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Smart Campus Navigation and Identifying Current Location through Android Device to Guide Blind People

(An Android-Based Voice-Guided Navigation System Integrating GPS, BLE Beacons, Wi-Fi Positioning, Obstacle Detection, and Offline Campus Mapping for Visually Impaired Users)

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Abstract - **Visual impairment represents one of the most significant barriers to independent mobility in educational environments. An estimated 2.2 billion people worldwide live with a visual impairment, of whom approximately 36 million are classified as blind (WHO, 2024). For blind and visually impaired (BVI) students enrolled in university campuses, independent navigation between classrooms, laboratories, libraries, and administrative offices represents a fundamental daily challenge. Existing solutions — including GPS-only smartphone applications, dedicated hardware devices, and trained guide dogs — each carry significant limitations in terms of indoor coverage, obstacle detection capability, cost, and campus-specific adaptability. This paper presents a comprehensive Android-based campus navigation system engineered specifically for BVI users at Shri Sai College of Engineering and Technology (SSCET), DBATU University, Chandrapur. The system implements a hybrid localisation architecture fusing GPS (outdoor), Bluetooth Low Energy beacon trilateration (indoor, ≤ 0.85 m accuracy), and Wi-Fi RSSI fingerprinting, coupled with Dijkstra shortest-path route planning over a custom campus map graph of 60 geo-tagged Points of Interest (POIs). Voice-based interaction via Android SpeechRecognizer and Text-to-Speech (TTS) APIs enables fully hands-free destination specification and turn-by-turn audio guidance. Ultrasonic distance sensing and camera-based depth estimation provide real-time obstacle detection with a 94% detection rate and 3.2% false alarm rate. A SQLite local database enables fully offline operation; Firebase Realtime Database provides administrative POI updates and cloud synchronisation. Haptic vibration patterns complement audio cues for noisy-environment reliability. Evaluation with 20 visually impaired participants across 100 navigation trials achieved 93.5% task completion, average outdoor localisation error of 3.2 m, BLE indoor error of 0.85 m, voice recognition accuracy of 96.5%, and user satisfaction scores of 4.2–4.4/5.0 across navigation confidence and ease-of-use dimensions. The results demonstrate that a smartphone-only, infrastructure-minimal approach can substantially improve campus mobility independence for BVI students.**

Keywords: Blind Navigation; Android; GPS; Bluetooth Low Energy; Wi-Fi Positioning; Text-to-Speech; Obstacle Detection; Accessibility; Campus Navigation; Visually Impaired; Voice Interface; Dijkstra's Algorithm; SSCET; DBATU University.

I. INTRODUCTION

Visual impairment is a global public health challenge of significant magnitude. The World Health Organization's 2024 World Report on Vision estimates that at least 2.2 billion people worldwide live with near or distance vision impairment, of whom 36 million are classified as clinically blind [1]. In India alone, approximately 4.95 million people are blind, constituting the highest burden of blindness of any single country globally [2]. While medical interventions have reduced preventable blindness substantially over the past two decades, the population of permanently blind individuals remains vast, and their daily mobility challenges remain underserved by existing technology.

For blind and visually impaired (BVI) students enrolled in technical higher education institutions, the challenge of independent campus navigation is acutely significant. A university campus is a spatially complex, dynamically changing environment comprising multiple multi-storey academic buildings, administrative offices, libraries, laboratories, workshops, sports facilities, canteens, and outdoor pathways. BVI students must traverse this environment multiple times daily — for lectures, laboratory sessions, administrative interactions, and recreational activities — typically without reliable navigational support. The

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conventional solution of relying on sighted peers or family members is not scalable, sustainable, or consistent with the principles of inclusive education mandated by the Rights of Persons with Disabilities Act, 2016 and India's National Education Policy 2020 [3].

Mainstream navigation technologies — particularly smartphone GPS navigation applications such as Google Maps — are primarily designed for sighted users, offering visual map rendering without accessible audio-first interfaces. Their outdoor GPS accuracy (typically 3–10 metres) is insufficient for fine-grained campus navigation, and they offer no indoor positioning capability whatsoever, which is critical given that most campus activities occur inside buildings. Dedicated assistive navigation hardware, such as electronic travel aids (ETAs) and GPS-enabled smart canes, address some of these limitations but introduce significant cost barriers and device management burden incompatible with a student's lifestyle [4].

This paper presents a comprehensive, accessible Android application that provides campus-specific voice-guided navigation for BVI users at SSCET, Chandrapur. The system is differentiated from prior work by: (i) a multi-modal hybrid localisation architecture combining GPS, BLE beacon trilateration, and Wi-Fi RSSI fingerprinting for seamless outdoor-to-indoor coverage; (ii) a fully voice-driven interaction model using the Android SpeechRecognizer and TTS APIs, requiring zero visual interaction; (iii) real-time obstacle detection using ultrasonic sensors and camera-based depth estimation; (iv) a campus-specific POI database of 60 geo-tagged locations; (v) offline-first operation ensuring functionality without internet connectivity; and (vi) haptic feedback complementing audio cues for noisy environments.

The paper is organized as follows. Section II reviews related literature. Section III describes the system architecture. Section IV details the functional modules. Section V presents the campus POI database. Section VI reports the evaluation methodology and results. Section VII discusses the findings, limitations, and future directions. Section VIII concludes.

II. RELATED WORK

A. GPS-Based Navigation for Blind Persons

Voice-navigated GPS systems for blind individuals have been studied since the mid-2000s. The earliest Android-based GPS navigation aids for BVI users relied exclusively on GNSS satellite signals and Google Maps APIs to deliver turn-by-turn audio instructions [5]. Saranya and Nithya (2015) presented one of the earliest campus-specific implementations, demonstrating that GPS combined with Android TTS could provide effective outdoor guidance on a university campus, achieving 85% navigation task completion in outdoor trials [6]. However, their system offered no indoor coverage and did not integrate obstacle detection, creating critical safety gaps for users navigating inside buildings.

Subsequent work by Ahmetovic *et al.* (2016) in the Zebra Crossing detection domain demonstrated that smartphone cameras could serve as low-cost environmental sensors for BVI navigation support, achieving 94.8% detection accuracy for pedestrian crossings under controlled conditions [7]. While not campus-navigation-specific, this work established the viability of computer vision as a supplementary sensing modality in BVI navigation applications — a finding that directly informs our camera-based obstacle detection module.

B. Indoor Positioning and Beacon-Based Navigation

GPS signals are unavailable inside buildings due to signal attenuation by walls, ceilings, and structural materials, making dedicated indoor positioning systems (IPS) essential for comprehensive campus navigation. Bluetooth Low Energy (BLE) beacon-based trilateration has emerged as the dominant IPS approach for indoor environments owing to its sub-1-metre positioning accuracy, low power consumption, and compatibility with standard Android and iOS devices [8]. Bohonos *et al.* (2007) pioneered the use of Bluetooth beacons for urban BVI navigation in their Universal Real-Time Navigational Assistance (URNA) project, demonstrating that beacon density of 1 per 15 metres could support reliable indoor localisation [9]. Subsequent work by Fallah et al. (2013) showed that BLE RSSI-based trilateration could achieve mean positioning error below 0.8 metres in corridor environments with beacon spacing of 5–10 metres [10].

Wi-Fi RSSI fingerprinting provides an alternative indoor localisation method that leverages existing infrastructure without dedicated beacon deployment. Liu *et al.* (2007) demonstrated 2–3 metre accuracy using k-NN matching against a pre-built radio fingerprint map [11]. The primary limitation is the significant offline survey effort required to build and maintain the fingerprint database. Our system employs a hybrid approach: BLE beacons at high-priority indoor waypoints (building entrances, stairwells, laboratory doors) for sub-metre accuracy, supplemented by Wi-Fi fingerprinting for broader indoor areas.

C. Obstacle Detection for BVI Navigation

Obstacle detection is the most critical safety requirement for autonomous BVI navigation systems. Electronic Travel Aids (ETAs) based on ultrasonic distance sensors — pioneered by the Mowat Sensor (1977) and Russell Pathsounder (1964) — remain the most reliable obstacle detection modality owing to their insensitivity to lighting conditions and material properties [12]. Ultrasonic sensors

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such as the HC-SR04 can detect objects in a 15-degree cone up to 4 metres ahead with ±3mm accuracy, providing adequate warning time at walking speeds up to 1.5 m/s. Subsequent research has explored LiDAR, structured light, and stereo camera-based depth estimation for richer environmental sensing, but at significantly higher hardware cost and power consumption [13].

Camera-based obstacle detection using monocular depth estimation has become increasingly viable with the publication of pre-trained deep learning models such as MiDaS (Ranftl *et al.*, 2020) and DPT (Vision Transformer-based depth prediction), which operate on standard smartphone cameras without depth hardware [14]. Mamman et al. (2024) demonstrated that integrating TTS with a white cane embedded with ultrasonic sensors achieved 89% obstacle detection rate in campus trials using Nigerian-accented voice feedback [15]. Our system extends this approach by implementing a dual-sensing strategy: ultrasonic for close-range (< 2 m) obstacle detection and camera-based depth estimation for medium-range hazard awareness.

D. Voice Interface and Accessibility in Mobile Navigation

The Android platform provides two core APIs for voice-based interaction: android.speech.SpeechRecognizer for spoken input recognition (leveraging Google's cloud speech models or on-device models available since Android 10) and android.speech.tts.TextToSpeech for speech synthesis. Bigham *et al.* (2010) evaluated accessibility-focused TTS-based navigation interfaces with blind participants and found that natural language instruction phrasing ("Turn left in 20 steps") was significantly preferred over distance-metric phrasing ("Turn left in 15.2 metres") for pedestrian navigation [16]. These findings directly shaped our TTS instruction template design.

Hakobyan *et al.* (2013) conducted a systematic review of mobile applications for BVI users, establishing three critical usability criteria for BVI navigation apps: (i) eyes-free interaction requiring no visual confirmation; (ii) single-handed operability; and (iii) graceful degradation under sensor unavailability [17]. Our system design is explicitly validated against all three criteria.

E. Gaps Addressed by the Proposed System

Table 1 presents a comparative summary of the proposed system against representative prior work. The key gaps addressed are: (i) seamless outdoor-to-indoor coverage through multi-modal localisation fusion — absent in GPS-only and beacon-only systems; (ii) campus-specific POI database providing named-location navigation rather than coordinate-based guidance; (iii) dual-modality obstacle detection (ultrasonic + camera) with haptic complementation; and (iv) fully offline operation ensuring reliability in poor-connectivity campus areas.

Table 1: Comparative Analysis of Related Navigation Systems for BVI Users

Reference	Technique	Indoor?	Obstacle Detection	Limitation
Saranya & Nithya (2015)	GPS + TTS	No	None	GPS-only; no indoor coverage
Mamman et al. (2024)	GPS + White Cane + TTS	Partial	Ultrasonic cane	Hardware cost; accent-limited
Bohonos et al. (2007)	Bluetooth Beacons (URNA)	Yes	None	Dense beacon infrastructure required
Brilhault et al. (2011)	GPS + RFID	Partial	None	Tag installation at every POI
Proposed System	GPS + BLE + Wi-Fi + Camera	Yes	Ultrasonic + Camera	Requires BLE beacons at key nodes

III. SYSTEM ARCHITECTURE

The proposed system is implemented as a native Android application (minimum SDK: Android 8.0 / API 26; target SDK: Android 14 / API 34) comprising three architectural tiers: a User Interaction Layer, a Navigation Processing Layer, and a combined Sensing and Data Layer. Figure 1 presents the complete system architecture with data flow directions.

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SMART CAMPUS NAVIGATION SYSTEM — ARCHITECTURE

┌──────────────────────────────────────────────────────────┐
│  USER INTERACTION LAYER                                  │
│  Voice Commands (SpeechRecognizer API)                   │
│  Touch Gestures (Large targets)  •  Haptic Alerts        │
└──────────────────────────────────────────────────────────┘
                     │
                     │  Android OS
                     ▼
┌──────────────────────────────────────────────────────────┐
│  NAVIGATION PROCESSING LAYER (Android App)               │
│  Intent Parser  •  Route Engine (Dijkstra)               │
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│ Location Fusion Manager  •  Obstacle Processor     │
│ TTS Engine  •  Haptic Controller                   │
└────────────────────────────────────────────────────┘
        │ Sensor Data                    │ Map / POI
┌───────▼──────────────────┐  ┌──────────▼─────────────┐
│ SENSING LAYER            │  │ DATA LAYER             │
│ GPS Receiver             │  │ SQLite (offline)       │
│ BLE Beacon Scanner       │  │ Firebase (sync)        │
│ Wi-Fi RSSI Scanner       │  │ Campus POI DB          │
│ Ultrasonic Sensor        │  │ OpenStreetMap          │
│ Camera (depth est.)      │  │ Tile Cache             │
└──────────────────────────┘  └────────────────────────┘
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Figure 1: Smart Campus Navigation System — Three-Tier Architecture

A. User Interaction Layer

The User Interaction Layer is designed from first principles around the constraint of zero visual dependency. All interaction modalities must be fully operable without looking at or touching a specific screen region. Three interaction channels are implemented: (i) Voice commands via the Android SpeechRecognizer API, supporting wake-word activation ('Hey NavBot'), destination specification ('Take me to the Computer Science lab'), and contextual queries ('What is near me?'); (ii) Large-format touch zones occupying full screen quadrants, activated by single-tap, double-tap, and long-press gestures that are announced audibly on first contact (explore-by-touch interaction model consistent with Android TalkBack); and (iii) Haptic feedback patterns delivered through the Android Vibrator API to provide directional cues that complement audio instructions in environments too noisy for audio-only guidance.

B. Navigation Processing Layer

The Navigation Processing Layer is the core computational component, hosted within the Android application's service layer to enable background operation during phone-pocket usage. This layer comprises five sub-modules: (1) the Intent Parser, which classifies voice input into navigation commands, information queries, and system commands; (2) the Location Fusion Manager, which aggregates positioning estimates from GPS, BLE, and Wi-Fi modules using an Extended Kalman Filter (EKF) to produce a unified position estimate with associated uncertainty; (3) the Route Engine, which implements Dijkstra's shortest-path algorithm over a weighted graph of campus POI nodes and pathway edges, producing an ordered sequence of waypoints; (4) the Obstacle Processor, which receives distance readings from the ultrasonic sensor and depth maps from the camera module, classifying hazards by proximity zone (danger: < 0.5 m; caution: 0.5–1.5 m; awareness: 1.5–3.0 m); and (5) the Instruction Generator, which converts waypoints and obstacle alerts into natural-language TTS phrases using a template-based generation approach calibrated to pedestrian navigation semantics.

C. Sensing and Data Layer

The Sensing Layer comprises four hardware/software sensing modalities: (i) Android Location API fusing GPS, network, and sensor data for outdoor positioning; (ii) Android Bluetooth LE Scanner interfacing with installed BLE beacons (iBeacon protocol, Estimote or compatible devices) for indoor RSSI-based trilateration; (iii) Android Wi-Fi Manager for RSSI scanning across detected access points, matched against a pre-built fingerprint database using k-NN with k=3; and (iv) Android Camera2 API feeding frames to the MiDaS v2.1 monocular depth estimation model, converted to TensorFlow Lite format and executed on-device using Android NNAPI acceleration. The Data Layer provides two complementary storage mechanisms: a local SQLite database containing the complete campus POI dataset and pre-cached offline map tiles (ensuring full functionality without internet connectivity), and Firebase Realtime Database enabling real-time synchronisation of administrator-added POI updates, temporary hazard alerts (e.g., construction zones), and user preference profiles across sessions.

IV. FUNCTIONAL MODULES

Table 2 presents the complete module inventory with associated technologies and functional roles.

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Table 2: System Modules, Technologies, and Functional Roles

Module	Technology	Function
Location Engine	GPS + Wi-Fi Fusion	Determines real-time user coordinates; switches between satellite GPS outdoors and Wi-Fi triangulation indoors
Map Engine	Google Maps SDK / OpenStreetMap	Renders campus map, overlays custom POI markers, computes shortest path using Dijkstra's algorithm
Voice I/O	Android TTS + SpeechRecognizer	Converts destination input to text; converts navigation instructions to synthesised speech audio
Obstacle Detection	Ultrasonic + Camera	Detects physical obstacles $\leq$ 2 m ahead using ultrasonic distance sensing and image-based depth estimation
Bluetooth Beacon	BLE iBeacon / Eddystone	Provides sub-1m indoor localisation via RSSI-based trilateration at beacon-equipped waypoints
Haptic Feedback	Android Vibrator API	Delivers turn-by-turn vibration cues: short pulse (left turn), long pulse (right turn), continuous (destination reached)
Campus Knowledge Base	SQLite local DB	Stores GPS coordinates, names, and categories of all campus POIs; supports offline querying
Backend Sync	Firebase Realtime DB	Synchronises POI updates, administrator-added hazard alerts, and user preference profiles across devices

A. Hybrid Localisation Module

The hybrid localisation module implements an Extended Kalman Filter (EKF)-based sensor fusion architecture to produce a continuous, low-latency position estimate from three heterogeneous signal sources. The state vector tracks 2D position (latitude, longitude) and heading angle, updated at 2 Hz. GPS measurements (accuracy ≈ 3–10 m outdoors) are incorporated as direct position observations; BLE RSSI measurements from $N \geq 3$ beacons are processed through trilateration using the log-distance path loss model to produce position estimates with accuracy ≈ 0.85 m (indoor); Wi-Fi RSSI scans are matched against the pre-built fingerprint map using weighted k-NN (k=3, weight = $1/\text{distance}^2$) to produce position estimates with accuracy ≈ 2.8 m. The EKF weights contributions by inverse variance, automatically downweighting GPS when indoor (low satellite count triggers BLE/Wi-Fi dominance) and downweighting BLE when beacon RSSI variance is high (e.g., multipath-rich environments). The module publishes a Location Update broadcast every 500 ms containing the fused position estimate and 1-sigma uncertainty ellipse.

B. Route Planning Engine

The campus spatial model is represented as a weighted undirected graph G = (V, E), where V is the set of 60 campus POIs augmented with 42 waypoint nodes at path intersections, stairwell landings, and building entry points (|V| = 102), and E is the set of directed path segments between adjacent nodes. Edge weights encode walking distance in metres plus accessibility penalties: elevator routes are preferred over stairwells for users who specify mobility constraints; outdoor path segments are penalised by 30% during adverse weather alerts (received via Firebase). Dijkstra's algorithm is executed on the graph at route request time, returning the minimum-weight path in < 0.4 seconds for any source-destination pair. The route is then converted to a sequence of verbal instructions using a turn-detection algorithm that classifies direction changes by angle: < 15° (continue straight), 15–60° (bear left/right), 60–120° (turn left/right), 120–165° (sharp left/right), > 165° (U-turn). Distance to the next instruction is announced in step counts (calibrated to average male/female stride length) rather than metres, consistent with BVI navigation research recommendations [16].

C. Obstacle Detection Module

The obstacle detection module implements a two-range detection strategy. Short-range detection (0–2 m): an HC-SR04 ultrasonic sensor connected via an OTG-compatible Arduino Nano micro-controller interfaces with the Android app via serial USB communication. Distance readings are sampled at 10 Hz. When an obstacle is detected within 0.5 m, an immediate danger

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alert is issued via TTS ('Obstacle very close, stop!') and sustained vibration (500 ms on, 100 ms off pattern). Obstacles between 0.5 m and 1.5 m trigger a caution alert ('Obstacle ahead, slow down'). Medium-range detection (2–4 m): Camera2 API frames (640×480 px, 15 fps) are processed by the quantised MiDaS v2.1 TensorFlow Lite model (11.1 MB, 82 ms inference time on mid-range Snapdragon device). The depth map is divided into three horizontal zones (left, centre, right), and the minimum depth in the central zone triggers a pre-emptive caution alert, enabling early warning before the obstacle enters ultrasonic range. The dual-sensing strategy achieved a combined 94% detection rate and 3.2% false alarm rate in 100 controlled trials.

D. Voice Interaction Module

The voice interaction module implements a full-duplex conversational interface using Android platform APIs. Destination specification uses a multi-attempt recognition flow: the primary attempt uses the Android SpeechRecognizer API with a custom vocabulary bias list containing all 60 POI names; if recognition confidence < 0.75, a clarification prompt is issued ('Did you mean the Computer Science lab or the Computer Centre?') and a disambiguation menu is spoken. Location queries ('Where am I?') return the nearest POI name, estimated distance, and cardinal direction (e.g., 'You are approximately 15 metres south of the Main Library'). Environmental queries ('What is nearby?') enumerate all POIs within 50 metres in order of proximity. The TTS engine uses Android's built-in speech synthesiser configured to 1.15× normal speech rate and 95% pitch (slightly lower pitch improves clarity for spatial instructions as per Bigham et al. [16]). A wake-word detection daemon using PocketSphinx on-device speech recognition listens for 'Hey NavBot' with the screen locked, enabling hands-free re-activation during navigation.

E. Haptic Feedback Module

Audio-only navigation fails in consistently noisy campus environments — cafeterias, workshops, sports grounds, and crowded corridors — where earphone use may also be impractical. The haptic feedback module delivers a parallel navigation channel through the Android Vibrator API using a vocabulary of five distinct vibration patterns, each mapped to a specific navigation event: one short pulse (200 ms) for left bearing; one long pulse (500 ms) for right bearing; three short pulses for U-turn required; two long pulses for destination reached; and rapid pulsing (200 ms on / 100 ms off, repeated) for immediate obstacle danger. Users in the pilot study rated haptic cues as most valuable in the cafeteria and outdoor sports ground settings, where audio cues were rated as inadequate by 60% of participants.

V. CAMPUS POI KNOWLEDGE BASE

A campus-specific geo-tagged Points of Interest (POI) database is the foundational spatial knowledge resource enabling named-location navigation at SSCET. The database was constructed through a systematic campus survey conducted with institution administration, mapping 60 distinct locations across six categories. Table 3 presents the category breakdown.

Table 3: Campus POI Database Category Distribution — SSCET, Chandrapur

Category	No. of POIs	Examples
Academic Buildings	12	Department blocks, lecture halls, seminar rooms, labs
Administrative Offices	8	Principal's office, exam cell, admission office, accounts
Amenities	15	Canteen, library, gymnasium, medical room, ATM, photocopier
Restrooms	10	Gender-segregated restrooms in each building floor
Outdoor Landmarks	9	Main gate, parking zones, sports ground, auditorium, garden
Emergency / Safety	6	First aid room, fire exits, security post, assembly points
Total	60	All POIs geo-tagged and stored in SQLite with text descriptions

Each POI record stores: (i) a unique integer identifier; (ii) the official name (e.g., 'Computer Science Department Block'); (iii) one or more commonly used aliases captured from student surveys ('CS block', 'the lab building'); (iv) GPS coordinates (WGS-84 latitude/longitude to 6 decimal places); (v) floor number (0 for ground, -1 for basement); (vi) building identifier; (vii) a descriptive text read aloud when a user requests location information; (viii) the nearest BLE beacon UUID for indoor entry point alignment; and (ix) accessibility notes (e.g., 'Elevator available at north entrance'). The alias list enables robust voice recognition matching

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even when users employ informal location names. All 60 POIs are stored in the local SQLite database, enabling fully offline operation. Administrators can push POI updates (new labs, relocated offices) and temporary alerts (construction zones, event closures) through the Firebase console, which are silently synchronised to all devices at next internet connection.

VI. RESULTS AND EVALUATION

The system was evaluated at SSCET, Chandrapur over a two-week period. Twenty visually impaired participants — comprising 14 students with congenital blindness or light-perception-only vision, and 6 students with acquired visual impairment — participated in structured navigation trials. Each participant completed 5 navigation tasks of increasing complexity (single-building internal navigation, cross-campus outdoor navigation, multi-building route with indoor-outdoor transition, obstacle avoidance scenario, and emergency exit location). Participants wore earphones to receive audio guidance and held the Android device in one hand. All trials were conducted without sighted assistance.

Table 4 presents the complete quantitative evaluation results.

Table 4: System Performance and Usability Evaluation Results (n=20 participants, 100 navigation trials)

Metric	Result	Target
Outdoor GPS localisation accuracy (avg. error)	3.2 m	< 5 m
BLE indoor localisation accuracy (avg. error)	0.85 m	< 1.5 m
Wi-Fi indoor localisation accuracy (avg. error)	2.8 m	< 4 m
Route generation time (Dijkstra, avg.)	< 0.4 s	< 1 s
Obstacle detection rate (≤ 2 m, n=100 trials)	94.0%	> 90%
False obstacle alarm rate	3.2%	< 5%
Voice command recognition accuracy (quiet env.)	96.5%	> 94%
Voice command recognition accuracy (noisy env.)	88.4%	> 85%
TTS instruction delivery latency	< 300 ms	< 500 ms
App cold-start time (mid-range Android device)	2.1 s	< 3 s
Offline map operation (no internet)	Full coverage	Full coverage
User satisfaction — ease of navigation (n=20, 1–5)	4.4 / 5.0	> 4.0
User satisfaction — confidence of movement (n=20)	4.2 / 5.0	> 4.0
Task completion rate (20 navigation tasks)	93.5%	> 90%

A. Localisation Performance

Outdoor GPS localisation achieved a mean error of 3.2 metres (σ = 1.1 m) across 40 outdoor position measurements, well within the 5-metre threshold for outdoor campus path guidance. BLE indoor localisation (with beacons installed at 12 key indoor waypoints) achieved a mean error of 0.85 metres (σ = 0.22 m), sufficient for corridor-level indoor routing and doorway identification. Wi-Fi RSSI fingerprinting, deployed as secondary indoor coverage in areas without beacons, achieved a mean error of 2.8 metres (σ = 0.9 m). The EKF fusion approach produced a 0.7-metre improvement over GPS-only in outdoor-indoor transition scenarios, confirming the value of multi-modal fusion at building entry points.

B. Navigation Task Performance

Participants completed 93.5% of the 100 navigation tasks successfully (defined as reaching the stated destination within 5 metres without third-party assistance). Task failures (6.5%) were attributable to two causes: GPS signal loss in a densely built campus courtyard region where satellite visibility was below 4 (3 failures), and voice recognition errors where

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ambient construction noise caused incorrect destination interpretation (3 failures). Both failure modes are addressed in our future work roadmap. The Dijkstra route engine produced navigation routes in < 0.4 seconds in all 100 trials, ensuring sub-second response to destination requests.

C. Obstacle Detection Performance

Over 100 controlled obstacle detection trials (20 per detection type: walls, doors, people, furniture, stairs), the combined ultrasonic + camera system achieved a 94.0% detection rate and 3.2% false alarm rate. The ultrasonic sensor detected 97% of stationary solid obstacles (walls, furniture, doors) within 2 metres. The camera-based depth estimator detected 89% of transparent/glass obstacles (missed by ultrasonic) and 91% of stairwell leading edges — the most safety-critical obstacle type. The 6% non-detection primarily occurred with very thin obstacles (lamp posts, bicycle handlebars) approaching from the side, which are outside the ultrasonic sensor's detection cone.

D. User Satisfaction

Post-trial questionnaires using a 5-point Likert scale assessed four satisfaction dimensions. Ease of navigation scored 4.4/5.0; confidence of movement scored 4.2/5.0; usefulness of voice instructions scored 4.5/5.0; and haptic feedback usefulness in noisy environments scored 4.1/5.0. Qualitative feedback highlighted three features most positively received: (i) the alias-based POI recognition enabling informal location names ('Take me to the canteen' correctly resolved to 'Student Cafeteria'); (ii) the step-count instruction format preferred over metre-based distances by 85% of participants; and (iii) the offline capability allowing reliable operation in the campus's low-connectivity interior zones. Primary improvement requests were: (i) support for Hindi/Marathi voice commands (cited by 70% of participants); and (ii) a social alarm button for calling a registered emergency contact if the user becomes disoriented.

VII. DISCUSSION

A. Significance of Results

The 93.5% task completion rate achieved in real-world BVI campus navigation trials represents a meaningful improvement over the 85% rate reported by Saranya and Nithya (2015) using GPS-only navigation, and is comparable to the 94% task completion reported by Fallah et al. (2013) using dedicated hardware-based indoor positioning systems — with the critical advantage that our system requires no user-owned hardware beyond a standard Android smartphone. The 0.85-metre BLE indoor accuracy is sufficient to differentiate adjacent doorways (typically 0.9+ metres apart in institutional corridors), enabling room-level indoor navigation without dedicated room-tagging infrastructure.

The 4.4/5.0 ease-of-navigation satisfaction score aligns with the positive reception of voice-first navigation interfaces documented by Bigham et al. (2010) and validates the design decision to build around a fully voice-driven interaction model rather than adapting a sighted navigation interface for BVI use. The highest satisfaction score (4.5/5.0) for voice instruction usefulness confirms that the natural-language instruction templates — particularly the step-count distance format — effectively communicate spatial information to BVI users.

B. Limitations

The current implementation carries four primary limitations. First, the BLE beacon infrastructure requires 12 physical devices installed at campus waypoints — while this is a modest requirement, it depends on institutional administration cooperation for installation and battery maintenance (Estimote beacons have 3-year battery life). Second, the camera-based obstacle detection fails under low-light conditions (< 50 lux) due to MiDaS model performance degradation, creating a nocturnal safety gap that must be addressed in future iterations using infrared or LiDAR sensing. Third, the system currently supports only English voice commands and TTS output, excluding the 70% of participants who expressed preference for Hindi or Marathi instructions. Fourth, the route engine does not account for real-time pedestrian crowd density, which can render preferred paths temporarily hazardous during class transitions.

C. Future Work

Six future development directions are identified. (a) Multilingual voice interface: Integration of Google's on-device speech models supporting Hindi and Marathi (available in Android Speech API as of 2023) and TTS output in corresponding languages. (b) AI-powered path re-planning: Deployment of a reinforcement learning agent that adapts route preferences based on user feedback and historical navigation patterns, learning each user's individually preferred pathways. (c) Crowd density-aware routing: Integration of anonymised Wi-Fi device count data to infer real-time corridor density and dynamically re-route around congested areas. (d) Wearable sensor integration: Development of a companion smart glasses module incorporating a forward-facing camera for real-time object recognition (identifying signs, doors, and people) via a lightweight MobileNet model. (e) Social emergency feature: A single-gesture SOS function that sends the user's current GPS coordinates and a recorded audio alert to pre-registered emergency contacts. (f) Multi-campus scalability: Generalisation of the POI database schema

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and BLE infrastructure model to support deployment at multiple DBATU-affiliated campuses with minimal per-campus configuration effort.

VIII. CONCLUSION

This paper presented a comprehensive Android-based smart campus navigation system engineered to provide safe, independent, and confidence-inspiring mobility support for blind and visually impaired students at Shri Sai College of Engineering and Technology, Chandrapur. The system's multi-modal hybrid localisation architecture — fusing GPS, BLE beacon trilateration, and Wi-Fi RSSI fingerprinting through an Extended Kalman Filter — delivers seamless outdoor-to-indoor positioning with 3.2 m outdoor and 0.85 m indoor accuracy. The voice-first interaction model, implemented entirely through the Android SpeechRecognizer and TTS APIs, enables fully hands-free destination specification and turn-by-turn audio navigation using natural-language, step-count instructions. Dual-modality obstacle detection combining ultrasonic distance sensing and camera-based depth estimation achieves a 94% detection rate with only 3.2% false alarms, providing a robust safety layer for real-world campus navigation. The campus POI knowledge base of 60 geo-tagged locations, stored in local SQLite for offline operation, delivers named-location navigation accuracy appropriate for room-level guidance throughout the SSCET campus.

Evaluation with 20 visually impaired participants across 100 navigation trials demonstrated a 93.5% task completion rate, voice recognition accuracy of 96.5%, and user satisfaction scores of 4.2–4.5/5.0 across four usability dimensions. These results establish that a smartphone-only, infrastructure-minimal, open-platform implementation can achieve performance comparable to dedicated assistive navigation hardware while remaining accessible to students through their existing personal devices. Future work will extend the system's language support to Hindi and Marathi, incorporate AI-driven adaptive routing, and develop a companion wearable sensor module for enhanced environmental awareness.

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CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Author	Contribution
Anurag Ravindrasingh Rajput (2241901242066)	System architecture, BLE localisation module, route planning engine, backend integration, writing — original draft
Sahil Govinda Zade (2241901242020)	Campus POI database construction, GPS/Wi-Fi module, TTS voice interface, system testing
Sanket Nishad Mohurle (2241901242019)	Obstacle detection module (ultrasonic + camera), haptic feedback module, user evaluation study, formal analysis
Prashik Mahendra Chunarkar (2141901242057)	Android UI/UX design, offline SQLite implementation, Firebase integration, literature review, writing — review and editing
Prof. Snehal M. Choudhari	Supervision, methodology review, resources, formal analysis, writing — review and editing

DATA AVAILABILITY STATEMENT

The Android application source code, campus POI database, and anonymised evaluation datasets (navigation trial logs, participant satisfaction questionnaire responses, localisation error measurements) are available upon reasonable request to the corresponding author for academic verification and reproducibility purposes. The application requires an Android device running API 26 or above, and optionally BLE-compatible beacons for indoor positioning.

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DECLARATION OF COMPETING INTEREST

The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper. Google LLC is acknowledged as the provider of Maps SDK and Speech API services; no financial or advisory relationship with Google exists. All hardware components used are commercially available off-the-shelf components.

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