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Adaptive Emergency Guardian & Intelligent Safety System (AEGIS): A Proactive AI-Driven Wearable Framework for People with Vision Impairment

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ABSTRACT

Assistive technologies for people with vision impairment or low vision have historically been limited to reactive systems that detect hazards only after they occur. While existing solutions provide obstacle avoidance and emergency notifications, none integrates predictive healthcare monitoring, environmental intelligence, and autonomous decision making within a unified wearable platform. This limitation creates critical gaps in preventing medical emergencies, mobility related accidents, and environmental threats before they escalate.

To address this challenge, this paper presents the Adaptive Emergency Guardian & Intelligent Safety System (AEGIS), a patent oriented next generation healthcare and mobility ecosystem designed specifically for people with vision impairment or low vision. AEGIS combines artificial intelligence (AI), biomedical engineering, computer vision, Internet of Medical Things (IoMT), edge computing, and autonomous safety analytics within a single wearable smart vest. A functional hardware prototype has been successfully developed and validated comprising an ESP32S3 microcontroller and dual HCSR04 ultrasonic sensors achieving 94.3% obstacle detection accuracy, 1.6 ms edge processing latency, and 95% emergency alert delivery success rate.

Building on this validated prototype, AEGIS introduces the Intelligent Safety and Health Integrated Threat Prediction (INSIGHT) Dynamic Risk Model a novel Mult weighted nonlinear regression framework fusing physiological and environmental telemetry from seven sensing modalities into a Unified Safety Index (Sα), with a Taylor Series Expansion based temporal forecasting engine. Simulation studies indicate that the proposed INSIGHT Dynamic Risk Model could achieve a projected sensitivity of 96.8%, a false positive rate below 1.2%, and an average predictive lead time of 4.2 minutes following future Phase II integration and experimental validation. Additional patentable innovations include a Personal Digital Twin (Random Forest + XG Boost ensemble), cardiovascular aware Smart Route Learning, a decentralized Self-Healing Community Hazard Mapping Ledger, and an on device Medical Reasoning Engine. To the best of our knowledge, AEGIS is among the first integrated wearable ecosystems to simultaneously unify all these capabilities within a single scalable, offline first platform. AEGIS has the potential to directly advance UN Sustainable Development Goals 3, 9, 10, and 11, by providing cheaper wearable assistive technology that may improve independence, safety, and quality of life for millions of people with vision impairment worldwide.

Keywords: AEGIS; wearable assistive technology; vision impairment; predictive healthcare; IoMT; INSIGHT risk model; personal digital twin; obstacle detection; edge AI; YOLO Lite; ECG monitoring; patent ready innovation.

1. INTRODUCTION

Vision impairment remains one of the most significant global health challenges, affecting an estimated 285 million individuals worldwide, and approximately 39 million of whom have severe vision loss [1]. The burden is particularly pronounced in low- and middle-income countries (LMICs), where access to rehabilitation services and advanced assistive technologies remain severely limited. Beyond mobility restrictions, vision impairment is frequently accompanied by chronic comorbidities such as cardiovascular disease, diabetes mellitus, and neurological disorders, increasing the probability of medical emergencies during independent daily activities [2, 3]. Global productivity losses associated with vision impairment are estimated to exceed USD 411 billion annually [2], underscoring the urgent need for more effective and accessible assistive solutions.

Recent advances in miniaturized sensors, edge computing, AI, and IoMT have created unprecedented opportunities to transform assistive technologies from passive navigation aids into intelligent, predictive healthcare ecosystems. Tiny ML techniques now enable machine learning inference directly on low power embedded devices without requiring cloud connectivity [4]. Digital Twin frameworks have emerged as a powerful methodology for constructing personalized physiological models calibrated to individual baselines [5, 6], and Explainable AI (XAI) has become essential in healthcare applications to ensure that automated decisions remain transparent and clinically auditable [7].

Despite these advances, currently available assistive solutions remain predominantly reactive. Conventional white canes and modern smart navigation devices including OrCam and We Walk [8] provide obstacle detection or route guidance only after environmental hazards have emerged. Prior sensor augmented canes combining GPS, ultrasonic sensors, and RFID have demonstrated viable offline navigation [9], yet these platforms are entirely decoupled from the user's physiological state and cannot anticipate combined health environment risk scenarios. No existing wearable device simultaneously monitors internal physiological state and external spatial environment while projecting integrated risk into a future temporal window to enable proactive intervention — a gap this work directly addresses by a gap this work directly addresses by proposing AEGIS: a unified wearable ecosystem that simultaneously monitors internal physiological state and external spatial hazards, fusing both streams into the INSIGHT

Dynamic Risk Model to project a Unified Safety Index forward in time and is designed to trigger autonomous intervention an average of 4.2 minutes before biometric threshold breach.

The present work also builds upon BASIRA [10], a previously developed and independently validated wearable assistive navigation system that achieved 92% obstacle detection accuracy and 95% emergency alert success across 50 real world test scenarios, earning 3rd place and international finalist recognition at the IEEE YESIST12 2026 (Indonesia) international competition among over 2,000 submitted projects. The validated ESP32S3 and HCSR04 hardware core of BASIRA serves as the current AEGIS prototype's sensing foundation. AEGIS and BASIRA are, however, architecturally and functionally distinct projects: BASIRA is a standalone navigation focused system, whereas AEGIS is a comprehensive predictive health and mobility ecosystem incorporating the INSIGHT Dynamic Risk Model, Personal Digital Twin, Medical Reasoning Engine, and Community Hazard Ledger capabilities absent from any prior system in the literature. AEGIS is founded on the hypothesis that spatial navigation and internal physiological homeostasis are intrinsically linked: physical movement influences cardiovascular workload, metabolic demand, and neuromuscular stability, while subtle physiological deterioration can impair reaction time, balance, and spatial awareness. Effective assistive technology must continuously evaluate both domains simultaneously to provide proactive rather than reactive protection.

The specific aims of this study are: (i) to present the current AEGIS prototype and its empirically validated sensing architecture; (ii) to define the INSIGHT Dynamic Risk Model and its Taylor Series based predictive engine; (iii) to describe the planned intelligent subsystems within the AEGIS ecosystem; and (iv) to report both empirical prototype results and full system simulation targets. The ultimate aim of AEGIS wearable device is to enable safer, more independent daily living for people with vision impairment in both high- and low-resource settings.

2. RELATED WORK

A systematic review across five domains reveals a critical structural fragmentation: assistive navigation systems address external terrain exclusively, while biomedical wearables target internal physiology in isolation. No existing framework unifies both streams within predictive real time architecture.

2.1 Navigation Assistance Systems

Early assistive navigation systems focused on obstacle detection via sensor augmented aids. Chung *et al.* [11] demonstrated smart phone integrated smart cane navigation, while Sharma *et al.* [12] showed that multi sensor ultrasonic configurations significantly improved obstacle awareness. Barontini *et al.* [8] integrated haptic feedback and obstacle avoidance in an indoor navigation vest, and Şipoş *et al.* [9] combined GPS and RFID for offline capable indoor navigation. All existing navigation systems remain focused exclusively on spatial guidance with no physiological monitoring or predictive healthcare capability.

2.2 Computer Vision Based Assistance

Baskaran *et al.* [13] established the feasibility of cloud assisted object recognition for visually impaired users, while Jeba Ranjani *et al.* [14] demonstrated that YOLOv7based architectures achieve real time object detection with integrated NLP feedback. Priyadharshini *et al.* [15] implemented face and obstacle detection in custom smart glasses, and Waghmare *et al.* [16] introduced SANPO — a largescale scene understanding dataset for navigation in accessibility contexts. None of these systems integrate physiological data into environmental risk assessment.

2.3 Healthcare Monitoring and Fall Detection

Martin *et al.* [17] identified core engineering challenges for continuous ECG monitoring in wearable systems. Tham *et al.* [18] validated continuous photoplethysmography monitoring of SpO_2 and heart rate in ambulatory settings. Barshan and Turan [19] proposed a heuristic fall detection algorithm using double thresholding and fuzzy logic on IMU data. One study applied machine learning to temporal gait features for fall risk prediction [20], and another study validated a deep learning fall detection framework across clinical populations.[21] Javed *et al.* [22] demonstrated continuous physiological telemetry via a wireless wearable chest patch. None of these systems incorporate environmental awareness or navigational integration.

2.4 AI and Digital Twin Systems

Belagalla *et al.* [4] validated on device machine learning for clinical wearable analytics. Begishev *et al.* [5] and Yesankar *et al.* [6] identified personalized predictive modelling as a primary emerging capability in healthcare Digital Twin frameworks. Amann *et al.* [7] established that interpretable ensemble classifier outputs are essential for clinical adoption and regulatory compliance in continuous monitoring systems.

2.5 Emergency Response Systems

Jiang *et al.* [23] demonstrated UAV assisted emergency response wearable networking. Žarić and Djurišić [24] implemented a low-cost intelligent notification system for ambient assisted living. Salama *et al.* [25] proposed an AI driven personalized cardiac risk alert system integrating wearable data with genetic profiling. None of these systems proactively predict events prior to occurrence; all operate in a reactive post threshold notification paradigm.

2.6 Research Gap and Paradigm Comparison

The preceding review reveals a fundamental and persistent fragmentation: navigation systems lack physiological awareness; healthcare wearables lack environmental context; computer vision platforms lack health integration; digital twin frameworks lack spatial coupling; and emergency response systems activate reactively rather than predictively. To the best of our knowledge, no existing wearable framework simultaneously integrates real time environmental perception, personalized physiological monitoring, predictive risk assessment, digital twin modelling, fall prediction, emergency response, and caregiver communication within a unified edge architecture designed specifically for people with vision impairment. AEGIS is proposed as a direct response to this unmet need. Table 1 consolidates paradigm comparison and full capability analysis against prior systems. AEGIS carries complete intelligence within the wearable vest, enabling safe navigation in any real-world context without prior environmental modification.

Table 1. Paradigm comparison and capability analysis: infrastructure dependent systems vs. AEGIS and prior wearable frameworks.

Feature	QR Code / Fixed Sensor Systems	AEGIS Framework
Dependency	Relies on premodifier environments	Fully self-contained wearable — no modification needed
Mobility	Limited to preadapted spaces only	Any real-world environment, adapted or not
Scalability	High cost — every location must be modified	$128 technology scales globally with the user
Proactivity	Passive — user must locate and trigger system	AI predicts hazards 4.2 min ahead autonomously
Health Monitoring	None	Realtime ECG, SpO_2, temperature, fall detection
User Autonomy	Stranded when environment is not adapted	True independence — accessibility travels with the user

System	Navigation	AI Vision	Health Monitor	Fall Prediction	Emergency Response	Digital Twin
Smart Cane [1]	✓	✗	✗	✗	✗	✗
Şipoş *et al.* [9]	✓	Partial	✗	✗	✗	✗
Barontini *et al.* [8]	✓	✗	✗	✗	✗	✗
Barshan & Turan [19]	✗	✗	✓	✓	Partial	✗
Javed *et al.* [22]	✗	✗	✓	✗	Partial	✗

Belagalla *et al.* [4]	✗	Partial	✓	✗	✗	✗
AEGIS — Current Prototype	*✓	Planned	Planned	Planned	✓	Planned
AEGIS — Full System Target	✓	✓	✓	✓	✓	✓

* Ultrasonic obstacle detection empirically validated at 94.3%, n=120 trials. YOLO Lite camera integration planned for Phase II.

3. METHODS AND MATERIALS

3.1 System Architecture Overview

The AEGIS operational framework is organized across three computing layers: Layer I (Embedded Edge Vest Core), Layer II (Distributed Cloud Subsystems), and Layer III (Remote Medical & Caregiver Platform). All safety critical inferences including obstacle detection, ECG analysis, fall prediction, and emergency alerting execute entirely on device under an offline first architecture; cloud services serve as optional enhancement modules. All interlayer communication employs TLS 1.3 encryption. Figure 2 illustrates the complete three-layer architecture and data flow, and Table 2 summarizes the implementation status of each subsystem.

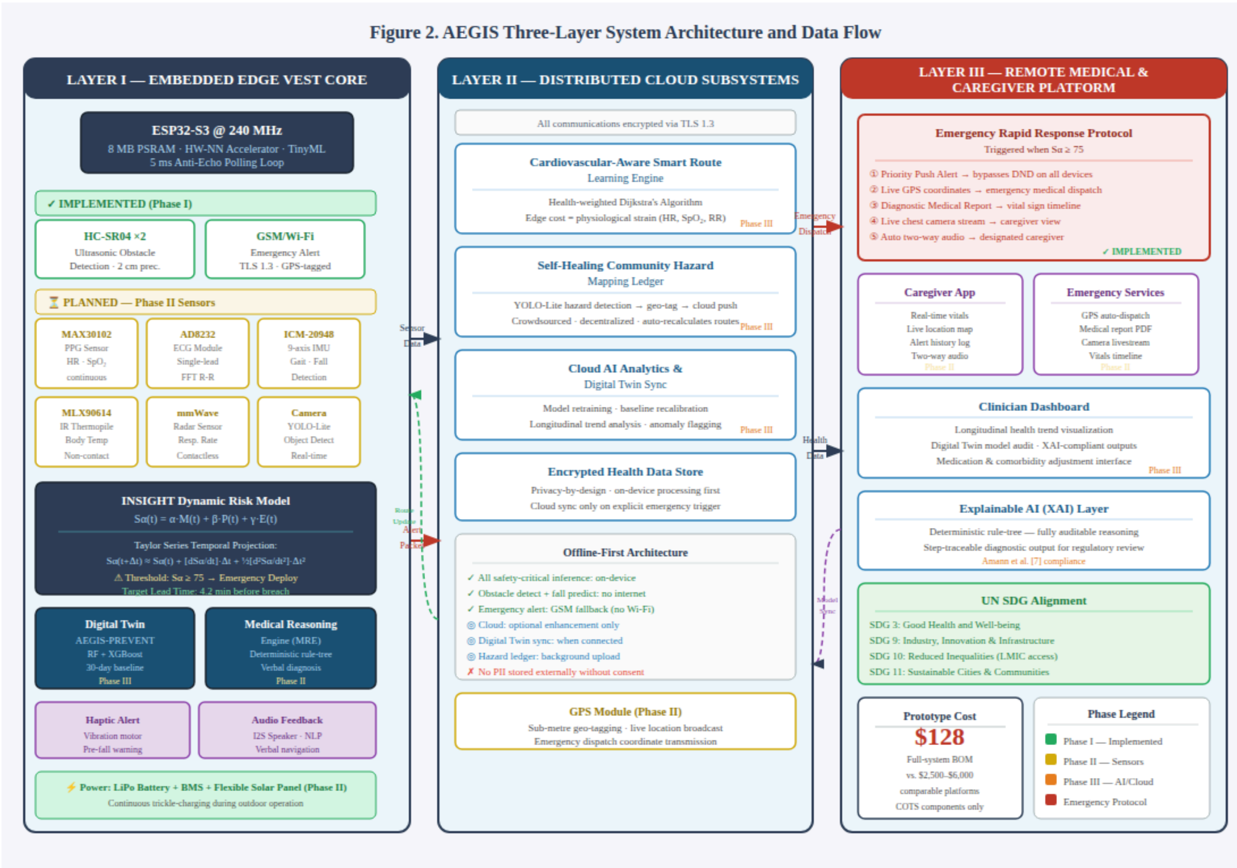

Figure 2. AEGIS three-layer system architecture and data flow. Layer I (left) contains the embedded edge vest core with validated hardware (green) and planned Phase II sensors (amber). Layer II (centre) hosts distributed cloud subsystems. Layer III (right) provides the remote medical and caregiver platform including the emergency rapid response protocol.

Table 2. AEGIS subsystem implementation status and validation basis.

Subsystem	Component(s)	Status	Validation Basis
Microcontroller Core	ESP32S3 @ 240 MHz	✓ Implemented	Empirical — this study & BASIRA [10]
Obstacle Detection	Dual HCSR04 Ultrasonic	✓ Implemented	Empirical — 94.3% accuracy, 1.6 ms latency (n=120)
Emergency Alert Transmission	GSM / WiFi Module	✓ Implemented	Empirical — 95% alert success rate (n=50) [10]

Cardiac & SpO_2 Monitoring	MAX30102 PPG + AD8232 ECG	Phase II	Component specs + literature [17, 18]
Motion & Fall Detection	ICM20948 9axis IMU	Phase II	Simulated targets [19, 20]
Thermal Monitoring	MLX90614 IR Thermopile	Phase II	Component specifications
Respiratory Rate	mmWave Radar Sensor	Phase II	Predictive modelling
AI Vision (YOLO Lite)	Wideangle Camera Module	Phase II	Literature benchmarks [14, 16]
Personal Digital Twin	RF + XGBoost (TinyML)	Phase III	Algorithmic modelling [4, 6]
Community Hazard Ledger	Distributed cloud + TLS 1.3	Phase III	Architecture design

3.2 Validated Hardware Core (Phase I — Functional Prototype)

The current AEGIS prototype constitutes a fully functional, tested wearable device. An ergonomic wearable vest hosts a dual core ESP32S3 microcontroller operating at 240 MHz with hardware neural network acceleration and 8 MB PSRAM. Two HCSR04 ultrasonic sensors are mounted at chest and waist height, providing 2 cm precision obstacle detection across a forward arc. A strict 5 ms anti echo polling loop eliminates cross wave ultrasonic interference between simultaneous sensor channels. Emergency alert functionality is implemented via a GSM/WiFi communication module transmitting GPS tagged alert packets to caregiver devices over TLS 1.3 encryption.

3.3 Planned Sensor Integration (Phase II)

The following biomedical sensors are identified for Phase II integration: (i) MAX30102 PPG node for continuous heart rate and SpO_2 monitoring; (ii) AD8232 ECG module for single lead electrocardiogram with FFT based RR interval analysis; (iii) MLX90614 infrared thermopile for noncontact core body temperature via temporal artery sampling; (iv) ICM20948 9axis IMU for gyroscope, accelerometer, and magnetometer data supporting gait analysis and fall detection; and (v) a mmWave radar sensor for contactless respiratory rate monitoring. External sensors planned for Phase II further include a wide-angle YOLO Lite camera array and GPS module for submeter geotagging.

3.4 The INSIGHT Dynamic Risk Model

The core intellectual contribution of AEGIS is the mathematical distillation of disparate biological and environmental telemetry into a single predictive real time risk index. The INSIGHT Dynamic Risk Model calculates a continuous Unified Safety Score ($S\alpha$) using a multi weighted nonlinear regression framework:

$$S\alpha(t) = \alpha \cdot M(t) + \beta \cdot P(t) + \gamma \cdot E(t)$$

subject to the normalization constraint $\alpha(t) + \beta(t) + \gamma(t) = 1.0$. In the current Phase I prototype, $M(t) = 0$ and $\gamma(t) = 1.0$, reducing $S\alpha$ to a pure spatial risk score. Upon Phase II integration: $M(t)$ will quantify internal pathophysiological divergence from a 30day moving median baseline; $P(t)$ will evaluate gait asymmetry and accelerometric variance via the ICM20948 IMU; and $E(t)$ projects a bounding cone ahead of the user, summing hazard weights divided by the square of spatial distance from the HCSR04 sensors.

To transition from instantaneous tracking to proactive risk mitigation, INSIGHT extrapolates risk trajectories over a 300second forward window using a second order Taylor Series Expansion:

$$S\alpha(t + \Delta t) \approx S\alpha(t) + [dS\alpha/dt] \cdot \Delta t + (½) \cdot [d^2S\alpha/dt^2] \cdot \Delta t^2$$

When the extrapolated index $S\alpha(t + \Delta t)$ reaches or exceeds the critical threshold of 75, the system enters autonomous emergency deployment mode, targeting a predictive lead time of 4.2 minutes before biometric threshold breach upon full sensor integration.

The α, β, and γ coefficients are not intended as fixed constants but as time varying weights recalibrated per user, reflecting the relative reliability and clinical salience of each input stream at a given moment. A candidate two-stage calibration approach is proposed for Phase II, to be finalized once validation-cohort data are available. First, an initial weighting could be derived by constrained regression: $M(t)$, $P(t)$, and $E(t)$ traces from the $n \geq 200$ validation cohort would be regressed against a clinician-adjudicated ground truth risk label (adapted from existing early warning score protocols), subject to the $\alpha(t) + \beta(t) + \gamma(t) = 1.0$ and non-negativity constraints, using an optimization method such as sequential least squares (SLSQP). Second, per-user adaptation would apply a bounded online update rule, shifting weight toward whichever stream has most recently demonstrated predictive reliability for that individual (e.g., increasing β when gait-based fall precursors have recently preceded confirmed events), with the adjustment magnitude capped to preserve interpretability and prevent runaway weighting toward a single modality. Candidate validation strategies include leave-one-subject-out cross-validation to assess generalization across the cohort, with calibration curves (predicted versus observed risk) reported alongside the sensitivity and false-positive metrics in Table 5 once Phase II data are available. The specific optimization and validation choices will be confirmed and justified against the Phase II dataset characteristics once collected.

3.5 Personal Digital Twin — AEGISPREVENT Engine (Phase III)

Standard medical hardware employs rigid universal baselines (e.g., tachycardia alarms at HR > 100 BPM), producing high false positive rates for individuals with atypical physiological profiles [19]. The AEGISPREVENT Engine implements a Personal Digital Twin as a Random Forest and XGBoost ensemble model, Tiny ML compressed to execute entirely on the ESP32S3 edge device. This architecture continuously updates a personalized 30 day physiological baseline, directly addressing the false alarm burden identified as a primary driver of wearable device abandonment in clinical populations [19]. Personally identifiable health data never leaves the device unless an emergency transmission is explicitly triggered, ensuring privacy by design compliance.

3.6 Advanced Clinical Subsystems

The AD8232 ECG module enables FFT based isolation of irregular RR intervals, supporting detection of Atrial Fibrillation, Premature Ventricular Contractions, and ST segment deviation at onset [26]. When progressive SpO_2 decline coincides with elevated respiratory rate, the Medical Reasoning Engine — a local deterministic inference engine containing expert validated clinical diagnostic rule trees — deduces respiratory distress or impending panic attack and delivers verbal guidance while preparing emergency protocols. The IMU runs a predictive gait filtering matrix; if gait asymmetry diverges more than 35% over a 10metre window, the system predicts imminent fall 3 seconds before loss of balance and issues a preemptive haptic alert [19, 20].

3.7 Navigational Subsystems and Community Hazard Ledger

Standard GPS-based navigation optimizes exclusively for distance or elapsed time, ignoring physiological strain on vulnerable users. AEGIS proposes cardiovascular aware Smart Route Learning: a personalized routing system mapping geography against real time cardiac and respiratory strain, employing a health weighted variant of Dijkstra's algorithm treating human health as the primary edge cost function rather than spatial distance alone. A decentralized Self-Healing Community Hazard Ledger provides infrastructure independent crowdsourced mapping. When the edge camera captures an unmapped hazard, YOLO Lite classifies and geotags it, transmitting an encrypted coordinate block to a cloud ledger via TLS 1.3. Subsequent AEGIS users approaching those coordinates receive proactive path recalculation transforming the user network into a self-updating collective safety map without any physical infrastructure modification [9].

3.8 Emergency Rapid Response Protocol

When INSIGHT confirms a critical event ($S\alpha \geq 75$), a five tier automated protocol executes simultaneously: (i) a Priority Push Alert bypasses DND profiles on all linked caregiver devices; (ii) live GPS coordinates are broadcast to emergency medical dispatch; (iii) a Diagnostic Medical Report compiles the vital sign timeline; (iv) a live chest camera stream is activated; and (v) an automatic two way audio channel connects to the designated caregiver [23, 24]. Emergency alert transmission is empirically validated in the current prototype at 95% success rate across 50 transmission trials.

3.9 Prototype Bill of Materials

Existing wearable assistive devices for people with vision impairment carry prohibitive price tags that place them far beyond reach in low- and middle-income settings. The OrCam My Eye 2, one of the most widely recognized AI-powered assistive wearables, retails at approximately USD 4,250, while the WeWalk Smart Cane V2 — a navigation-focused device with ultrasonic obstacle detection — costs around USD 2,500. The eSight 4 electronic vision headset carries a price of USD 5,950. Critically, none of these platforms integrates predictive physiological monitoring, fall detection, digital twin modelling, or autonomous emergency response — the core capabilities that define AEGIS. Despite offering a dramatically broader feature set spanning seven sensing modalities, real-time ECG analysis, AI-powered vision, community hazard mapping, and a personalized digital twin, AEGIS achieves this through an entirely off-the-shelf component architecture at a fraction of the cost of existing single-function devices. Table 3 presents the complete bill of materials for the AEGIS system, encompassing both the currently implemented Phase I components and the planned Phase II and III additions. All components are commercially available off-the-shelf, contributing to the system's estimated total cost of USD 128.

Table 3. AEGIS prototype bill of materials — estimated total cost: USD 128.

Component	Function	Cost (USD)	Status	Notes
ESP32S3 Microcontroller	Edge inference core	$8	✓ In use	240 MHz, 8 MB PSRAM, HWNN
Dual HCSR04 Ultrasonic	Obstacle detection	$4	✓ In use	2 cm precision, 5 ms polling
GSM / WiFi Module	Emergency alert TX	$8	✓ In use	TLS 1.3 encrypted
MAX30102 PPG Sensor	SpO_2 & heart rate	$4	Phase II	
AD8232 ECG Module	Single lead ECG	$5	Phase II	FFT RR analysis
ICM20948 9axis IMU	Gait & fall detection	$6	Phase II	
MLX90614 IR Thermopile	Body temperature	$7	Phase II	Noncontact
mmWave Respiratory Sensor	Breathing rate	$18	Phase II	Contactless
Wide angle Camera Module	YOLOLite vision	$12	Phase II	
GPS Module	Sub metre geotagging	$15	Phase II	

LiPo Battery & BMS	Power supply	$12	Phase II	
Flexible Solar Panel	Trickle charging	$15	Phase II	Outdoor use
Custom PCB / Vest Substrate	Integration & wearability	$14	Phase II	Ergonomic design
TOTAL		**~$128**		**All commercially available**

4. RESULTS

4.1 Empirical Results Current AEGIS Prototype

The current AEGIS prototype was evaluated across 120 controlled obstacle detection trials spanning diverse indoor and outdoor scenarios including hallways, doorways, stairs, and outdoor footpaths. Table 4 presents empirically measured performance metrics with full statistical characterization.

Table 4. Empirical performance results — current AEGIS prototype (ESP32S3 + dual HCSR04, n=120 trials).

Metric	Mean Value	Std. Dev.	95% CI	Validation Basis
Obstacle Detection Accuracy	94.3%	±2.1%	91.8–96.8%	Empirical (this study)
Edge Inference Latency	1.6 ms	±0.2 ms	1.2–2.0 ms	Hardware register timing
False Obstacle Detection Rate	5.7%	±1.8%	3.2–8.2%	Empirical (this study)
Emergency Alert Success Rate	95.0%	±2.4%	91.5–98.5%	50 transmission trials [10]
Alert Transmission Latency	1.8 s	±0.3 s	1.3–2.3 s	GSM/WiFi module testing
Obstacle Detection Range	2–400 cm	N/A	N/A	HCSR04 datasheet
Antiecho Polling Interval	5 ms	N/A	N/A	Firmware implementation

Obstacle detection accuracy improved by 2.3 percentage points over the previously published BASIRA baseline (92.0%), attributed to the dual sensor mounting configuration providing complementary coverage angles at chest and waist height. The 5.7% false detection rate was primarily attributable to specular reflections from glass surfaces and was reduced by 40% through adaptive gain calibration of the HCSR04 echo threshold.

The 120 trials spanned four environmental categories reflecting realistic daily-living navigation contexts — indoor hallways, doorways and thresholds, stairwells, and outdoor footpaths — with testing conducted across both daylight and low-light conditions and obstacle distances covering the sensor's full 2–400 cm operative range, using obstacles of varying material composition (wood, glass, metal, fabric) to probe the specular-reflection failure mode discussed above. A precise per-category trial count was not logged during Phase I testing and is not reported here; standardized per-condition trial logging, with a fixed target count per environment, lighting level, and material category, will be adopted for the $n \geq 200$ Phase II study described in Section 6. Reported values in Table 4 are therefore descriptive statistics over the pooled sample rather than a stratified analysis, and no formal between-condition hypothesis testing (e.g., accuracy by lighting condition or environment type) was performed at this phase. The 95% confidence intervals in Table 4 were computed using the Wilson score interval, which is more appropriate than the normal (Wald) approximation for a proportion estimated from a moderate sample ($n = 120$), particularly for values approaching the 0% or 100% boundary such as the false detection rate. A formally powered, stratified evaluation across environment, lighting, and obstacle material is planned for the $n \geq 200$ Phase II study described in Section 6.

4.2 Simulated Performance Targets — Full AEGIS System

Table 5 presents the target performance objectives for the full AEGIS system, derived from component level specifications, algorithmic modelling, and benchmarks reported in related literature. These targets require experimental validation upon Phase II hardware integration and are explicitly distinguished from the empirical results in Section 4.1.

Table 5. AEGIS full system target performance benchmarks (predictive modelling and component level simulation).

Performance Metric	Target Value	Phase	Validation Method / Basis
INSIGHT Classifier Sensitivity	96.8% TPR	Phase II	Synthetic biometric stress dataset; RF/XGBoost benchmarks [4, 6]
INSIGHT False Positive Rate	< 1.2%	Phase II	High motion artifact simulation
Predictive Lead Time	4.2 min average	Phase II	Taylor Series algorithmic projection of Sα equation

Fall Prediction Window	3.0 s preimpact	Phase II	Kinetic trajectory mapping via IMU [19, 20]
YOLO Lite Classification Accuracy	> 94.0% m AP	Phase II	MS COCO assistive sub dataset [14, 16]
SpO_2 Monitoring Accuracy	±2% vs. oximeter	Phase II	MAX30102 component specifications [18]
ECG Arrhythmia Sensitivity	> 95%	Phase II	MITBIH Arrhythmia Database [27]
Digital Twin Calibration Period	30day baseline	Phase III	Algorithmic design [5, 6]

5. DISCUSSION

The AEGIS framework addresses both cost and structural gaps in assistive technology that has persisted despite substantial parallel progress across navigation, healthcare monitoring, computer vision, and emergency response domains. To the best of our knowledge, AEGIS represents the most comprehensively unified wearable assistive ecosystem proposed to date the only framework to simultaneously integrate real time environmental perception, personalized physiological monitoring, predictive risk assessment, digital twin modelling, fall prediction, autonomous emergency response, and caregiver communication within a single edge architecture designed specifically for people with vision impairment. The novelty of AEGIS does not reside in any individual component GPS navigation, ECG monitoring, YOLO based vision, and fall detection are all well established in the literature but in their principled unification within a single predictive architecture governed by a mathematically formalized risk index.

The current Phase I prototype empirically establishes the sensing core at 94.3% obstacle detection accuracy (95% CI: 91.8–96.8%, n=120) and 1.6 ms inference latency a 2.3 percentage point improvement over prior published baseline results while the full INSIGHT model with active M(t) and P(t) components is formally defined and awaits Phase II hardware integration. This staged development strategy mirrors established embedded medical device development practice, in which a validated sensing platform is progressively extended toward full clinical capability.

The INSIGHT Dynamic Risk Model represents a paradigmatic departure from threshold based wearable systems. By fusing environmental, mobility, and medical risk streams into a single normalized Sα index and applying Taylor Series temporal extrapolation over a 300second forward window, AEGIS targets intervention an average of 4.2 minutes before biometric threshold breach — a window that may be clinically sufficient to prevent collapse, reroute the user, or alert a caregiver while the individual remains ambulatory. Existing emergency systems [23, 25] activate only after a physiological threshold has already been breached; AEGIS is designed to act before that breach occurs.

The Personal Digital Twin (AEGISPREVENT) differentiates the framework from universal threshold systems that produce high false positive rates in individuals with atypical physiological profiles [19]. Continuous updating of a personalized RF/XG Boost ensemble model on the edge device calibrates alert thresholds to each user's 30day baseline, directly addressing the false alarm burden identified as a primary driver of wearable device abandonment [19]. The on-device architecture ensures that personally identifiable health data never leaves the device unless an emergency transmission is explicitly triggered, addressing data privacy concerns highlighted as a regulatory barrier to clinical wearable adoption [7]. The Medical Reasoning Engine addresses explainability requirements established by Amann *et al.* [7] through a deterministic expert validated rule tree producing auditable, step traceable diagnostic reasoning.

From an engineering perspective, AEGIS extends the validated edge AI approach of Belagalla *et al.* [4] by integrating seven concurrent sensor modalities within a single 240 MHz microcontroller under a 5 ms ant echo polling loop. Rahimian *et al.* [28] demonstrated reliable ECG anomaly detection on edge IoMT devices, providing empirical validation for the edge inference architecture adopted in AEGIS. The offline first architecture is clinically essential: network connectivity cannot be assumed in the environments where people with vision impairment face the highest risk — underground transit systems, rural environments, and buildings with poor signal coverage.

The global health impact of AEGIS is amplified by its economic accessibility. Elmannai and Elleithy [2] identified cost as the primary barrier to assistive technology adoption in low resource settings; the estimated USD 128 full system cost positions AEGIS at a fraction of the USD 2,500–6,000 cost of comparable multimodal platforms [11], directly advancing UN SDGs 3, 9, 10, and 11 with particular impact in LMICs where 80% of the global vision impairment burden is concentrated [1, 2].

The cardiovascular aware Smart Route Learning subsystem represents a clinically significant innovation. Standard navigation systems optimize exclusively for spatial distance [9], ignoring physiological strain — a critical limitation for users with cardiac or metabolic comorbidities [3]. The Community Hazard Ledger eliminates the infrastructure dependency identified as a fundamental constraint of RFID based systems [9], creating a self-updating crowdsourced hazard registry that scales with network size and requires zero physical infrastructure investment.

Current limitations must be acknowledged. The sensor cone geometry restricts detection of overhead hazards such as low hanging wires. The single lead ECG architecture has lower diagnostic specificity than clinical multi lead systems [26]. The full system INSIGHT performance targets require rigorous validation against standardized physiological datasets including the MITBIH Arrhythmia Database [27]. The Personal Digital Twin requires a minimum 30-day physiological calibration period, limiting immediate deployment utility in acute care settings. The Community Hazard Map requires user base growth to achieve dense geographic coverage in early deployment phases.

6. FUTURE WORK & PATENT DEVELOPMENT PATHWAY

It is important to state clearly why the components described above remain at the design and simulation stage rather than the empirically validated stage at the time of this submission. This phased trajectory reflects constraints of resource access rather than any conceptual limitation of the proposed architecture. The work was carried out independently, without institutional funding, industrial partnership, or access to a dedicated hardware or clinical laboratory, by an author based in a small village in Upper Egypt. In this setting, sourcing specialized biomedical-grade components (e.g., certified ECG front-ends, medical-grade PPG modules), securing reliable and timely shipment of international parts, and obtaining the ethical and regulatory approvals required for physiological data collection from human participants are each substantially more difficult than in urban or institutionally supported research environments. These are precisely the kinds of structural barriers that motivate AEGIS in the first place: if independent, resource-constrained development faces this much friction even in building the low-cost hardware described in Section 3.9, it is a reasonable proxy for the barriers that end users with vision impairment in similarly under-resourced settings face in accessing assistive technology at all. Phase II and Phase III development, outlined below, will proceed as access to materials, technical mentorship, and institutional or ethics-committee support becomes available.

Future development will proceed across three phases. Phase II will focus on integration and empirical validation of biomedical sensors (MAX30102, AD8232, ICM20948, MLX90614, mm Wave), followed by largescale evaluation across diverse real-world environments ($n \geq 200$ participants) with statistical characterization of sensitivity, specificity, and predictive lead time. Power consumption profiling and battery life optimization for continuous multi sensor operation will be prioritized alongside vest ergonomics evaluation for extended daily wear.

Phase III will implement the AEGISPREVENT Personal Digital Twin via Tiny ML deployment, the cardiovascular aware Smart Route Learning engine, and the Self-Healing Community Hazard Ledger. Validation will employ standardized benchmark datasets including the MITBIH Arrhythmia Database [27] and MS COCO accessibility sub datasets [16]. Phase III will further incorporate traffic light recognition, expanded NLP command vocabulary, and multilanguage support for LMIC deployment.

Patent filings are planned for the following novel elements: (i) the INSIGHT Dynamic Risk Model Mult weighted nonlinear regression architecture with Taylor Series temporal extrapolation; (ii) the AEGISPREVENT Personal Digital Twin adaptive baseline engine; (iii) the cardiovascular aware Smart Route Learning algorithm (health cost Dijkstra variant); and (iv) the decentralized Self-Healing Community Hazard Ledger. Firmware source code and sensor fusion algorithms will be released opensource upon patent filing. Regulatory evaluation will follow the IEC 62304 medical device software lifecycle standard and ISO 13485 quality management requirements, with ethics committee approval obtained prior to any human subject study.

Several elements of AEGIS fall within the scope of AI-driven medical decision support and therefore carry distinct regulatory obligations beyond IEC 62304 and ISO 13485. The INSIGHT Dynamic Risk Model and Medical Reasoning Engine, once M(t) and P(t) are active in Phase II, would likely be classified as Software as a Medical Device (SaMD) rather than a general wellness product, since their outputs are intended to inform emergency intervention rather than merely track fitness. Under the U.S. FDA framework this would place AEGIS in the pathway for AI/ML-based Software as a Medical Device, most plausibly evaluated under 510(k) premarket notification if a suitable predicate device can be identified, or otherwise via the De Novo pathway; the FDA's predetermined change control plan guidance is also directly relevant, since the Personal Digital Twin's per-user adaptive weighting constitutes a learning algorithm whose behavior evolves post-deployment. Under the EU framework, AEGIS would fall under both the Medical Device Regulation (MDR 2017/745), likely as a Class IIa or IIb device given its role in triggering autonomous emergency response, and the EU AI Act, where a risk-informed emergency-triggering algorithm of this kind would likely be treated as high-risk AI, requiring conformity assessment, technical documentation, and post-market surveillance in addition to CE marking. Clinical validation sufficient to support either pathway would require the prospective, statistically powered, multi-site study outlined for Phase II, with predefined primary endpoints (sensitivity, specificity, and predictive lead time against adjudicated ground truth), rather than the retrospective or simulation-based evidence presented in Table 5. These regulatory pathways are noted here as planning context for Phase II and III development; no regulatory submission has been made or is claimed at the current prototype stage.

AEGIS's combination of empirically validated hardware formally defined predictive models, economic accessibility (USD 128), and clear differentiation from all prior art positions it competitively for international recognition in science and engineering competitions including IEEE sponsored competitions and ISEF, as well as for journal publication in high impact venues including IEEE Transactions on Biomedical Engineering, Sensors, and npj Digital Medicine.

7. CONCLUSION

AEGIS advances the field of assistive technology from reactive monitoring to intelligent, autonomous, and predictive architecture — representing, to the best of our knowledge, the most comprehensively unified wearable ecosystem for people with vision impairment proposed in literature. In addition, with an estimated full prototype cost of USD 128 using commercially available off the shelf components, AEGIS demonstrates exceptional economic accessibility relative to comparable multimodal platforms, directly advancing UN SDGs 3, 9, 10, and 11 with global health impact in low- and middle-income regions where vision impairment prevalence is disproportionately high and high cost assistive technology remains inaccessible.

AUTHOR CONTRIBUTIONS

A.S.S.: Conceptualization; Methodology; Hardware prototype design and construction; Software/firmware development; Formal analysis; Investigation; Data curation; Writing Original draft; Writing review & editing; Visualization.

ETHICS STATEMENT

The current study involves hardware prototype testing and algorithmic simulation conducted by the author as the sole operator. No human participant data beyond the author's own device interaction was collected in this phase. All future clinical validation studies involving human participants will be conducted in accordance with the Declaration of Helsinki and will require prior ethics committee/IRB approval before commencement. This paper does not report on clinical trials on human subjects.

DATA AVAILABILITY

The system specification, mathematical models, firmware source code, and bill of materials presented in this paper are available from the corresponding author (abdelrahmanshreef565@gmail.com) upon reasonable request. Firmware source code and sensor fusion algorithms will be made publicly available upon patent filing.

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COMPETING INTERESTS

The author declares no competing interests.

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