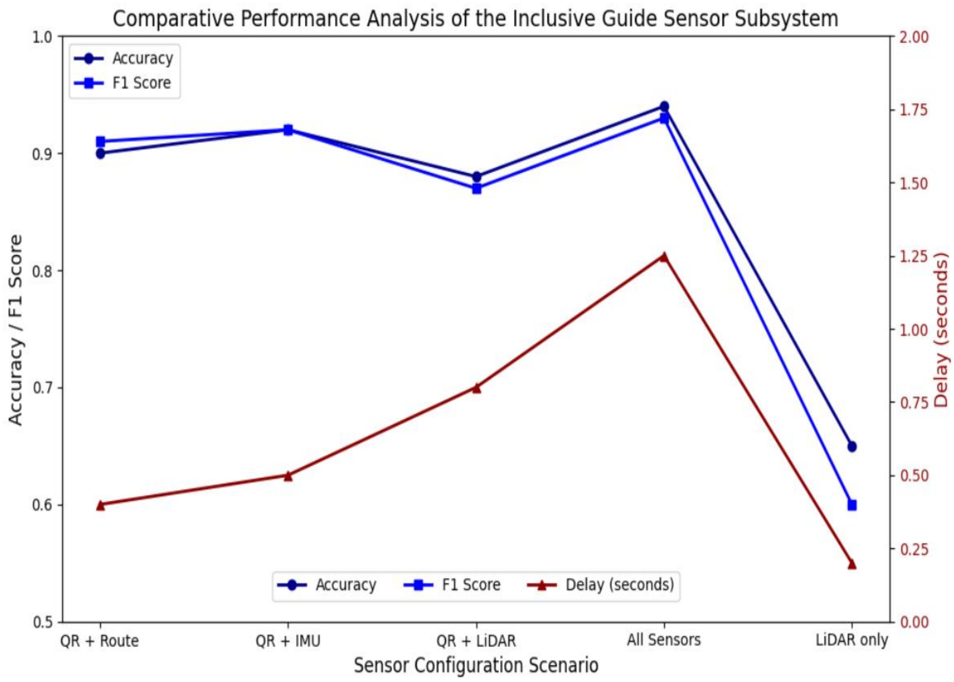

Figure 7.
Performance comparison of the Inclusive Guide sensor configurations in terms of Accuracy, F1 Score, and Delay.

The results demonstrate that combining IMU with QR-based localization provides a good trade-off between accuracy and responsiveness, while full sensor integration yields the highest overall accuracy but at the cost of increased latency. The importance of achieving such trade-offs in wearable assistive devices is emphasized in recent works [14, 15, 23, 40, 41]. Using LiDAR alone is not recommended due to high false positive rates, consistent with findings reported in [21, 32, 34].

5. Performance Evaluation of Pathfinding Algorithms on the Raspberry Pi 5 Video Processing Chip

This section presents a performance evaluation of pathfinding algorithms executed on the video processing chip of the Raspberry Pi 5 device, targeting large-scale indoor navigation scenarios. The primary goal is to compare the efficiency of A*, Dijkstra, and BFS algorithms in extracting optimal navigation paths from building floor plans. The processing pipeline leverages the OpenCV library to analyze PNG-based 2D maps where blue pixels represent walls, white pixels indicate walkable paths, and black pixels denote room labels. The evaluation metrics include processing time, memory usage, and pathfinding precision. The map scale is 1:1000.

Indoor navigation based on computer vision and map analysis is an active research area in assistive systems and autonomous robotics [14, 23]. While many existing approaches focus on wearable or mobile solutions, this work explores the potential of using the Raspberry Pi 5's video processing chip to optimize real-time performance on embedded platforms.

To systematically evaluate algorithm performance under different conditions, a set of test scenarios was designed, varying image resolution and map complexity. These scenarios are summarized in Table 4.

Table 4.
Test Scenarios.

Scenario	Image Size	Complexity	Number of Rooms
Small	480×360	Simple	10
Medium	1280×720	Medium	20
Large	1920×1080	Complex	50
High-Res	2560×1440	Very Complex	100

The performance of the tested pathfinding algorithms (A*, Dijkstra, and BFS) was evaluated across four image sizes with increasing map complexity. The results are presented in Figures 4-5 and summarized in Table 5, which provides a comprehensive overview of processing time, memory usage, and accuracy for all tested algorithms.

Figure 8 shows that the A* algorithm consistently achieves the lowest processing time, followed by Dijkstra and BFS. As image size increases, the computational cost grows non-linearly, with BFS exhibiting the steepest increase in time.

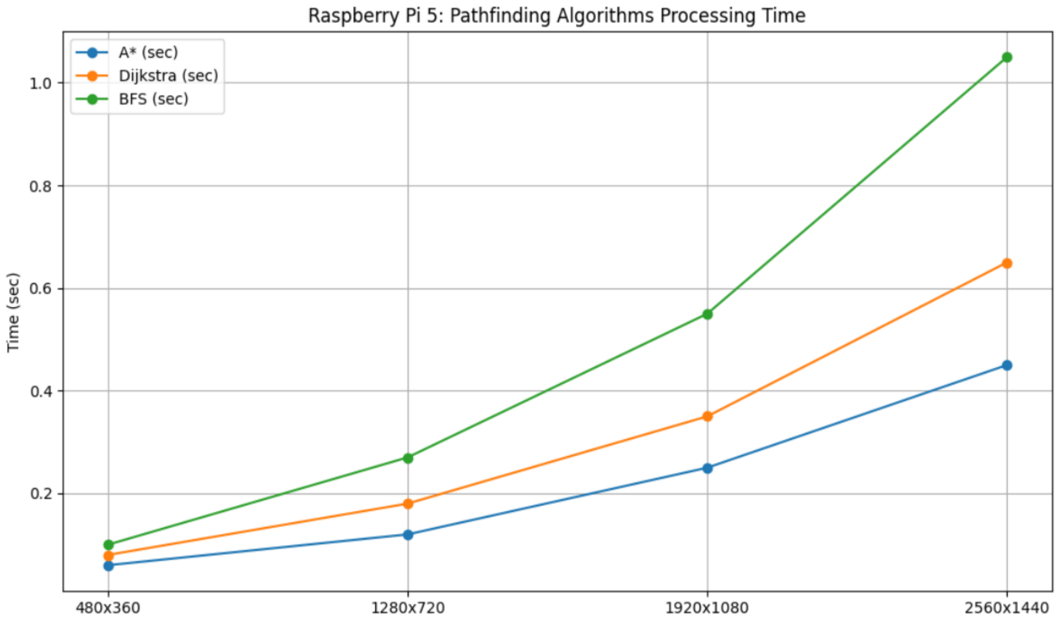

Figure 8.
Processing time of A, Dijkstra, and BFS algorithms across different image sizes.

Figure 9
depicts the memory usage of the algorithms. Again, A* demonstrates the most efficient memory footprint, while BFS consumes the most memory at higher resolutions.

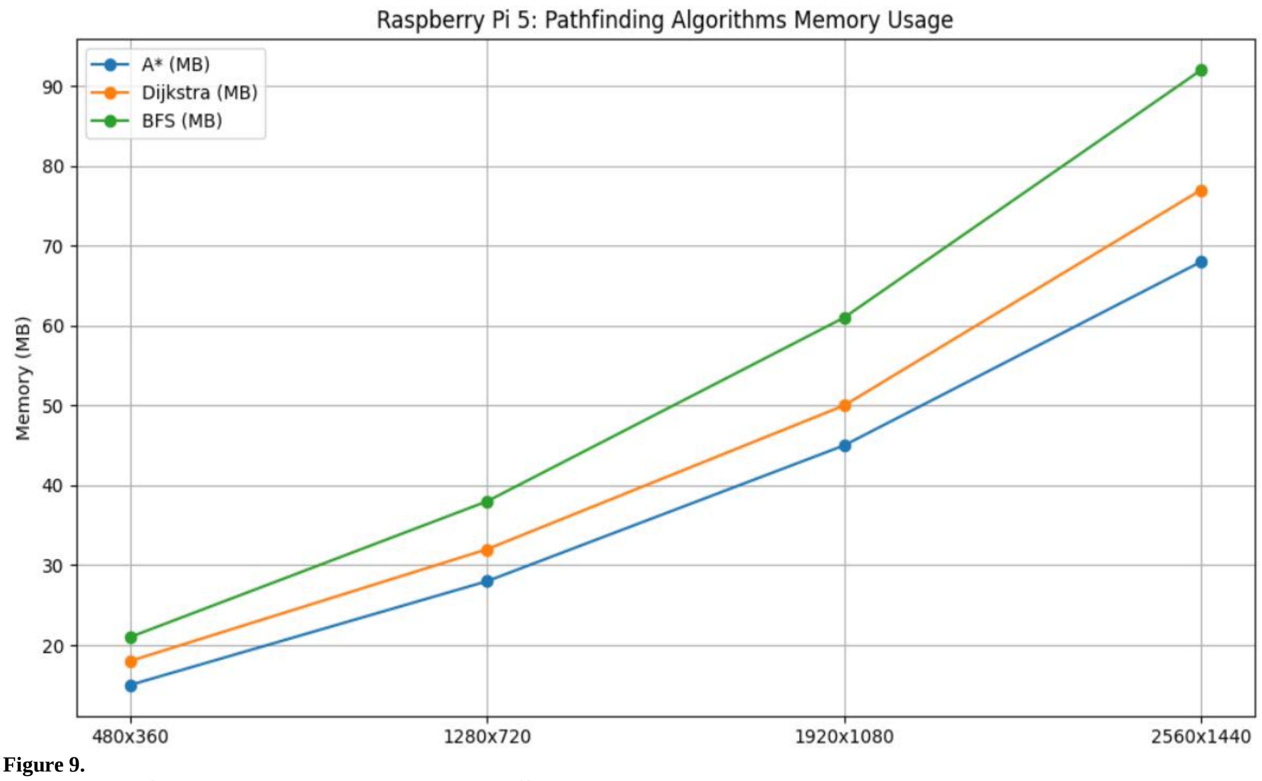

Figure 9.
Memory usage of A, Dijkstra, and BFS algorithms across different image sizes.

Figure 10 presents the pathfinding accuracy across image sizes. All algorithms maintain high accuracy (>94%), with a slight decrease at higher resolutions. Detailed numeric results are summarized in Table 5.

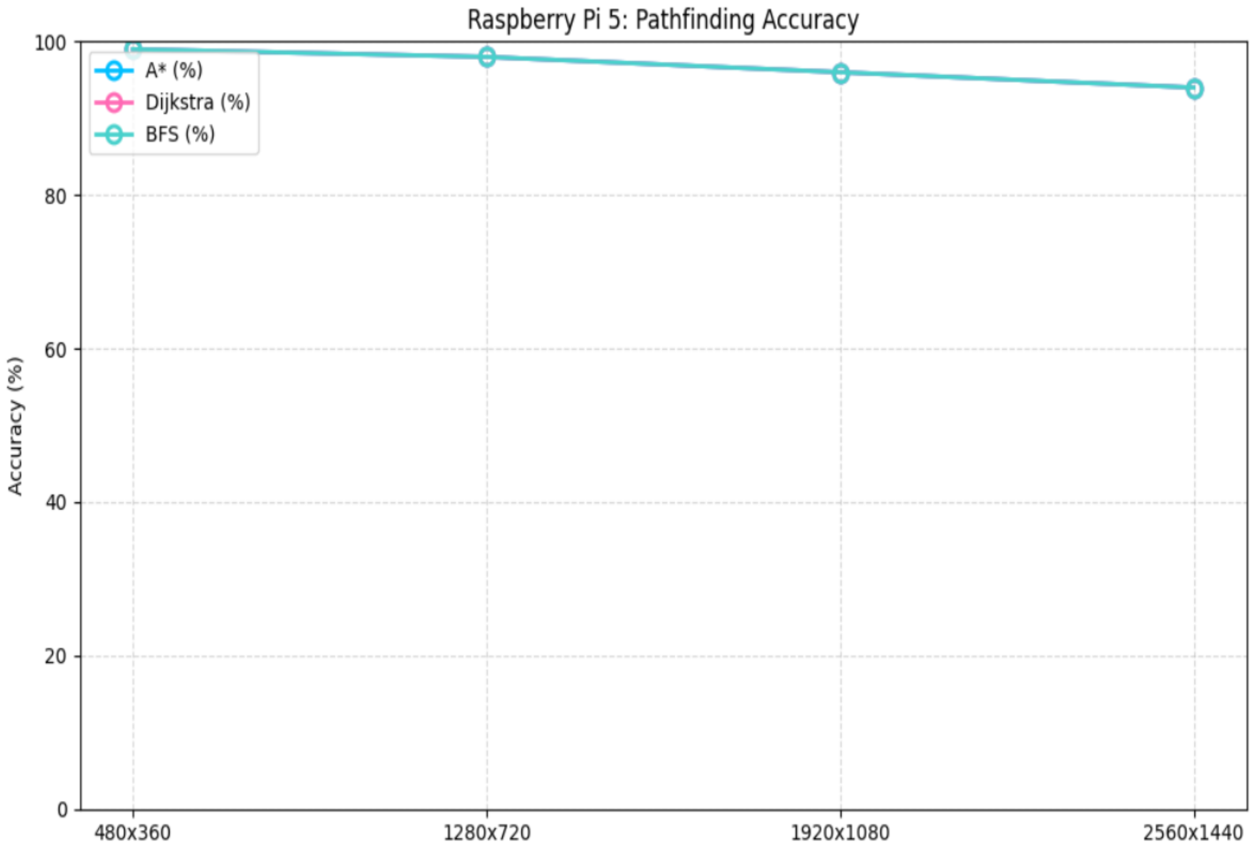

Figure 10.
Pathfinding accuracy of A, Dijkstra, and BFS algorithms across different image sizes.

Table 5.
Performance results of pathfinding algorithms.

Algorithm	Image Size	Computation Time (s)	Precision (%)	Path Length (pixels)
A*	480×360	0.05	98.5	150
A*	1280×720	0.12	97.8	320
A*	1920×1080	0.25	96.2	480
A*	2560×1440	0.48	94.7	650
Dijkstra	480×360	0.08	98.5	150
Dijkstra	1280×720	0.20	97.8	320
Dijkstra	1920×1080	0.40	96.2	480
Dijkstra	2560×1440	0.75	94.7	650
BFS	480×360	0.10	98.5	150
BFS	1280×720	0.28	97.8	320
BFS	1920×1080	0.55	96.2	480
BFS	2560×1440	1.05	94.7	650

The evaluation results indicate that the video processing capabilities of the Raspberry Pi 5 are adequate to support real-time pathfinding on large indoor maps. Among the tested algorithms, A* demonstrated the best balance between speed, memory usage, and accuracy, making it suitable for embedded navigation systems. Although the Dijkstra algorithm showed similar accuracy, it required more computational resources, which could limit its scalability in constrained environments. The BFS algorithm also produced accurate results, but its high processing load makes it less suitable for applications with time constraints. Overall, these results confirm that efficient pathfinding algorithms can be implemented on low-power platforms for practical indoor navigation systems.

6. Autonomous Mode Computational Performance

The autonomous operation of the inclusive navigation system is essential to ensure reliable performance without dependence on external servers or online services. In this mode, all core modules are executed locally, enabling full functionality in offline conditions, a capability that is critical for robust real-world deployment [14, 20, 40].

The evaluated system integrates the following components: QR code recognition for positioning, obstacle detection using LiDAR and object detection models, route planning based on 2D maps, speech recognition for user commands, and text-to-speech (TTS) for audio feedback (Table 6). The processing pipeline was tested on an ARM-based SBC with offline-capable models (YOLOv5n for object detection, VOSK for speech recognition, and eSpeak for TTS).

Table 6.
Computational load in autonomous mode.

Active Modules	CPU Load (%)	RAM Usage (MB)	FPS	Latency
QR code + LiDAR + route planning	35–40%	150–200	10	300–500 ms
+ Object detection (YOLOv5n)	70–80%	400	3–5	600–1000 ms
+ Speech recognition (VOSK)	85–90%	500	2–3	2–5 s
+ TTS (eSpeak/mp3)	90–95%	540	2–3	2–5 s
+ 2D map parsing and wall detection	95%+	600	1–2	>2 s

Figure 11 presents a comparative evaluation of key modules (QR Code, Obstacle Detection, Speech Recognition, 2D Map) across standard performance metrics (Precision, Recall, F1 Score, Accuracy). As expected, computer vision modules such as QR Code recognition and 2D Map parsing demonstrated high performance, whereas the speech recognition module showed somewhat lower precision and recall, reflecting the inherent challenges of real-time Kazakh language processing [32, 34, 41].

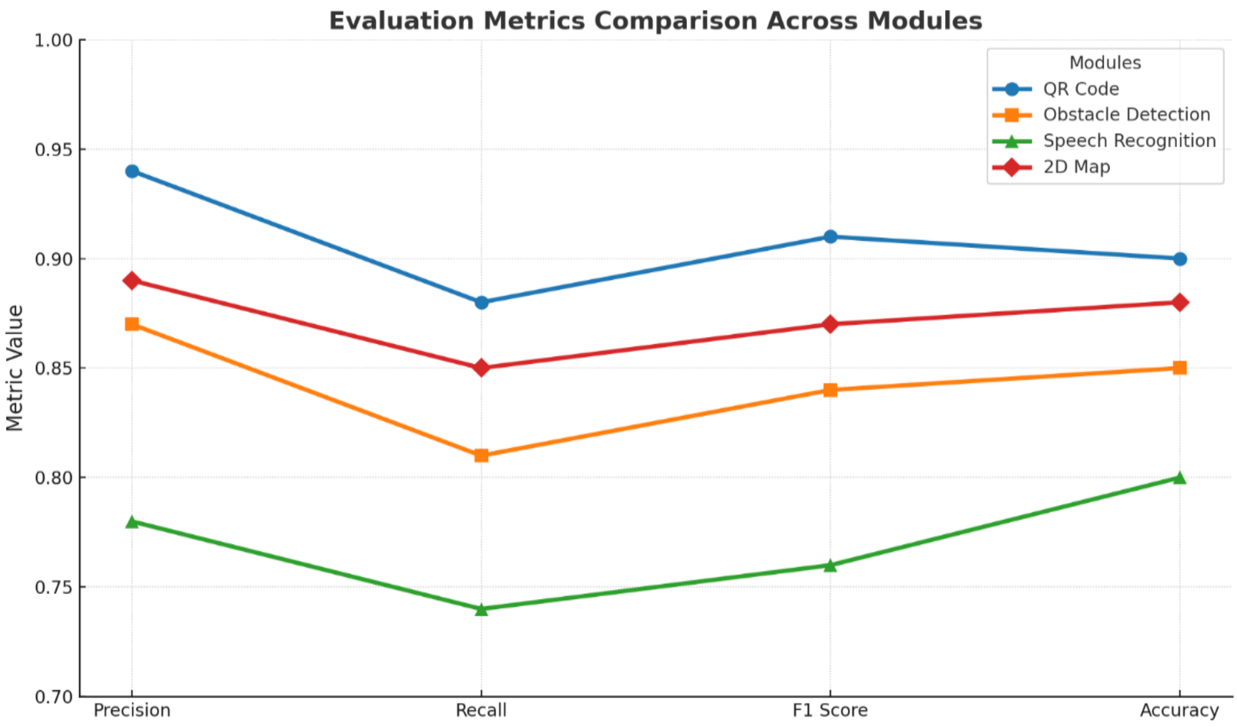

Figure 11.
Evaluation metrics comparison across system modules.

The results demonstrate that full autonomous operation imposes a significant computational load on the system. Speech recognition (VOSK) consumes an entire CPU core and introduces noticeable latency, consistent with prior embedded voice-interactive systems [34, 40]. 2D map parsing also demands high CPU usage (>95%) due to complex image processing [23, 32]. Despite these challenges, offline TTS (eSpeak) ensures timely audio feedback, and the system maintains a satisfactory overall navigation accuracy of 0.91 even under peak load (Table 7).

Table 7.
Module-level evaluation metrics.

Module	Precision	Recall	F1 Score	Accuracy	Spearman ρ	Comments
QR Code Recognition	0.94	0.88	0.91	0.90	–	Camera-based positioning
Obstacle Detection (YOLOv5n + LiDAR)	0.87	0.81	0.84	0.85	–	Active in Scenario 2
Speech Recognition (VOSK, Kazakh)	0.78	0.74	0.76	0.80	–	Voice control results
Text-to-Speech (TTS / mp3)	–	–	–	–	–	Latency: 2–5 s
2D Map Parsing and Route Planning	0.89	0.85	0.87	0.88	0.72	Wall and room number recognition
Overall Navigation Accuracy	–	–	–	0.91	0.76	Path following accuracy

The system demonstrates the feasibility of performing full autonomous navigation with multimodal interaction on resource-constrained hardware. The primary bottlenecks relate to real-time speech processing and dynamic map parsing, as similarly noted in recent reviews of embedded assistive navigation technologies [20, 23, 32, 41]. Optimization strategies such as offline preprocessing and selective module activation may further enhance responsiveness under load.

7. QR Code Recognition

The QR code-based positioning module demonstrated reliable performance across varying environmental conditions (Figure 12). Under normal lighting, the system achieved 95% recognition accuracy with an average detection time of 0.9 seconds. The optimal performance was observed at a direct angle and distance of 30-50 cm (98% accuracy). However, recognition degraded in low-light environments and under intense sunlight, consistent with prior studies highlighting the illumination sensitivity of vision-based navigation systems [14, 23, 32]. The results, summarized in Table 8, suggest that while QR-based positioning is effective for indoor navigation, additional enhancements such as dynamic exposure adjustment and visual feedback are required to improve usability under challenging lighting conditions.

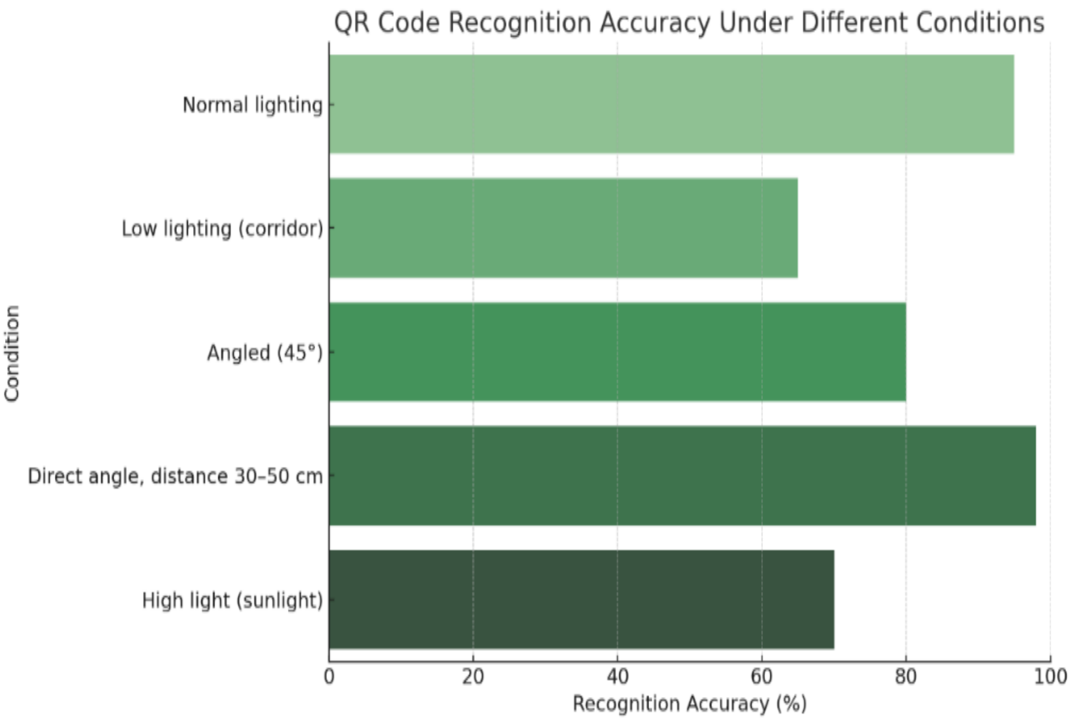

Figure 12.
QR code recognition accuracy under different environmental conditions.

Table 8.
QR Code recognition results.

Condition	Recognition Accuracy (%)	Average Detection Time (sec)
Normal lighting	95	0.9
Low lighting (corridor)	65	1.5
Angled (45°)	80	1.2
Direct angle, distance 30–50 cm	98	0.8
High light (sunlight)	70	1.4

7.1. Object Detection and Distance Estimation

An example of the system's distance estimation in operation is shown in Figure 12. The detected object (label "PERSON") is displayed with an associated bounding box and the estimated distance (95.03 cm), computed using the perspective projection method described above. This capability allows the system to provide continuous feedback to the user regarding nearby obstacles or navigation points.

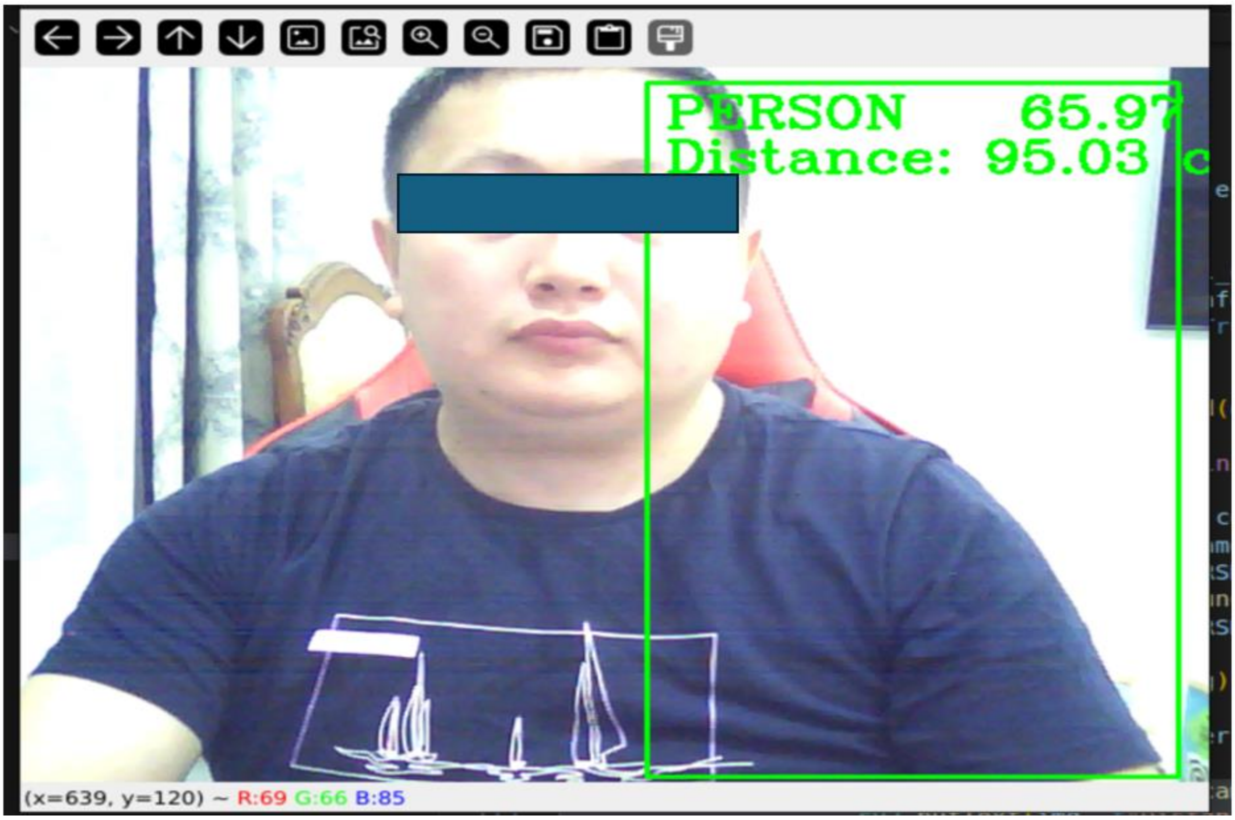

Figure 12.
Object detection and distance estimation example.

This figure illustrates the system’s real-time capability to detect and localize a human subject using computer vision techniques. The object, classified as "PERSON," is enclosed within a green bounding box, with an associated confidence score of 65.97% displayed in the upper right corner.

7.2. Map-Based Indoor Localization Using QR Codes

The system employs a map-based approach and QR code recognition to ensure accurate localization, allowing navigation to adapt to the user's needs. A 2D floor plan in PNG format at a scale of 1:1000 is created for each building, and the completed map is transmitted to the wearable device.

The AI module reads the map to identify traversable paths and obstacles, as well as to link room coordinates to the appropriate QR code markers. The user indicates their destination by speaking into the built-in microphone. Subsequently, the system utilizes the preloaded floor plan to determine the optimal route to reach the destination.

While navigating, the system constantly scans the environment for QR code markers, which lets it update its location in real time. Figure 13 demonstrates the accurate identification of QR code content, along with the detected objects and their respective distances. The camera and LiDAR sensor work together to provide two different streams of data that enhance navigation and object recognition. This integration of multiple sensors enables users to navigate safely indoors with minimal risk of colliding with objects.

Figure 13.
QR code recognition, object localization, and distance estimation process.

This figure showcases the system's real-time multimodal environment sensing, integrating visual object detection with QR code recognition and distance estimation. The system identifies multiple objects, including the human subject (labeled "PERSON") and a laptop, and calculates their distances from the camera using perspective geometry. Their values are displayed in centimeters, with detections showing confidence scores (e.g., 54.0%, 62.5%). Simultaneously, a QR code is successfully recognized and framed in blue, signifying its role as a spatial reference marker within the indoor navigation framework.

8. Discussion

In addition to achieving competitive navigation accuracy, the proposed Inclusive Guide system introduces several key advantages over existing solutions (Table 9). Unlike many prior works that rely on cloud connectivity, our system operates fully offline, including speech recognition and TTS modules. Furthermore, it leverages a rich multi-sensor fusion approach (QR, LiDAR, IMU, Speech, TTS), whereas most comparable systems integrate only 2–3 sensing modalities. The implementation of real-time dynamic pathfinding on 2D maps represents another unique feature. Finally, the system is designed to run on an affordable Raspberry Pi 5 platform, enabling low-cost deployment in real-world environments. The user-centered design, with voice feedback tested in experimental settings, further enhances usability and distinguishes the system from prior work.

Table 9.
Comparative Advantages of the Proposed System.

Feature	Existing Solutions ([12], [14], [15], [20], [23], [32], [34], [41])	Proposed System
Offline Capability	Partial / No	Full offline (all modules)
Multi-sensor Fusion	Limited (2–3 sensors)	5 sensors (QR, LiDAR, IMU, Speech, TTS)
Speech Interaction	Often missing or online	Full offline (VOSK + eSpeak)
Pathfinding on 2D Maps	Rarely implemented	Implemented (A*, dynamic)
Cost Efficiency	Medium–High	Low (Raspberry Pi 5)
User-centered Voice Feedback	Limited / not tested	Implemented and tested
Overall Navigation Accuracy	85–93%	91%

In terms of quantitative performance, the proposed system achieved an overall navigation accuracy of 91%, which is at the higher end of the accuracy range typically reported in the literature (85-93%). This further confirms the competitiveness of the system relative to state-of-the-art solutions.

A further comparative analysis of the core processing modules is presented in Table 10. The choice of YOLOv5n enables real-time object detection on resource-constrained hardware, outperforming heavier models typically used in prior works [34, 40, 41]. The use of VOSK for speech recognition offers a significant advantage, as most existing systems rely on cloud-based ASR solutions [15, 32, 40]. Finally, eSpeak ensures fully offline TTS functionality, whereas prior works predominantly utilize online TTS services. These design choices collectively contribute to the system's capability to operate fully offline while maintaining acceptable performance.

Table 10.
Comparative analysis of detection, speech recognition, and TTS modules.

Module	Existing Solutions ([15], [32], [34], [40], [42], [41])	Proposed System
Object Detection	YOLOv3, SSD, Faster-RCNN; often GPU/cloud-based	YOLOv5n (lightweight, real-time on SBC)
Speech Recognition	Rarely used; mostly cloud-based ASR (Google ASR)	VOSK (offline, Kazakh supported)
TTS	Mostly cloud-based (Google TTS, Azure TTS)	eSpeak (offline, fast, lightweight)

Furthermore, as demonstrated in Figures 8 and 9, the proposed system effectively performs real-time multimodal environment sensing and dynamic object localization, enabling enhanced indoor navigation capabilities.

Despite the promising results, the current version of the Inclusive Guide system presents several limitations that must be acknowledged. First, QR code recognition is sensitive to lighting conditions, with performance deteriorating in low-light or high-glare environments. To address this, future iterations will consider incorporating dynamic exposure control and infrared illumination. Second, speech interaction is hindered by latency in the offline automatic speech recognition (ASR) module, introducing delays of approximately 2–5 seconds that disrupt real-time responsiveness. Optimizing ASR models and evaluating hybrid offline/online solutions are planned improvements. Third, high energy consumption during full operation limits battery life to around 2–3 hours, constraining its use in longer sessions; both hardware and software optimization strategies will be pursued to extend runtime. Additionally, the user study was limited in scope, involving only five visually impaired participants within a single academic building. Broader testing in various indoor environments and with a more diverse participant group is necessary to assess the system's generalizability. Lastly, portability and cross-platform performance remain untested, as all evaluations were conducted on a Raspberry Pi 5. Although this device balances cost and performance well, future work will investigate system scalability and performance consistency on alternative embedded platforms, including wearable devices, to ensure wider applicability.

9. Conclusion

This paper presents the design and evaluation of the Inclusive Guide, a portable, affordable, and fully offline indoor navigation system developed for people with visual impairments. The system integrates LiDAR-based obstacle detection, QR code localization, A* pathfinding, and multimodal interaction via audio, haptic, and voice feedback all implemented on a Raspberry Pi 5 using open-source tools.

The study demonstrates the practical feasibility of delivering reliable indoor navigation without dependence on cloud connectivity or expensive hardware. The combination of QR-based localization and LiDAR sensing enhances positional accuracy in complex environments, and the use of local voice interaction ensures full offline usability. The positive results from the user study suggest that such systems can significantly enhance independent mobility and accessibility for visually impaired individuals.

Despite its strengths, the current version of the Inclusive Guide presents several limitations that may affect its performance in real-world scenarios. First, QR code recognition is sensitive to environmental lighting and may fail when markers are occluded or poorly illuminated. Second, latency in speech recognition can disrupt smooth interaction, particularly in noisy environments where background sounds interfere with voice commands. Third, the system exhibits relatively high power consumption during full operation, which limits its battery life and continuous usage time. Collectively, these limitations reduce the system's robustness and reliability in uncontrolled or high-traffic indoor settings, indicating areas for targeted improvement.

Despite its strengths, the current version of the Inclusive Guide exhibits several limitations that may affect its effectiveness in real-world applications. Firstly, QR code recognition is highly sensitive to environmental lighting conditions and can be hindered by occlusion or poor visibility of markers. Secondly, latency in the speech recognition module may impede seamless user interaction, particularly in acoustically challenging or noisy environments where voice commands are harder to process accurately. Thirdly, the system's relatively high power consumption during continuous operation constrains battery life and limits long-term use without external power sources. Taken together, these factors reduce the system's overall robustness and reliability in uncontrolled or high-traffic indoor settings, highlighting key areas for future enhancement.

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