Universal Access in the Information Society (2026) 25:100
https://doi.org/10.1007/s10209-026-01363-2

LONG PAPER

# Enhancing the well-being of individuals with vision impairments: a comprehensive examination of the MoSIoT framework

Shahab Nasabeh[1] · Santiago Meliá[1] · Barbara Leporini[2] · Diana Gadzhimusieva[1]

Received: 5 July 2025 / Accepted: 29 June 2026



## Abstract

The global prevalence of visual disabilities is increasing, significantly impacting the quality of life and social inclusion of those affected. Existing technologies, while helpful, continue to face challenges in terms of cost, accessibility, and real-time effectiveness. Individuals with visual impairments face significant barriers in their daily interactions with the environment, limiting their independence and social participation. The lack of adaptable and personalized solutions that address these specific needs remains a significant barrier. This study presents an extension of the Modeling Scenarios of the Internet of Things (MoSIoT) framework, a platform designed to improve the quality of life of people with disabilities by enhancing their interactions with IoT devices. The enhanced MoSIoT framework uses artificial intelligence and augmented reality technologies to significantly improve navigation and environmental interaction, enhancing the well-being of individuals with visual impairments. The proposed enhancements include advanced object detection, scene recognition, and augmented reality geolocation, all tailored to provide a richer and more autonomous user experience. A case study conducted as part of this research illustrates the practical application of these technologies in a real-world scenario, demonstrating how they can be used to support individuals with visual impairments in various everyday contexts. Practical tests conducted using tools such as YOLO for object recognition and Azure IoT for device integration have significantly improved user autonomy and quality of life. The results show that the enhanced framework can facilitate more effective environmental interaction and better social inclusion, highlighting its potential for implementation across different contexts and devices.


**Keywords** Accessibility · Assistive technology (AT) · Visual impairments · Artificial intelligence (AI) · Internet of things (IoT) · Quality of life (QoL)

## 1 Introduction

According to the World Health Organization (WHO), 2.2 billion people are affected by visual impairment, at least one billion of whom have preventable or untreated conditions [1]. The problem significantly affects people across the age spectrum, causing developmental delays in children, lower academic achievement, reduced employment opportunities, and increased rates of depression and anxiety in adults. For older adults, vision impairment leads to social isolation, mobility problems, and a greater likelihood of institutionalization.

Research shows that visual impairment not only diminishes the ability to perform daily tasks but also significantly reduces the overall quality of life (QoL) due to mobility challenges. For example, a study by Kuyk, Weaver, and Elliott [2] shows a clear correlation between visual impairment and

This research forms part of Shahab Nasabeh's doctoral thesis at the University of Alicante, which focuses on developing an IoT system for individuals with disabilities.

✉ Shahab Nasabeh
nasabeh@ua.es

✉ Santiago Meliá
santi@ua.es

Barbara Leporini
barbara.leporini@unipi.it

Diana Gadzhimusieva
diana.gadzhimusieva@ua.es

1 University of Alicante, Carretera San Vicente del Raspeig s/n, San Vicente del Raspeig, 03690 Alicante, Spain

2 University of Pisa, Lungarno Antonio Pacinotti, 43, 56126 Pisa, Italy

Published online: 17 July 2026

reduced QoL, with mobility as a critical factor. This study suggests that individuals with visual impairments often experience a significant reduction in their QoL, as mobility limitations affect their ability to navigate their environment independently, leading to a reliance on assistance and a resulting sense of loss of autonomy.

Recent research has highlighted the importance of improving mobility for visually impaired individuals. This research includes assessing the QoL of visually impaired individuals, uncovering different facets of their well-being, and investigating the specific challenges associated with other visual impairments [3, 4]. These findings underscore the critical importance of addressing mobility issues to improve the overall well-being of visually impaired communities. Scholars such as Verdugo et al. [5, 6] advocate for a more comprehensive approach to assessing and improving the well-being of individuals with disabilities. This broader perspective considers several dimensions: emotional wellness, interpersonal connections, personal development, material security, physical health, autonomy, social integration, and rights.

One of the most widely used techniques to increase the autonomy and social inclusion of visually impaired individuals is Assistive Technology (AT) [7]. AT for the visually impaired encompasses a range of devices and systems designed to help people who have lost sight navigate the complexities of their environment and daily activities. This technology includes tactile systems, audio devices, and digital applications that convert visual information into accessible formats. In mobility, which is critical to independence, AT solutions, such as GPS-based navigation aids, obstacle detection software, and sensor-equipped white canes, aim to increase the autonomy of blind individuals. These tools enable users to navigate different terrains and public spaces with greater confidence and safety and promote social inclusion by encouraging participation in community activities that would otherwise be challenging.

However, a significant problem with current AT solutions is the lack of integration among visually impaired individuals' devices. This fragmentation means that there is no cohesive system to ensure that the different technologies work in harmony, potentially compromising the effectiveness of each tool when used in isolation. In addition, more metrics are needed to measure user satisfaction and the actual impact of these technologies on QoL. Without comprehensive feedback mechanisms, it remains unclear whether the AT solutions are being used to their full potential or effectively addressing each user's needs and preferences. This gap underscores the need for more integrated and user-centered approaches to developing assistive technology for individuals who are blind or visually impaired.

Regarding mobile solutions, existing ATs support object detection and localization for visually impaired individuals, and their effectiveness, including lack of real-time responsiveness, limited range, and technology dependencies [8]. Furthermore, the shortcomings of these technologies extend to geolocation aids, as conventional systems fail to describe the environment adequately and address specific needs such as dangerous intersections or open spaces, leaving the visually impaired individuals navigating through an ill-defined and potentially hazardous landscape [9].

This article presents an expansion of the Modeling Scenarios of the Internet of Things (MoSIoT) framework [10], a platform designed to improve the QoL of people with disabilities [11] by enhancing their interaction with the IoT. The enhanced MoSIoT framework integrates artificial intelligence (AI) and augmented reality (AR) technologies to significantly improve navigation and environmental interaction, enhancing the well-being of individuals with visual impairment. At the heart of this proposal is an Internet of Things (IoT) architecture based on Model-Driven Engineering (MDE) [12]. This architecture relies on two main models: The first is a Domain Model, where experts in the field build a knowledge base that collects immutable information derived from established standards for accessibility (AFA) [13], IoT systems (Web of Things), and healthcare (FHIR) [14]. The second is the Scenario Model, where domain experts define entities' static and dynamic behavior in real-world IoT scenarios for individuals with disabilities. Thus, MoSIoT allows for the acceleration of the implementation of specific cases for people with one or more disabilities, defining the mechanisms of communication through accessible communication of that person with one or more devices in their environment and determining the objectives to improve that person's QoL.

Starting from the leading architecture, this work has introduced new technologies based on auditory AR and AI designed to connect seamlessly to the MoSIoT core. These technologies enhance the interaction of visually impaired individuals with their environment, enabling them to locate themselves, estimate travel times to specific destinations, and detect and avoid obstacles or objects in their path. Each technology - Object Detection (OD), Scene Recognition (SR), Object Measurement (OM), and Augmented Reality Geolocation (ARG) - plays a key role in extending the perceptual capabilities of the visually impaired: (1) Object Detection excels at identifying and describing objects in the environment, providing users with detailed auditory information about the presence, type, and location of detected objects. Similarly, (2) using AI and computer vision, Scene Recognition takes the experience further by providing comprehensive audio descriptions of entire scenes, contributing to a more immersive understanding of the environment.

On the other hand, (3) Object Measurement provides spatial awareness by accurately measuring the distances of objects, allowing users to navigate and interact with their environment more confidently. Finally, (4) Augmented Reality Geolocation facilitates outdoor navigation by providing GPS-based directions and relevant information about nearby buildings, helping users to create a mental map of their surroundings. These solutions have been made possible through specific technology tools and platforms, such as YOLO (You Only Look Once) object recognition and Azure IoT, which facilitate the integration and management of IoT devices. In addition, AI vision technologies are used for advanced image processing and analysis, enhancing object recognition and scene understanding capabilities. Together, these technologies form the backbone of the proposed solution, enabling its implementation and effectiveness in improving the perceptual abilities of people with visual impairments.

To examine the practical applicability of the proposed extension, this study presents an exploratory case study involving a participant with severe visual impairment. The study focuses on the configuration, deployment, and monitoring of a personalized MoSIoT scenario in real-world conditions. This evaluation provides initial evidence of the framework's potential and underscores the importance of inclusive technologies that integrate IoT, AI, and AR to support the emotional and physical well-being of individuals with visual impairments. It also provides a foundation for future validation with a larger and more diverse group of participants.

The paper is organized as follows: Sect. 2 provides insights into the background challenges and preferences of people with visual impairments and examines the state of the art in assistive technologies for this community. In Sect. 3, the narrative shifts to a detailed examination of the MoSIoT framework. It provides a comprehensive overview of the MoSIoT framework, highlights its components and adaptations, and focuses on improving accessibility for people with visual impairments by adopting new technologies. Section 4 presents a case study that illustrates the application of the MoSIoT framework to enhance accessibility, remote monitoring, and well-being by presenting customized scenarios and devices for people with visual impairments. Section 5 presents the evaluation of the results, highlighting advances in well-being and areas for improvement, and demonstrates how advanced technologies can support QoL-oriented assessment and personalized assistive interventions for people with visual impairments. Section 6, Discussion, summarizes the main findings and implications of the analysis in Sects. 3, 4, and 5. Finally, Sect. 7, Conclusions and Future Work, highlights the importance of these technologies in the MoSIoT framework for creating a more accessible and equitable future.

## 2 Background

This section begins with a data collection process, employing a set of keywords designed to encompass areas relevant to the research questions and stated objectives. These keywords include terms related to visual impairments, aging, physical disabilities, IoT, AI, Augmented Reality/Extended Reality (AR/XR), accessibility, and assistive technologies. In addition, smart environments such as smart buildings and smart homes are explored. The search strategy, applied in search engines (such as SpringerLink, SCOPUS, etc.), seeks to lay the groundwork for a comprehensive examination of assistive technologies. It then discusses the daily challenges faced by people with visual impairments, highlighting the crucial role of assistive technologies in promoting self-sufficiency and inclusion. Finally, it examines the current state of assistive technologies to address these challenges, providing an overview of available solutions and identifying areas for future improvements that consider this community's evolving preferences and needs.

We designed a comprehensive set of keywords to extract data from various sources that were aligned with our research questions and objectives. These keywords encompassed terms relevant to visual impairments ("Blind", "Vision rehabilitation", "Partial blindness", and "Vision impairment"), the elderly, and disability ("Elderly", "Disability," "Physical disability"), IoT ("Internet of things," "Web of things," and "Internet of medical things"), AI ("Artificial Intelligence", and "AI") and AR/XR ("Augmented reality", "AR" and "Extended Reality"). Additionally, keywords associated with accessibility ("Accessibility" and "Assistive Technology") were included. Furthermore, we incorporated keywords related to smart environments ("Smart building" and "Smart houses") to capture literature about these topics.

Once the keywords set was established, we expanded it by including alternative spellings and synonyms identified from our systematic review. The final list of keywords was optimized and consolidated.

The search string derived from these keywords is as follows:

*( ( "blind*" ) OR ( "vision impairment" ) OR ( "vision rehabilitation" ) OR ( "partial blindness" ) ) AND ( ( "Disab*" ) OR ( "Physical disab*" ) OR ( "Elderly" ) ) AND ( ( "internet of things" ) OR ( "web of things" ) OR ( "internet of medical things" ) OR ( "Assistive Technolog*" ) OR ( at ) OR ( "Artificial Intelligence" ) OR (a.i.) ) OR ( ( "Augmented reality" ) OR (ar) OR ( "Extended Reality"*

*) ) AND ( "Accessibility" ) OR ( ("smart building*" ) OR ("Smart hous*") ).*

This search strategy was subsequently applied to the following search engines: SpringerLink, SCOPUS, IEEE Xplore, PubMed, IOPscience, and Science Direct, which were selected as part of our search space to retrieve pertinent papers.

Table 1 shows the results obtained from the search string, providing detailed insight into AT solutions that enhance mobility, safety, and independence for individuals with visual impairments. Each entry delineates the technologies employed and their advantages and disadvantages.

In their comprehensive examination of technology applications for individuals with visual impairments, Siddesh G M et al. [15] discuss the application of IoT infrastructure to assist individuals with visual impairments in mobility. They address the challenges visually impaired people face in their daily travels and the limitations of existing solutions. The proposed system integrates hardware components, such as a smart blind stick with ultrasonic sensors and a microcontroller, an Android application, and IoT infrastructure to aid in obstacle detection and safe navigation. By leveraging IoT technology, this system aims to enhance the independence and safety of visually impaired individuals, helping them navigate outdoor environments more effectively. The authors also describe the software and hardware architectures and algorithms for optimized route selection.

By building upon this foundation, Chang et al. [16] contribute by introducing an intelligent assistive system to enhance the safety and independence of visually impaired

**Table 1** Comparative advantages and disadvantages of assistive technologies for visually impaired

| Author | Technology used | Advantages | Disadvantages |
|---|---|---|---|
| Siddesh G M et al. [15] | IoT infrastructure, smart blind stick, ultrasonic sensors, Android app, GPS, real-time tracing. | Enhanced mobility and independence for visually impaired individuals, obstacle detection, optimized route selection, and real-time tracking. | Limited range of ultrasonic sensors, potential connectivity issues. |
| Chang et al. [16] | Wearable smart glasses, intelligent walking stick, mobile device app, cloud-based platform. | Aerial obstacle detection, fall detection, immediate notification, enhanced safety. | Potential false alarms require a fusion of two fall recognition methods and may not detect certain obstacles. |
| Dr. Pramod S. Modi et al. [17] | Text-to-speech and speech-to-text translation, Natural language processing, Image and video processing and recognition, Binaural image mapping, and Various sensors. | It enables users to detect and differentiate between objects, provides Navigational assistance and text recognition, and provides vibrational and audio feedback. | The development field has many technologies in prototypical stages, and it is dependent on technology and has limited coverage of specific environments. |
| Singh et al. [18] | Computer vision, machine learning, cloud computing, IoT, mobile application, artificial intelligence. | Collision prevention for the visually impaired, better navigation through roads and crowded places, and real-time guidance. | Limited coverage beyond the camera range. |
| Koutny et al. [19] | Location-based service, Digital Graffiti, GPS, Wi-Fi positioning, Android app | Enhanced support for people with disabilities in using public transportation, up-to-date context-aware information, crowd-sourced information updates, automatic route adjustments | There are challenges in indoor navigation, especially indoors, where specific navigation hints and precise positioning are required, and routes for different user groups are complex. |
| Sreeraj Ma et al. [20] | Machine Learning (Deep Learning), Image Processing, OpenCV, Python, Arduino Uno, Raspberry Pi | Efficient object detection provides audio feedback for detected objects and their distances and is affordable and accessible for visually impaired users. | It may be limited in detecting very small or complex objects and requires some hardware components (Raspberry Pi, Pi camera, ultrasonic sensor). |
| Ashiq et al. [21] | Raspberry Pi 3 Model B, GSM module, GPS module, MobileNet architecture, Convolutional Neural Network (CNN), Text-to-Speech converter (SAPI), JPEG encoder, Django web framework, TensorFlow API | It provides real-time navigation and safety features for visually impaired individuals, low computational complexity, Audio feedback via headphones, tracking and safety monitoring, and high accuracy in object detection. | Potential difficulties in detecting road curbs, changes in road surfaces, and staircases in outdoor environments. May miss small-sized objects in outdoor environments. |

individuals. It combines smart glasses, an intelligent walking stick, a mobile app, and a cloud-based platform to detect aerial obstacles within 3 m and achieve 98.3% fall detection accuracy. The system alerts caregivers in case of a fall, addressing critical safety needs. Future work aims to integrate deep learning for improved obstacle avoidance and navigation.

Exploring broader applications, Pramod S. Modi et al. [17] explore advancements in assistive technology for the visually impaired, focusing on object detection, text recognition, and sensory feedback via vibrations and audio cues. Techniques like text-to-speech, image recognition, and sensor integration support mobility and safety. These technologies include innovations like 3D binaural noise conversion and RFID-based object recognition, offering cost-effective solutions to improve daily interactions and independence.

Singh et al. [18] discuss a collision detection and prevention system for individuals with visual impairments. Unlike traditional tools like white canes, it addresses challenges with moving objects and crowded spaces. Using a head-mounted camera, cloud computing, and machine learning, the system processes real-time data to deliver auditory cues, enhancing mobility and safety. Its hands-free design leverages advancing cloud technology for continuous improvement.

Furthering the discussion, Koutny et al. [19] present VIATOR, a mobile platform designed to improve mobility for individuals with disabilities on public transportation. It offers timetable details, route planning, boarding guidance, and real-time route adjustments for disruptions. Tailored for users like wheelchairs and visually impaired individuals, it provides vehicle accessibility and footpath routing data using Digital Graffiti, a context-aware service. By collaborating with transit companies, VIATOR accesses live data for adaptive planning. User evaluations highlight its effectiveness but reveal challenges with indoor navigation and complex routes.

Sreeraj Ma et al. [20] discuss the development of a cost-effective handheld device to assist visually impaired individuals in identifying obstacles and objects in their surroundings. The device, called VIZIYON, utilizes IoT technology, including distance vector and object detection based on Convolutional Neural Networks (CNNs) to identify objects and provide audio feedback to users. The device can accurately recognize objects and their distances with an accuracy of 91% and a recall of 94%.

Similarly, Ashiq et al. [21] introduce a system designed to aid visually impaired individuals by offering real-time navigation and safety functionalities, utilizing the MobileNet architecture for low computational complexity. This system employs a deep Convolutional Neural Network (CNN) for object detection and recognition, delivers audio feedback, and features a web-based application that allows family members to track the user's location and access snapshots for safety purposes.

In the domain of assistive technologies for the visually impaired, several research papers offer innovative solutions to enhance safety and mobility. Table 2 compares the technologies discussed by various authors, including MoSIoT, and their coverage of adaptive remote monitoring systems, audio descriptive object detection, audio descriptive scene recognition, audio descriptive object measurement, QoL measurement, adaptive accessibility, and audio descriptive geolocation. While all the papers emphasize object recognition and adaptive accessibility as critical components of their systems, none directly address adaptive remote monitoring, QoL measurement, descriptive geolocation, and audio descriptive scene recognition. The degree to which they focus on measuring the distance of objects varies across the papers, with some incorporating distance measurement as part of their solutions.

Compared with other authors who have discussed specific aspects of assistive technology for visually impaired individuals, MoSIoT is a comprehensive solution encompassing the essential technologies and needs of individuals with visual impairments. Unlike the other papers that focus on specific aspects, MoSIoT covers various technologies

**Table 2** Comparative analysis of embedded technologies in assistive technologies for the visually impaired

| Authors | Adaptive remote monitoring systems | Audio descriptive object detection | Audio descriptive scene recognition | Audio descriptive object measurement | Quality of life measurement | Adaptive accessibility | Audio descriptive geolocation |
|---|---|---|---|---|---|---|---|
| Siddesh G M et al. [15] | ✗ | ✓ | ✗ | ✓ | ✗ | ∝ | ✗ |
| Chang et al. [16] | ✗ | ✓ | ✗ | ✓ | ✗ | ∝ | ✗ |
| Dr. Pramod S. Modi et al. [17] | ✗ | ✓ | ✗ | ✗ | ✗ | ✓ | ✗ |
| Singh et al. [18] | ✗ | ✓ | ✗ | ✗ | ✗ | ∝ | ✗ |
| Koutny et al. [19] | ✗ | ∝ | ✗ | ✗ | ✗ | ✓ | ✗ |
| Sreeraj Ma et al. [20] | ✗ | ✓ | ✗ | ✓ | ✗ | ✓ | ✗ |
| Ashiq et al. [21] | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ |
| MoSIoT | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

✓ Direct address ∝ Indirect address ✗ No impact and requirements. It is designed to assist individuals with visual impairments in adaptive remote monitoring systems while recognizing and navigating their surroundings.

It incorporates features related to object detection, measuring the distance of objects, QoL measurement, descriptive geolocation, and adaptive accessibility. MoSIoT's use of IoT technology implies that distance measurement features for obstacle detection and safe navigation contribute to an enhanced QoL for its users.

Based on this comparison, the contribution of the proposed MoSIoT extension can be summarized in four main aspects: (i) It extends the MoSIoT Scenario Model to represent visual-impairment-specific Artificial Intelligence services, including object detection, distance estimation, scene recognition, and audio-descriptive geolocation, as configurable elements of a model-driven IoT scenario; (ii) It provides a personalization mechanism that links accessibility profiles, assistive devices, access modes, care-plan goals, and AI/AR services within the same scenario configuration process; (iii) It connects user interactions and device telemetry with QoL indicators, allowing domain experts to monitor the relationship between assistive interventions and QoL dimensions such as physical well-being, emotional well-being, and personal development; (iv) It demonstrates the practical application of the extension through a structured exploratory case study, showing how the scenario can be configured, deployed, monitored, and refined in a real-world assistive context. Together, these contributions distinguish MoSIoT from existing assistive solutions that mainly focus on isolated navigation, object detection, or accessibility functions rather than integrating model-driven personalization, IoT monitoring, and QoL-oriented assessment.

## 3 Methodology for enhancing the MoSIoT framework for people with vision impairment

A rigorous research process requires the development of assistive technologies and an in-depth case study following a structured methodology to evaluate their impact in the real world. This study takes a research-driven approach, using the MoSIoT framework not only as a system implementation but also as a tool to investigate how integrated IoT and AI-based solutions can improve the QoL of people with visual impairments. A detailed system description is essential to understand how these technologies are configured and interact with user needs and to validate them empirically through scenario modeling, telemetry data collection, and QoL assessment. By embedding these elements in a structured ecosystem, MoSIoT enables the simulation and evaluation of assistive interventions in a manner that supports reproducibility, personalization, and scientific rigor.

To make the methodological process more transparent, this section is organized around three complementary elements: (i) the model-driven extension of MoSIoT for visual-impairment scenarios, (ii) the algorithmic workflow used to configure and execute personalized assistive interventions, and (iii) the experimental setup used to evaluate the feasibility of the proposed extension. The architectural description is therefore presented as part of the methodology, since the Domain Model, Scenario Model, device configuration, care-plan definition, and telemetry mechanisms are the elements that make the intervention configurable, traceable, and reproducible.

To support this research methodology, MoSIoT leverages MDE, which not only facilitates intricate simulations but also expedites the realization of final IoT scenarios. This capability is crucial for the rapid iteration and deployment of IoT solutions, addressing the evolving and diverse needs of users with disabilities. As a comprehensive tool, MoSIoT enables the meticulous development and assessment of various scenarios, allowing for thorough and efficient optimization of assistive environments within the IoT ecosystem. The framework comprises a Domain Model, where a domain expert specifies a knowledge base that gathers invariant information from recognized standards, and a Scenario Model allows a medical expert to introduce the static and dynamic behavior of specific entities for a given scenario.

In this work, the Scenario Model is extended to represent visual-impairment-specific assistive services and connect them with QoL-oriented goals and telemetry indicators. This extension allows AI- and AR-based functions to be configured as part of a personalized assistive scenario, rather than as independent applications. As a result, MoSIoT provides a unified mechanism for linking user needs, device capabilities, assistive interactions, and measurable QoL outcomes.

On the one hand, the Domain Model, which sits at the heart of the MoSIoT framework, comprises three foundational packages designed to synergize and create an IoT system for enhancing the lives of individuals with disabilities. The AFA standard underpins the Patient Profile package [13], allowing for an intricate and personalized configuration of user profiles. This package finely maps accessibility needs to individual preferences, medical information, and the unique characteristics of users' disabilities, tailoring the system's communication methods to each user. Complementing the personalization offered by the Patient Profile, the Healthcare package is grounded in the medical standard FHIR (Fast Healthcare Interoperability Resources) provided by HL7 [14]. This standardization enables the creation of detailed care plans that articulate the specific health interventions, goals, and communication strategies required for each patient, thereby making medical and therapeutic interventions more precise and effective.

The Device package adheres to the Web of Things (W3C) standard [22], the backbone for device interoperability within the IoT landscape. Defining IoT devices through this standard allows MoSIoT to facilitate seamless communication and implement devices according to industry best practices. On the other hand, the Scenario Model acts as a dynamic extension of the Domain Model, allowing for the practical application and testing of these standards in real-world situations. It enables medical experts to visualize and operationalize the interaction between patient profiles, healthcare protocols, and IoT devices within customized scenarios. This model is pivotal for validating the efficacy of the MoSIoT system in a controlled yet adaptable simulated environment that mirrors the complexity of real-world patient interactions with technology.

However, it is important to emphasize that the main purpose of the MoSIoT architecture is to improve the QoL of people with disabilities. To this end, it includes an integral model of the dimensions of QoL proposed by Verdugo et al. [5, 6], which allows us to measure whether people improve in their different facets of life. These dimensions span emotional well-being, interpersonal relationships, personal development, material well-being, physical well-being, self-determination, social inclusion, and rights. Each dimension holds intrinsic significance and offers avenues for improvement, irrespective of disability status or the level of support required. Specifically, this framework delves into the physical and emotional well-being dimensions concerning individuals with disabilities. These dimensions play a central role in shaping the overall QoL of this population and require tailored strategies for improvement. On the one hand, improving physical well-being involves providing health care, maximizing mobility, promoting meaningful leisure opportunities, supporting proper nutrition, and promoting overall wellness through healthy lifestyles and stress management. On the other hand, emotional well-being focuses on security, happiness, spirituality, absence of stress, self-concept, and self-satisfaction. Enhancing emotional well-being includes increasing safety, fostering spirituality, providing positive feedback, reducing stress, and creating a stable, predictable environment.

Based on this framework, this work extends MoSIoT by implementing elements based on AI and AR to improve the well-being of visually impaired people. This approach addresses individuals' unique challenges with vision impairment, enriching their QoL through tailored physical and emotional well-being solutions. Figure 1 provides an overview of the MoSIoT extension to meet the specific requirements of individuals with vision impairments. The main components are described as follows:

At the top (Fig. 1, Sect. 1), we find the MoSIoT framework, in which we highlight the core constituted by the business logic and REST facade that allows the modeling of scenarios, an IoT Hub (e.g., Azure) that allows the dynamic management of the devices, maintaining a secure and fast installation. In addition, the interaction of users through two applications: the MoSIoT Administrator App [23] (Fig. 1, Sect. 2), which manages the knowledge base obtained from the domain model and the domain expert App [24] (Fig. 1, Sect. 3), allows the modeling of specific scenarios, retrieving information from the Domain Model related to user profiles, connected devices, and care plan templates. At this point, the extension of this work has focused on including the necessary concepts to represent scenarios for blind people, allowing the definition of objectives in the dimensions of QoL, such as emotional and physical well-being.

We continue with the lower part of Fig. 1, where MoSIoT prioritizes accessibility by ensuring visually impaired users can interact efficiently with the system. To achieve this, it incorporates Google Cloud TTS [25] (Fig. 1, Sect. 4) for a more inclusive experience, allowing users to receive audible notifications and reducing reliance on visual feedback, facilitating seamless interaction. This feature is particularly beneficial for individuals who prefer or require spoken communication. In addition, Speech-to-Text (STT) [26] allows voice-based input, further enhancing accessibility and usability. The combination of TTS and STT provides a more intuitive and efficient user experience that meets various accessibility needs.

Continuing with the lower part of Fig. 1, where adaptive visual accessibility technologies are one of the main contributions of this work. These technologies are implemented within the user application [27] (Fig. 1, Sect. 5) playing a multifaceted role for individuals with vision impairments. Beyond receiving adaptive audio notifications and monitoring patient systems, these components also autonomously adapt themselves to the specific needs of users with vision impairments. They are composed of three components: the Descriptive Scene Recognition (Fig. 1, Sect. 6), which provides detailed audio descriptions of surroundings; the Descriptive Geolocation System (Fig. 1, Sect. 7), which offers GPS-based guidance and auditory AR feedback for outdoor navigation; and the Object Detection System (Fig. 1, Sect. 8), which utilizes deep learning algorithms to detect objects and convey information through audio alerts.

Sections 3.1, 3.2, and 3.3 elaborate on the details of these technologies, explaining their functionalities and roles in the MoSIoT system.

Figure 2 summarizes the structured workflow of MoSIoT, detailing the refinement process for assistive scenarios.

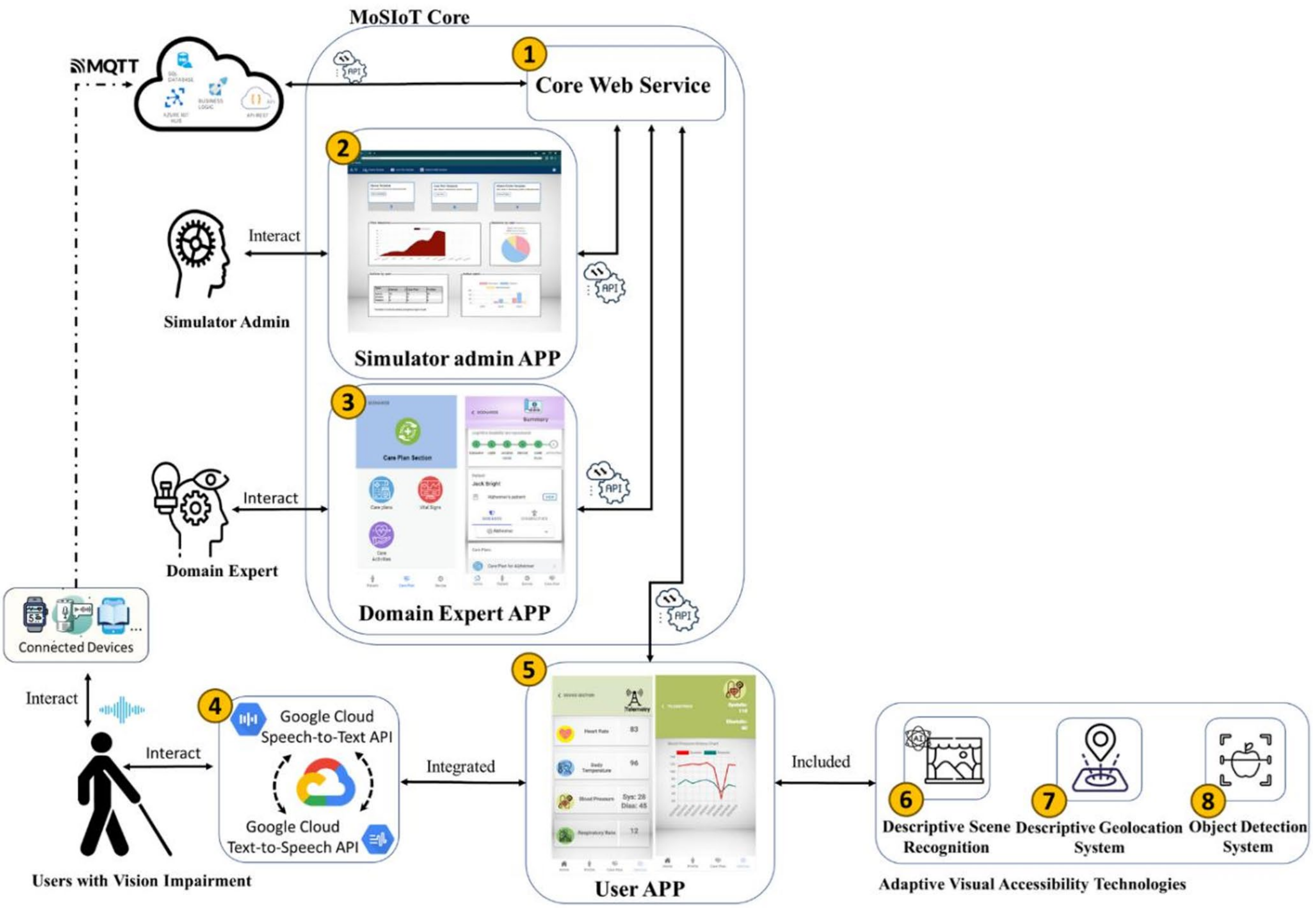


**Fig. 1** MoSIoT overview: empowering the framework to enhance accessibility for individuals with vision impairments

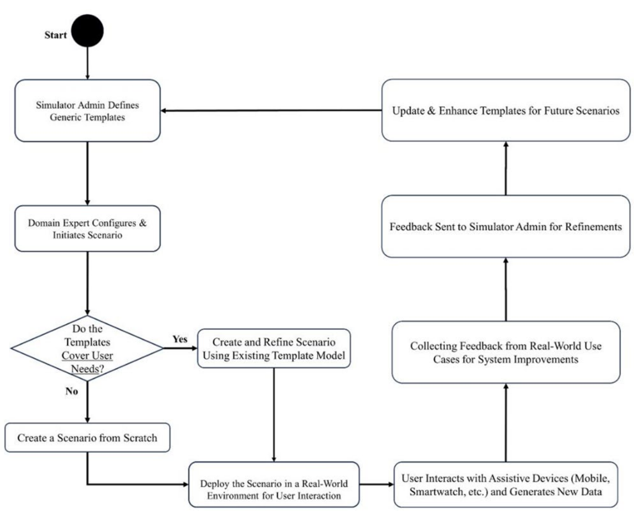


**Fig. 2** MoSIoT scenario workflow diagram illustrating the iterative process of scenario creation, deployment, user interaction, and feedback-driven template refinement

The process starts with the Simulator Admin, who defines generic templates based on predefined accessibility models. Next, the domain expert evaluates and adapts these templates, assessing whether existing models meet user needs or whether new scenarios need to be created. Once a scenario is configured, it is deployed in a real-world environment where users interact with assistive devices such as smartphones and smartwatches. During this phase, user interactions generate telemetry data that is collected and analyzed to evaluate system performance and identify areas for improvement. This workflow includes a continuous feedback loop incorporating real-world insights into the system to refine and enhance future templates. This iterative approach ensures that assistive technologies remain adaptive, effective, and responsive to the evolving needs of people with visual impairments.

To make the workflow shown in Fig. 2 reproducible, Algorithm 3 presents the corresponding scenario configuration and feedback process in step-by-step form.

**Input:** Domain Model templates, user needs, available devices, and care-plan requirements.
**Output:** Configured and refined MoSIoT scenario.

1. The Simulator Admin defines generic Domain Model templates.
2. The Domain Expert configures and initiates a scenario.
3. The Domain Expert evaluates whether existing templates cover the user's needs.
4. If the templates cover the user's needs, the scenario is created and refined using the existing template model.
5. Otherwise, a new scenario is created from scratch.
6. The configured scenario is deployed in a real-world environment for user interaction.
7. The user interacts with assistive devices, such as smartphones, smartwatches, and e-books, generating new interaction and telemetry data.
8. Feedback is collected from the real-world use case to identify system improvements.
9. The collected feedback is sent to the Simulator Admin for refinement.
10. The Simulator Admin updates and enhances the templates for future scenarios.
11. The process is repeated to support continuous refinement of the MoSIoT knowledge base.

**Fig. 3** MoSIoT scenario configuration and feedback workflow

This algorithm clarifies how MoSIoT moves from reusable templates to a configured scenario, real-world interaction, telemetry collection, and feedback-driven template refinement.

In summary, implementing these tools enhances users' ability to understand and interact with their environment, improving their emotional well-being. However, MoSIoT faces challenges in making these tools work together while prioritizing user feedback and satisfaction. A key concern in integrating multiple assistive technologies is the potential for cognitive overload, where users may struggle to process excessive or redundant information from different system components. At the same time, the current lack of solutions effectively connecting all the devices in use and assessing user satisfaction severely limits the ability to determine whether interventions are truly improving their QoL. To address these challenges, MoSIoT incorporates adaptive interaction mechanisms that enhance usability while minimizing cognitive load. Speech-based controls allow users to interact using voice commands rather than complex manual input. At the same time, context-aware automation dynamically adjusts the level of detail provided based on real-time user needs and environmental factors.

In addition, the system's interface adapts to optimize interaction patterns, ensuring that users receive only the most relevant and actionable information. These strategies help prevent information overload while improving navigation, autonomy, and user experience. This balance between integration and accessibility is critical, as the ultimate success of MoSIoT depends on its ability to meaningfully improve the daily lives of those it aims to support.

The following section briefly explains each technology employed in MoSIoT and its role within the system.

### 3.1 Object detection alert and distance measurement

This technology is crafted for precise object detection and distance measurement in the environment, utilizing audio alerts to convey information about detected objects.

It emphasizes delivering concise and immediate notifications suitable for a broad user base. Employing deep

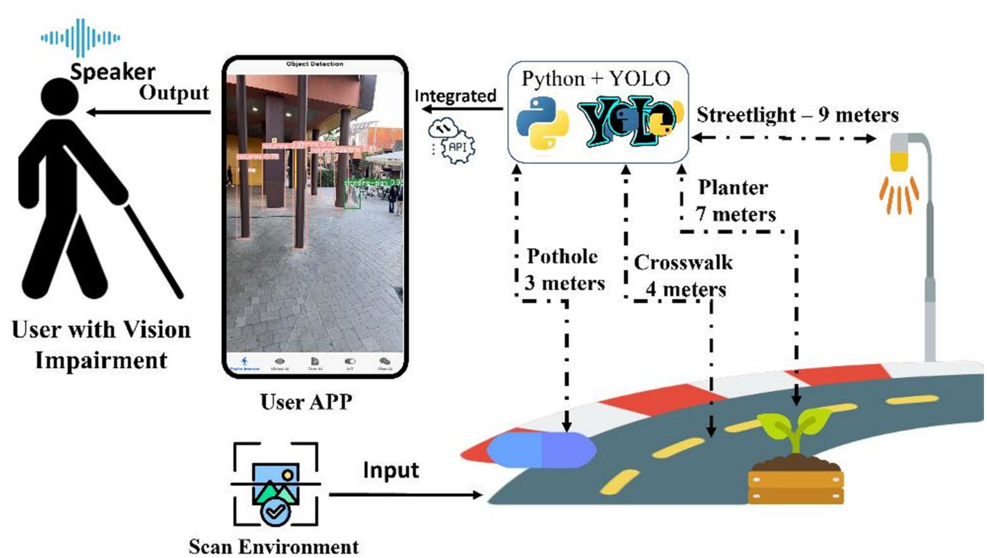


**Fig. 4** Object detection and distance measurement with audio alert technology for vision impairment

learning algorithms for object detection, the generated audio descriptions are designed to meet the specific requirements of individuals with visual impairments. Utilizing innovative technologies such as Python [28] and the YOLO framework [29] to enhance the system's capabilities and further empower users with vision impairments to better understand their environment through real-time object detection and distance estimation (Fig. 4).

### 3.2 Audio descriptive scene recognition enhanced with AI

The previously discussed technology centers around object detection and distance measurement, utilizing audio alerts to promptly convey information about detected objects, including their presence, type, and location. Employing deep learning algorithms, this system generates audio descriptions tailored to the specific needs of individuals with visual impairments. It excels in providing a fundamental level of situational awareness by offering detailed insights into individual objects within the environment. However, its focus is primarily on discrete objects. While valuable for users with some visual understanding, it may have limitations for individuals who are blind from birth and lack preconceived notions of object forms.

In contrast, "Audio Descriptive Scene Recognition Enhanced with AI" elevates the technology's capabilities by extending its focus beyond individual objects to the entire scene. This advancement allows for a more comprehensive understanding of the environment, offering rich, immersive audio descriptions encompassing spatial relationships between objects. By leveraging AI, this technology provides nuanced and contextually relevant details, resulting in a more holistic auditory experience. Particularly beneficial for individuals with visual impairments, including those without prior visual experiences, it bridges the gap by delivering a broader and more immersive understanding of the surroundings. In this process, the user initiates by capturing an image, a snapshot of the visual environment. This image is then channeled into an AI Vision API. The relevant data is extracted from the generated JSON file after the AI Vision API identifies key elements within an uploaded image, such as objects, colors, and their spatial arrangement. This JSON file encapsulates the analyzed information, acting as a structured format that includes details about the visual content of the image (Fig. 5).

Subsequently, this refined information is seamlessly passed on to OpenAI's Chatbot with LLM (Large Language Model). The Chatbot with LLM, an advanced AI model, processes the extracted data to generate a nuanced and detailed description of the scene captured in the image. The essence of this step involves translating the visual context into a comprehensive narrative that can be conveyed through audio.

The generated description, enriched with AI-driven insights, is then converted into speech. This conversion transforms the textual output from the Chatbot with LLM into an audible format, making it accessible for individuals with visual impairments.

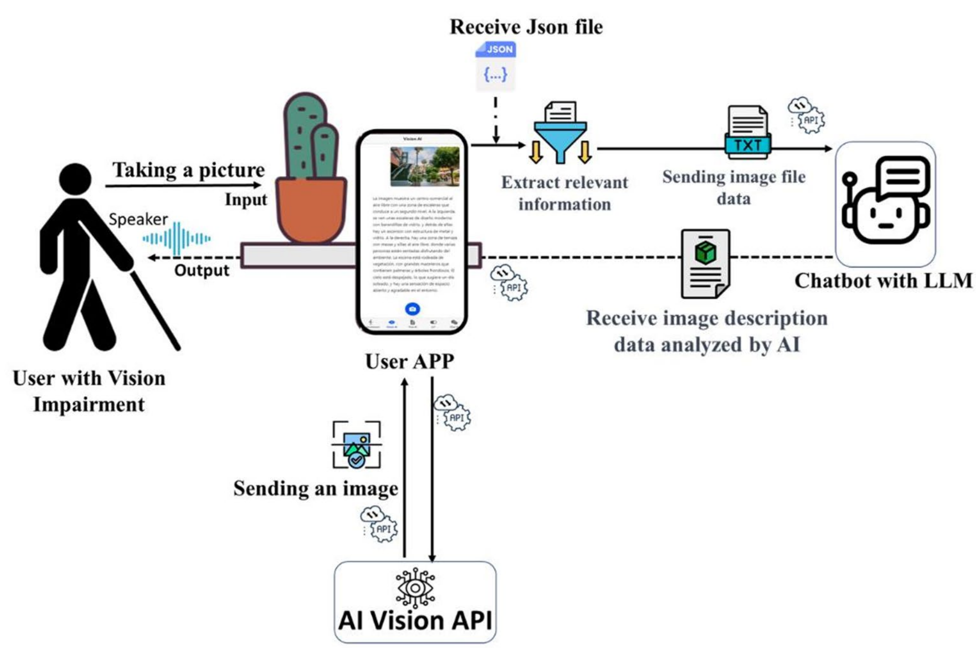


**Fig. 5** Computer vision and AI technologies for audio scene description

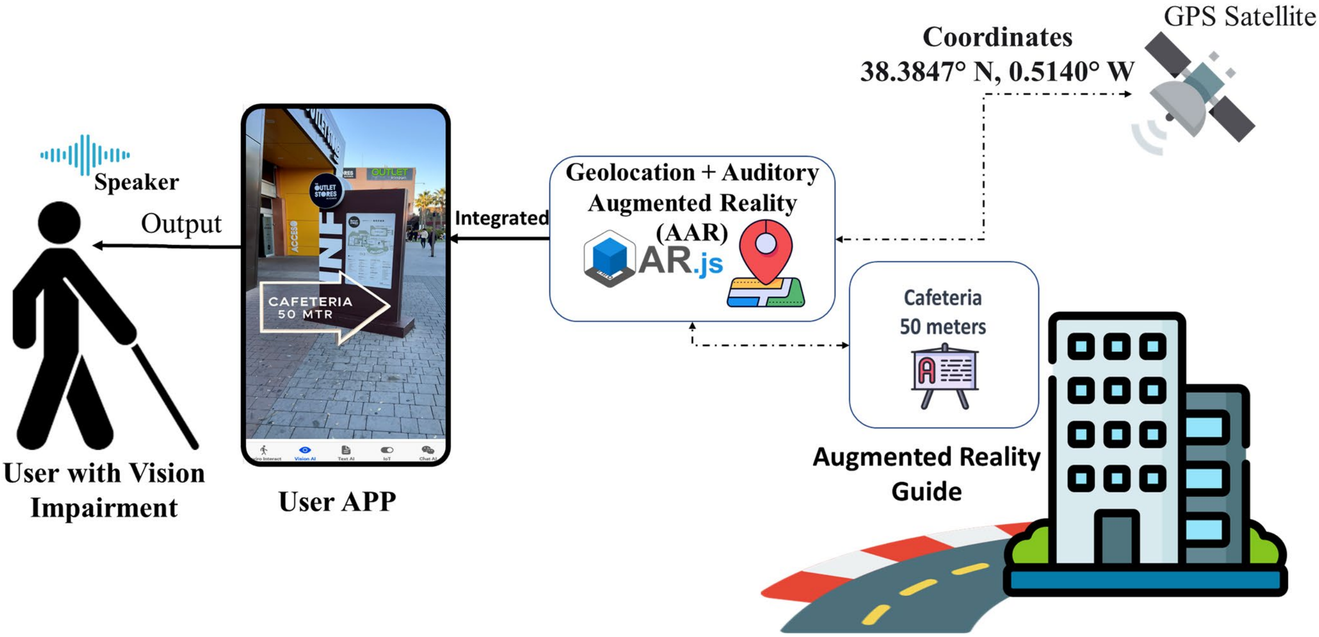


**Fig. 6** Audio descriptive geolocated outdoor navigation system for visually impaired

### 3.3 Audio descriptive geolocation

This image showcases a component of the MoSIoT system designed for outdoor navigation, specifically tailored to individuals with visual impairments.

It provides GPS-based guidance and information about nearby buildings and distances through three primary components: a GPS satellite, a geolocation, and an AR system, along with a speaker for audio output. The GPS satellite accurately determines the user's coordinates, transmitting this data to the geolocation and AR system. Developed with AR.js, the system generates practical audio feedback for users, offering details about nearby buildings, including their names and distances (Fig. 6). For example, the system might announce, "Cafeteria, 50 meters." This feature empowers individuals with visual impairments to navigate outdoor environments more efficiently and safely, enabling them to avoid potential obstacles like construction works on pathways. Furthermore, it retains location coordinates associated with obstacles in the system, using them to generate alerts for other visually impaired individuals intending to traverse the same route, thereby enhancing collective safety. This system can be seamlessly utilized with devices like smartphones and smart glasses.

In summary, the assistive technologies integrated into MoSIoT enhance users' ability to navigate their environment, interact more effectively, and improve their autonomy and emotional well-being. However, assessing the real-world impact of these solutions requires a structured evaluation. Therefore, this study presents a case study to analyze the effectiveness of MoSIoT in improving accessibility, usability, and QoL for people with visual impairments.

The following section describes this case study in detail, beginning with a review of existing research on QoL assessment for people with visual impairments. It then outlines the methodology used to apply MoSIoT in a real-world scenario, describing the process of defining personalized assistive solutions, deploying them, and analyzing user interactions. Finally, the study evaluates the impact of these interventions based on data collected from IoT- and AI-powered technologies, informing potential refinements to improve the accessibility features of the system.

## 4 Case study: assessing the impact of MoSIoT interventions on the daily lives of individuals with vision impairment

Understanding how assistive technologies may affect the QoL of visually impaired people is critical for evaluating their practical value. This case study examines the application of MoSIoT interventions to support accessibility, mobility, and emotional well-being through tailored IoT and AI-driven solutions. The case study is organized into distinct phases to ensure a structured and comprehensive approach.

Due to the exploratory and formative nature of this study, a single-case design was adopted to assess the feasibility of the proposed MoSIoT extension in a real-world assistive context. The objective was to provide analytic insight into how the framework can be configured, deployed, and

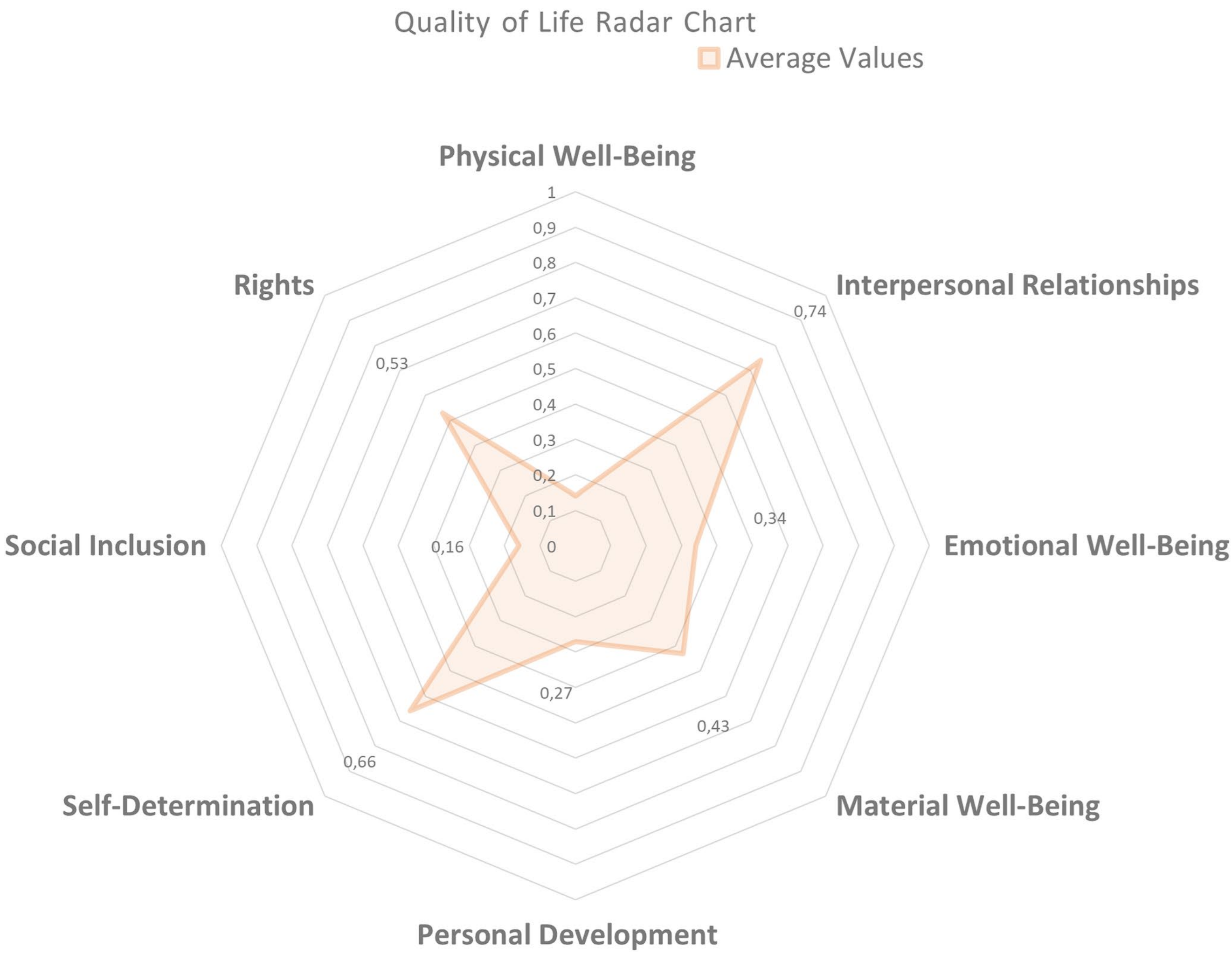


**Fig. 7** The quality-of-life radar chart for vision-impaired individuals with initial values

monitored for a complex, highly personalized user profile, rather than to achieve statistical generalization. This design is well suited to early-stage assistive technology research, where user needs, functional limitations, care-plan goals, environmental conditions, and interaction preferences can vary significantly from person to person [30, 31]. A two-phase baseline/intervention structure, longitudinal telemetry collection, repeated monitoring, and the mapping of collected indicators to QoL dimensions support the methodological rigor of the case study.

Section 4.1 reviews studies that quantify QoL for visually impaired individuals, identifies key dimensions, and outlines baseline measurement techniques. Section 4.2 presents MoSIoT as a structured framework for personalized interventions by refining domain models, defining IoT-based scenarios, and integrating user feedback. Section 4.3 highlights standardized templates for customization, including patient profiles, assistive devices, and health care plans. Section 4.4 applies these elements in a single-subject case study, illustrating real-world interactions and examining the potential impact of MoSIoT on daily life.

### 4.1 Establishing quality of life baselines for the case study

In order to assess the effectiveness of MoSIoT interventions, it is essential to first establish baseline QoL values derived from existing evaluations. This begins with an examination of the antecedents and analysis of state-of-the-art methodologies that have attempted to quantify QoL for persons with visual impairments. By reviewing both qualitative and quantitative approaches, this analysis provides a comprehensive understanding of the multifaceted aspects of living with visual impairment.

We begin with the study conducted by Rebouças et al. [3], the objective is to evaluate the QoL of visually impaired individuals using the WHOQoL-100 instrument, and the findings revealed various aspects of the participant's well-being. The study involved 20 visually impaired individuals from the Blind Association of Ceará. Despite financial limitations − 70% earned less than the minimum wage − 68.75% rated their QoL as good. The highest-rated facets included personal relationships (74.06%) and spirituality (65%), while financial resources (43.44%) and medication dependency (8.25%) scored the lowest. Among the domains, psychological well-being received the highest score (71.69%), while the environmental domain received the lowest score (48.48%).

In line with these, Khorrami-Nejad et al. [4] studied 121 visually impaired individuals, assessing visual acuity and stereopsis. Women and those without stereopsis had lower QoL scores, particularly in the social and leisure domains. While 64.5% reported satisfaction with self-care, 63.6% were dissatisfied with leisure activities. Mobility scores were mixed, with 54.5% reporting moderate satisfaction. Emotional health scores were evenly distributed, with 35.5% reporting desirable or somewhat desirable outcomes.

Given the extensive research on various aspects of QoL, each with its unique standards, and recognizing that our quality measurement radar adheres to the criteria of Verdugo et al. [5, 6], we leveraged the insights from the studies above to initialize the values of our QoL radar by extracting the average values relevant to each dimension from these studies. These dimensions are critical components contributing to an individual's overall well-being. Emotional well-being, which encompasses safety, happiness, spirituality, and self-satisfaction, was calculated to have an average impact of approximately 34.27%. Interpersonal relationships, emphasizing intimacy, affection, and support, displayed the highest average impact at approximately 74.06%. Personal development, focusing on education, skills, and personal fulfillment, exhibited an average effect of around 27.11%. Material well-being, including economic stability and access to resources, was found to have an average impact of approximately 43.44%. Physical well-being, covering health, nutrition, and daily activities, showed a relatively lower average impact at around 14.31%. Self-determination, emphasizing autonomy and decision-making, had an average effect of about 66.88%. Social inclusion, which involves acceptance, support, and community integration, exhibited an average impact of approximately 16.76%. Finally, rights, encompassing various freedoms and protections, showed an average effect of around 53.08%.

Figure 6 illustrates the values obtained from various dimensions. It shows a polygon shape with points positioned according to the importance given to each dimension, with values ranging between 0 and 1. This graph visually represents the satisfaction levels across different aspects of QoL.

The radar chart will serve as a visual tool to pinpoint areas of high satisfaction and aspects where there is room for improvement. By interpreting this chart, healthcare providers and researchers can better understand the impact of current interventions and identify targeted strategies that could significantly improve the lived experiences of blind individuals.

### 4.2 Applying MoSIoT for enhancing the well-being of individuals with vision impairment

At this point, we started to apply the contribution of our work, which consists of applying MoSIoT to define a personalized scenario that improves the emotional and physical well-being of people with visual impairment. Starting with the MoSIoT process, we delineate the sequential stages involved: (1) refining or definition of new generic templates within the domain model, (2) definition of IoT scenarios, (3) execution of real-world applications, and 4) obtaining feedback from real scenarios to adjust the information in the domain model.

Our approach begins with the MoSIoT Administrator (Fig. 8, Sect. 1), either defining or readjusting the templates to accommodate case studies associated with the visually impaired. First, start with device templates, such as a smartphone device, facilitating command generation through STT functionality. Furthermore, templates for care plans are tailored to incorporate psychoeducational components aimed at fostering a complete understanding of blindness, imparting adaptive techniques for daily functioning, furnishing emotional support, nurturing social and advocacy skills, enabling goal establishment, and addressing mental health issues. Further configuration includes specifying access modes and care activities, improving environmental accessibility, and incorporating orientation and mobility training.

The next step is to define the scenario model from the domain model templates (Fig. 8, Sect. 2). For this, the Domain expert is responsible for customizing the scenario for a visually impaired person with their specific needs. The definition of the scenario model begins by selecting the devices to be used, defining new ones, or starting from templates. In this case, we start from the device template to define the smartphone, allowing the configuration of the object detection and geolocation modules, which allow greater accessibility for mobility; in both cases, they are established as Patient Access type elements. On the other hand, two more devices have been selected, the Smartwatch and the E-Book, which, in its patient access configuration, allows the generation of a text-to-speech for the content of both devices. Regarding health, two care plans are chosen: psychoeducation and mindfulness techniques. Regarding the care activities, orientation and mobility training, along

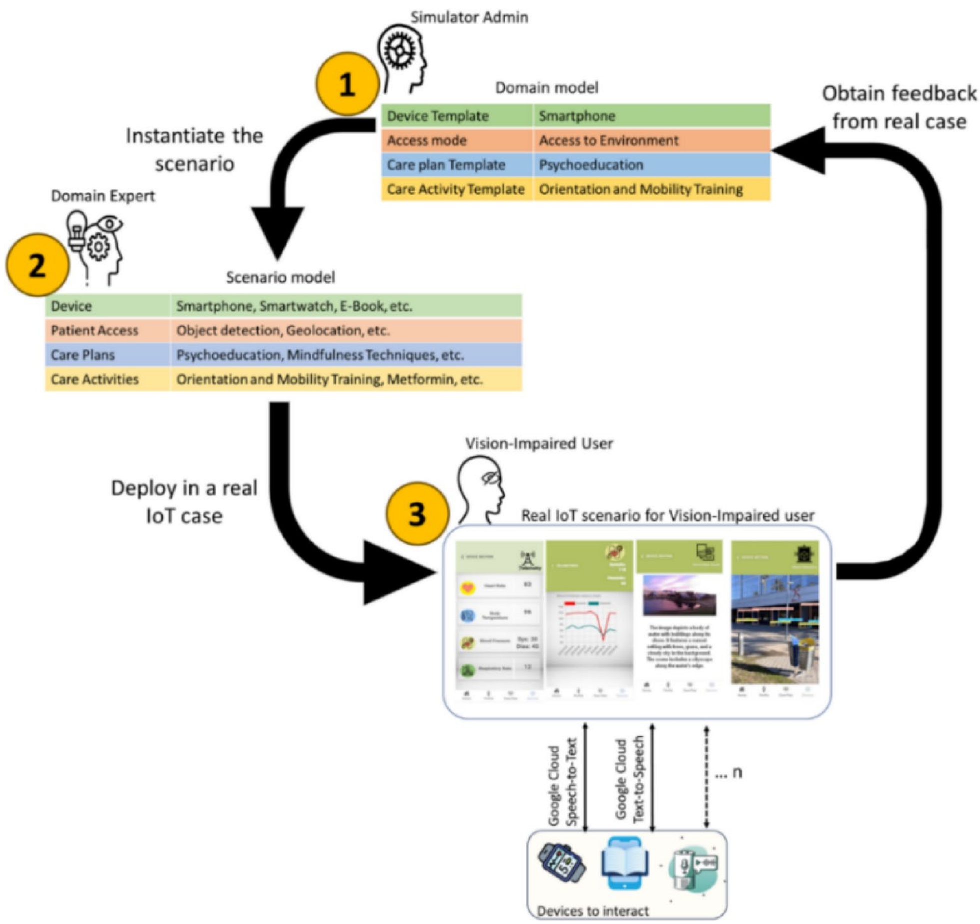


**Fig. 8** An overview of the MoSIoT process cycle involving admin, domain expert, and user, showcasing the evolution from generic template introduction to real-life scenarios, integrating personalized IoT solutions tailored for individuals with visual impairments

with taking metformin, were chosen because the patient is pre-diabetic.

Once the model scenario is defined, we can validate the behavior of the elements that make up the scenario, simulating the behavior of devices, care plans, and patients, all through digital twins that send telemetric data to the IoT Hub, and collecting the data so that rules, notifications, etc. can be adjusted. Finally, we proceed through MDE transformations, obtaining the real scenario where the system is deployed using the final devices and the apps of the visually impaired users. Several pages of the user's app (Fig. 8, Sect. 3). show the different health telemetries, a graph of the telemetry with the evolution of blood pressure, a view in which the device performs a textual description of an image, and a view of an image of the object detection module. In all cases, the pages using the STT and TTS modules are accessible to the visually impaired person.

Finally, the information collected from real scenario use serves as feedback to the system, allowing relevant data to be stored in the Domain Model and used to refine future scenarios.

To make this process explicit, the proposed extension can be formalized as a template-to-scenario modeling process. At the first level, the Domain Model defines reusable templates, expressed as DM = {PPT, DT, CPT, AMT}, where PPT denotes patient-profile templates, DT denotes device templates, CPT denotes care-plan templates, and AMT denotes accessibility/access-mode templates. These templates capture reusable knowledge related to disability characteristics, compatible devices, accessibility adaptations, care activities, care-plan goals, and QoL-related indicators.

At the second level, the Scenario Model instantiates these templates for a specific user, expressed as SM = {P, PP, D, CP, AM, PAS, T, Q, PR}. In this representation, P denotes the patient; PP, D, CP, and AM denote the scenario-specific instances derived from the corresponding domain templates PPT, DT, CPT, and AMT; PAS denotes patient-access services; T denotes telemetry indicators; Q denotes QoL dimensions; and PR denotes the practitioner or domain expert. The main mappings can be summarized as PPT → PP → P, DT → D, CPT → CP, AMT → AM, AM ↔ D, AM ↔ PAS, D/PAS → T, and T → Q. In the visual-impairment scenario, patient-access services include object detection, distance estimation, scene recognition, audio-descriptive geolocation, and accessible audio interaction. Telemetry generated by devices and patient-access services is then mapped to QoL dimensions, allowing the practitioner to monitor the intervention and refine the scenario according to the user's needs and observed outcomes.

Once we have defined an overview of the MoSIoT process, we will go into detail for each phase. We start by defining the templates; specifically, in this case, we focus on the case study, i.e., those that improve the well-being of visually impaired people.

### 4.3 Domain model templates for individuals with vision impairment

In order to show the definition of the different templates. They will be separated by each of the packages that make up the domain template:

1) *Patient profile package*: This involves customizing user profiles based on different disabilities and conditions
2) *Device package*: Here, Device templates and telemetry types used in these systems are defined, along with their attributes.
3) *Healthcare package*: This package provides various care plan templates containing care activities, goals, and communication strategies for users with specific conditions and disabilities.

To understand the information the MoSIoT Admin provides, we will show the screens you would have to edit or enter for each template in the Simulator Admin App.

#### 4.3.1 Domain model: patient profile configuration

We start with the Patient Profile section, which defines all general information about a stereotypical patient based on literature or previous case studies. In Fig. 9, you can see the patient's configuration, where the left page shows the patient's details. This is a patient profile who has been diagnosed with blindness due to Retinitis Pigmentosa and glaucoma. In addition, location information is entered, such as his country, Spain, and the Spanish language. In the central part, his conditions are specified; he currently suffers from depression, which has symptoms of withdrawal, hopelessness, and fatigue.

Moreover, he suffers from type 2 diabetes, which needs to be treated. Finally, in the right-side view, his disability information is indicated; for this, we rely on the W3C classification [22], categorizing it as a "visual" disability, which impacts his daily activities and is of severe severity. While current IoT standards lack provisions for addressing disabilities, MoSIoT is based on initiatives like the ISO/IEC 24751 AFA [13] specification. This specification introduces a reference model that addresses users' diverse accessibility

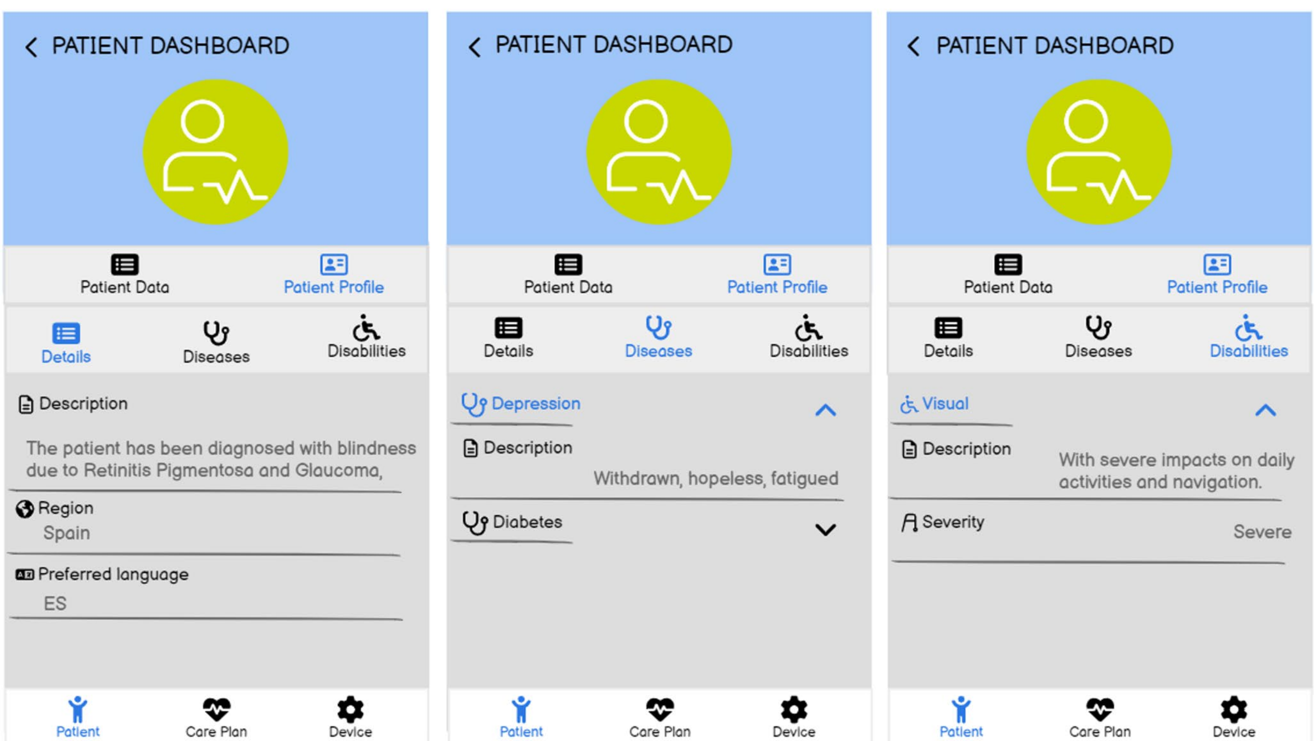


**Fig. 9** Domain model Configuring views for individuals with vision impairment includes the Patient Profile, which encompasses essential patient information and specific details of diseases and disabilities

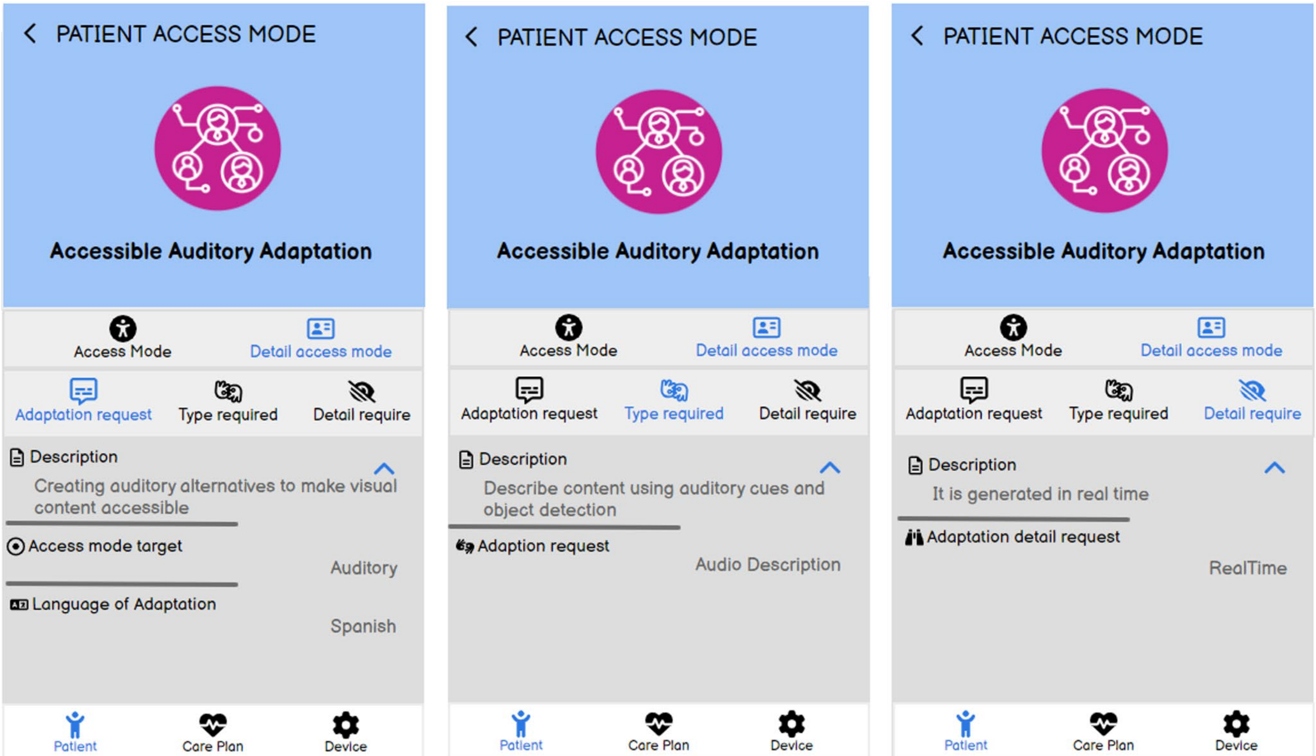


**Fig. 10** Domain model—Configuring preferred access modes for individuals with vision impairments, incorporating real-time audio descriptions

needs, making information presentation inclusive and tailored to individuals with disabilities.

Once the devices have been selected, the next step is establishing how the user will access them correctly. This is what we call access mode. Specifically, for this case study, we can retrieve access modes that incorporate specific features for visually impaired people. For example, when interacting with devices that provide visual cues, such as displays or indicator lights, options such as audio output are provided, allowing individuals with low vision to access information independently and inclusively.

Figure 10 represents three AccessMode views within the domain model: The left view introduces the AdaptationRequest function, empowering users to specify their preferred interaction method with a device. For example, if a smartphone offers visual interaction in environment modes, users can prioritize auditory over visual cues, tailoring the device to their preferred mode of information reception.

In the center section, the AdaptationTypeRequired feature identifies the specific adaptation required based on the user's disability. For instance, if a smartphone primarily relies on visual interaction, such as displaying notifications of object detection on a screen, users with visual impairments can select an adaptation type like AudioDescription, enabling the device to deliver spoken descriptions of visual information.

Finally, on the right is AdaptationTypeDetail, which refines settings for real-time interpretation within the audio description or speech output adaptation, facilitating effective communication for users with visual impairments.

### 4.3.2 Domain model: device configuration

The subsequent phase involves integrating components into the device package to streamline the creation of IoT device templates.

Figure 11 shows the details of the Smartphone device to be used by the framework. It is important to note that we need to collect the brand and model information (Samsung Galaxy M14) since this device must be integrated into our system. In this sense, the domain model will register the devices that are compatible and can be used by the IoT scenarios. At this point, it should be noted that one of the access modes that we had previously selected for the patient profile is assigned to this device; specifically, in this example, we chose the Accessible Auditory Adaption defined in Fig. 10. This access mode allows the contents of smartphones to be described in real time by means of audio cues and object detection.

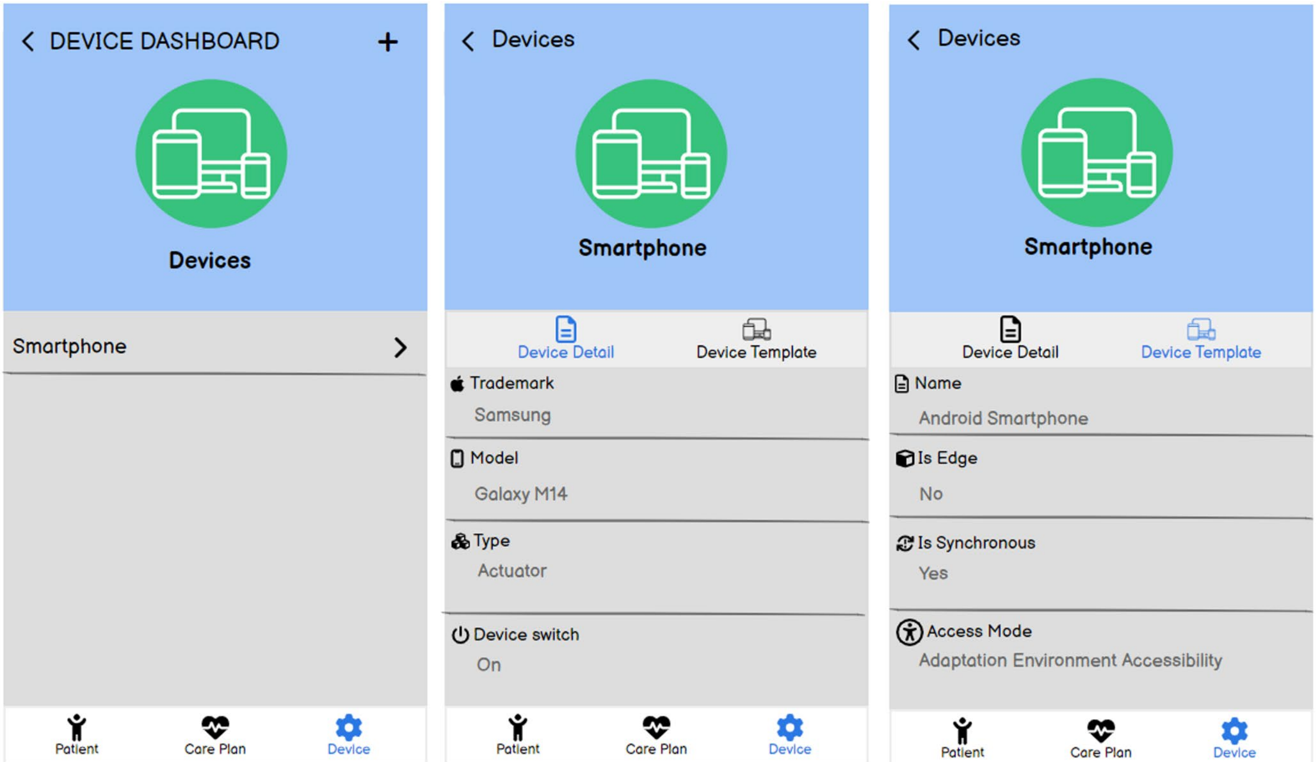


**Fig. 11** Domain model—Equipping the system with a smartphone device featuring an audio description feature, facilitating real-time interaction through auditory cues tailored for individuals with visual impairments

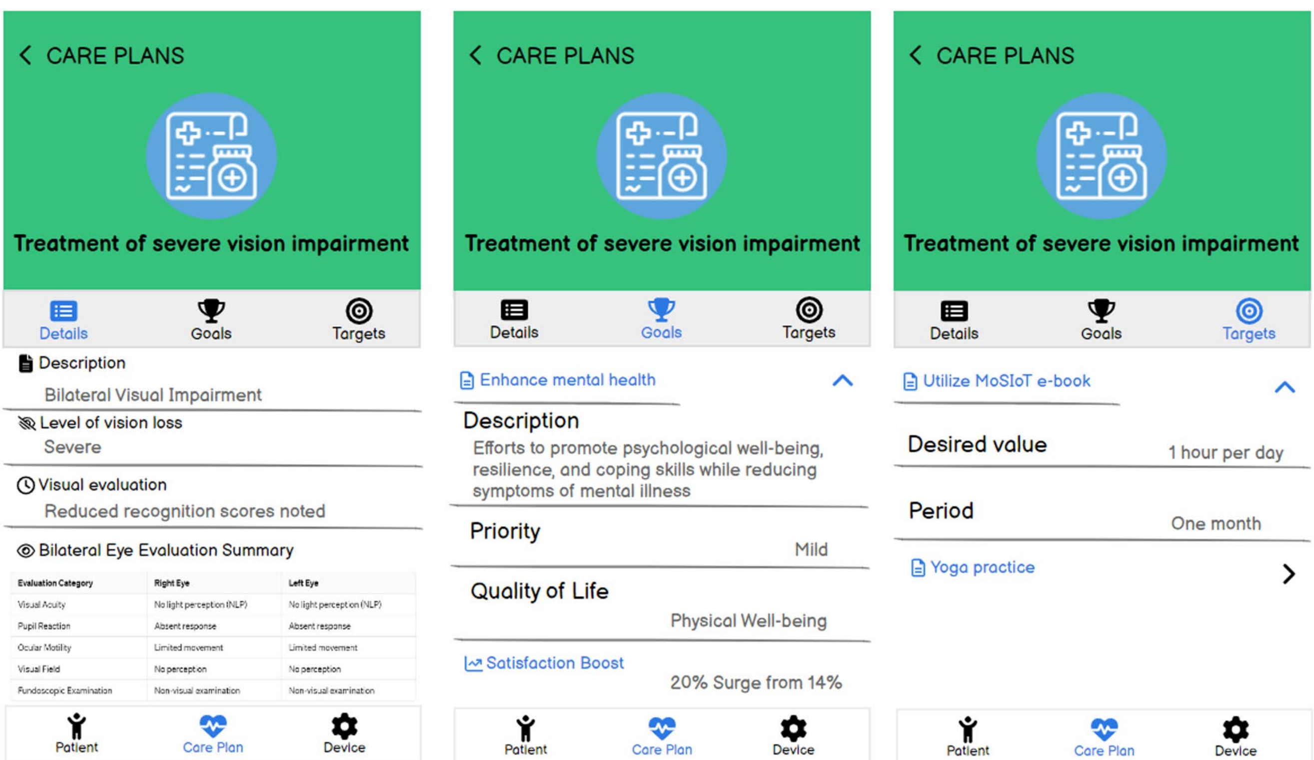


**Fig. 12** Domain model—A care plan template for severe vision impairment outlines strategies, targets, and goals to address the challenges associated with profound visual impairment, all integrated to enhance the quality of life

#### 4.3.3 Domain model: healthcare configuration

The third pillar of the MoSIoT domain model is the definition of a set of care plan templates for medical follow-up of people with disabilities. A care plan template based on the HL7 FHIR standard [14] allows the collection of generic treatment information for a person with one or more disabilities and diseases. It collects essential information that can be shared with other physicians, and that has been elaborated on thanks to previous treatments. Of course, this is a non-patient-specific care plan; the patient's specifics are collected later in the scenario definition.

Thus, a care plan template sets a treatment composed of a set of care activities, which may be that the patient has a set of medication intake, physical activities, a specific diet, and a set of appointments with the physician. All this is pursuing an overall goal, which must be met with measurable targets. Our case study is specified in Fig. 12 of a care plan template for severe vision impairment that outlines the severity of the condition, visual evaluation, and a Bilateral Eye Evaluation Summary (Fig. 12, left). The care plan also includes a set of targets and goals linked to various dimensions of QoL. For example, a care plan aims to improve the Accessible Wellness Program by incorporating adaptable devices for easier interaction in various environments. This goal element prioritizes enhancing mental health with a mild priority, focusing on efforts to promote psychological well-being, resilience, and coping skills while also aiming to reduce symptoms of mental illness and improve physical well-being as one of the dimensions of QoL.

The objective is to increase satisfaction by 20% from a baseline of 14% satisfaction, as shown in (Fig. 12, middle). These are specific and measurable goals that enable effective progress monitoring. The first target is for the patient to spend at least one hour per day reading, with a completion period of one month. This activity is complemented by yoga to promote psychological well-being (Fig. 12, right). Both activities encourage blind individuals to engage in practices that improve their mental health and overall QoL.

**Table 3** Reproducible experimental setup of the MoSIoT case study

| Element | Description |
|---|---|
| Study type | Exploratory single-subject case study |
| Study duration | Eight weeks |
| Baseline phase | Two weeks without MoSIoT intervention |
| Intervention phase | Six weeks using MoSIoT-enabled services |
| Participant profile | Adult participant with severe visual impairment |
| Main devices | Smartphone, smartwatch, e-book, and IoT Hub-connected components |
| Accessibility services | Speech-to-text, text-to-speech, audio alerts, and accessible auditory adaptation |
| AI/AR services | Object detection, distance estimation, AI-based scene recognition, and audio-descriptive geolocation |
| Data collected | HRV, sleep quality, physical activity, interaction logs, audiobook use, and voice-command use |
| QoL framework | QoL dimensions based on Verdugo et al. |
| Analysis strategy | Baseline/intervention comparison, telemetry-to-QoL mapping, and descriptive individual-level interpretation |

### 4.4 Scenario model of a vision-impaired person

To examine the practical implementation of the MoSIoT framework and assess its feasibility in a real-world assistive context, we conducted a single-subject case study involving a participant with severe vision impairment. The aim was to analyze how personalized IoT-based assistive interventions can support the individual's autonomy, mobility, and emotional well-being. This multifactorial clinical and psychosocial context makes him an information-rich case for exploratory validation of the MoSIoT system in real-world conditions. The methodological design of the study, including its procedural phases, data collection strategy, and scenario configuration, is presented in detail in the following subsection.

#### 4.4.1 Scenario model methodology

To assess the real-world applicability of the MoSIoT framework, we conducted an in-depth single-subject case study following a structured methodology grounded in empirical design principles for assistive technologies. The objective was to evaluate the impact of IoT and AI-driven interventions on the accessibility, autonomy, and emotional well-being of a person with severe visual impairment.

To improve reproducibility and avoid scattering methodological details across the case-study description, Table 3 summarizes the experimental setup used in the MoSIoT evaluation.

**4.4.1.1 Participant selection and context** The selected participant is a 55-year-old Spanish male diagnosed with Retinitis Pigmentosa (RP) and Glaucoma—two progressive, vision-degenerative conditions that severely limit the visual field and are among the leading causes of irreversible blindness worldwide [32, 33]. In addition to his visual impairment, the participant also experiences comorbidities, including type 2 diabetes and clinical depression, further increasing the complexity of his health profile and the need for adaptive support mechanisms. Despite these challenges, he lives independently and is highly motivated to adopt assistive technologies to regain functional autonomy in daily life. This profile was selected as an information-rich case for exploratory validation because it combines severe visual impairment, independent living, comorbid health conditions, and the need for personalized assistive support.

Therefore, the case is not intended to represent the broader population statistically, but to provide detailed insight into the configuration, deployment, and monitoring of a complex MoSIoT scenario.

**4.4.1.2** Study design and procedure

The study followed a two-phase design over eight weeks:

1. Baseline phase (2 weeks)

During this phase, baseline measurements were collected using wearable and mobile IoT devices without any MoSIoT intervention. The participant's physiological and behavioral data - including heart rate variability (HRV), sleep patterns, physical activity (e.g., step count, sedentary time), and interaction logs - were continuously monitored using a smartwatch and smartphone.

2. Intervention phase (6 weeks)

The participant then engaged with MoSIoT-enabled functionalities, including:

- Accessible auditory interfaces (STT/TTS).
- Object detection and audio-based distance alerts.
- AI-powered descriptive scene recognition.
- Geolocation with augmented audio guidance.
- E-book interaction via accessible audio output.
- Voice interpreter commands for navigation and health queries

These modules were individually configured based on a personalized Scenario Model derived from previously defined Domain Model templates. Throughout this phase, telemetry data were collected and transmitted to an IoT Hub for real-time monitoring and adaptive feedback.

To make the runtime interaction process explicit, Algorithm 13 summarizes how user interactions are processed through the configured Scenario Model and translated into accessible feedback, telemetry records, and monitoring inputs.

**Input:** Active Scenario Model, user interaction, configured access mode, patient-access services, connected devices.
**Output:** Accessible feedback, telemetry record, practitioner monitoring input.

1. The user initiates an interaction through voice input, camera capture, device use, or sensor data.
2. The system identifies the configured patient-access service associated with the interaction.
3. The selected service is executed using the current input or device context.
4. The result is converted into the user's configured access mode, such as audio description, warning, navigation cue, or text-to-speech output.
5. The user receives accessible feedback through the smartphone or connected device.
6. The user application and connected devices generate interaction and telemetry data.
7. Telemetry data are associated with care-plan goals and mapped to the corresponding QoL indicators.
8. The practitioner or domain expert monitors the user's state and interaction records.
9. If relevant changes or threshold deviations are detected, the care plan, access mode, or scenario configuration is refined when necessary.

**Fig. 13** Runtime assistive interaction and telemetry workflow

**4.4.1.3 Data collection and evaluation metrics** Quantitative telemetry data (e.g., sleep quality, activity levels, HRV, app usage metrics) were complemented with structured feedback from the participant through weekly interviews conducted by the domain expert. Indicators were mapped to eight dimensions of QoL following Verdugo et al. [5, 6], enabling systematic comparison between pre- and post-intervention outcomes.

**4.4.1.4 Adaptive feedback and iteration** A continuous feedback loop was implemented to adapt the care plan and system interactions in real-time. For instance, if excessive wakefulness or poor sleep quality was detected, the practitioner adjusted the intervention, e.g., recommending mindfulness audio routines or modifying device prompts.

To support this adaptability, the scenario starts with the Patient as the central element. To define the Patient, an appropriate patient profile had to be selected from the options provided in the domain model. In this case, we chose the profile specific to vision impairment, as defined in Fig. 9. The scenario model made it possible to capture differences in vision impairments among patients, i.e., a physician could define the model for multiple patients at the same stage of the disease. However, the scenario model was created for each patient to address intrapatient variability, which could change as the patient's condition progresses.

After selecting and defining the patient profile, a set of access modes is also offered. These are the accessible methods that the patient, in this case the visually impaired, has to interact with the IoT devices. Specifically, the Accessible Auditory Adaptation (see Fig. 10) is selected, which proposes a real-time audio description. However, these access modes must be instantiated in the scenario to represent the concerted needs of the patient.

Linked to the patient is an essential component that guides the patient's ongoing care, known as the CarePlan. As mentioned, this CarePlan can be defined from the CarePlan Template within the domain model, offering a possible configuration of this specific condition. Within the CarePlan exists a period of validity from the start to the end date and a set of Goals aligned with various vital sign parameters. Based on earlier studies [34–36], we identified critical vital sign metrics relevant to patient monitoring. These studies suggest various interventions, including vision rehabilitation, cognitive-behavioral techniques, and engagement in social and physical activities, to improve mental health outcomes for this demographic. Initially, we focused on Sleep Time, as studies on individuals with vision impairment have highlighted potential disruptions in sleep patterns within this population.

Thus, Roomkham et al. [37] suggest utilizing a Smartwatch, known for its superior accuracy in tracking sleep stages. Within the VitalSign entity named SleepQuality, we record various metrics associated with different stages of sleep, including awake time, REM time, deep time, and light time. Additionally, we have implemented notification systems to alert for prolonged wakefulness and diminished REM sleep. This VitalSign is closely linked to the Smartwatch device used to gather this data.

The second VitalSign identified was heart-rate variability (HRV), which measures the time intervals between heartbeats. It results from the heart's modulation by both the sympathetic and parasympathetic nervous systems. In adults, HRV is linked to various physiological functions, making it a valuable tool for analyzing stress levels related to blindness [38].

Another parameter monitored through the CarePlan was Movement. Studies utilizing actigraphy data from accelerometers have proven effective in objectively assessing activity levels [39]. Consequently, the scenario specified that the Smartwatch would gather data on steps taken throughout the day, calories expended, and periods of inactivity.

The Smartwatch continuously monitored the body's signals, capturing daily habits and assessing the patient's readiness for mental, emotional, and physical activities. This Readiness measure served as an indicator of the patient's ability to engage in various tasks and activities.

In the scenario, a critical entity was the Practitioner or Domain Expert, who was responsible for monitoring the patient's condition, tracking the progress of the CarePlan, and assessing the patient's readiness and sleep quality. Communication between the practitioner and the patient was critical and was facilitated by a dedicated communication entity that kept both parties well-informed. Recognizing the importance of accessible communication for patients with visual impairments, a PatientAdapter entity was introduced. This adapter served as a bridge between the patient and the smartphone, enabling the conversion of text messages into auditory cues. By leveraging elements of the domain model's accessibility package, this accessibility adaptive audio feature effectively conveyed messages through text-to-speech conversion, meeting the patient's accessibility needs.

Continuing the scenario settings, Domain experts employ a voice interpreter as a unified voice-command interface to capture relevant metrics, empowering users through auditory cues. Data collection involves interactions with an E-book adapted for auditory accessibility, tracked using the audioBook_time_counter telemetry, and voice interpretation interactions counted via an audio message counter.

Moreover, the system incorporates object detection, AI descriptive scene, and descriptive geolocation technologies into mobile devices to involve the patient in social and physical activities actively. It facilitates real-time identification and description of surroundings through auditory adaptation, empowering the Domain expert to assess these technologies' potential advantages in improving the mental health of the patient with vision impairment.

Figure 14 depicts the data flow between the different actors in the vision-impaired model scenario. The diagram shows how the patient sends data using two devices with an accessible interface: a smartwatch and a smartphone. The smartwatch and smartphone generate the HRV, movement, and sleep, which the Domain expert reads. Telemetry data from e-book interactions can contribute to identifying patterns or changes in the patient's mood and behavior over time. Reading frequency or duration may signal improvements in mood and coping skills or indicate periods of heightened distress or disengagement, prompting timely intervention or adjustments to the treatment plan [40]. At the same time, the data collected from voice interpreters can include usage patterns, such as frequency and duration of use. This data provides insight into how users navigate interfaces, which functionalities are most valuable, and where improvements are needed. For example, Domain experts can monitor whether patients are accessing educational materials, medication instructions, or appointment reminders through voice interpretation technology.

Additionally, in this scenario, trigger-action sequences determine how devices interact based on specific events or conditions. For example, a rule could state: "Upon waking up, activate the coffee machine and provide a weather forecast notification through audio cues." Integrating machine

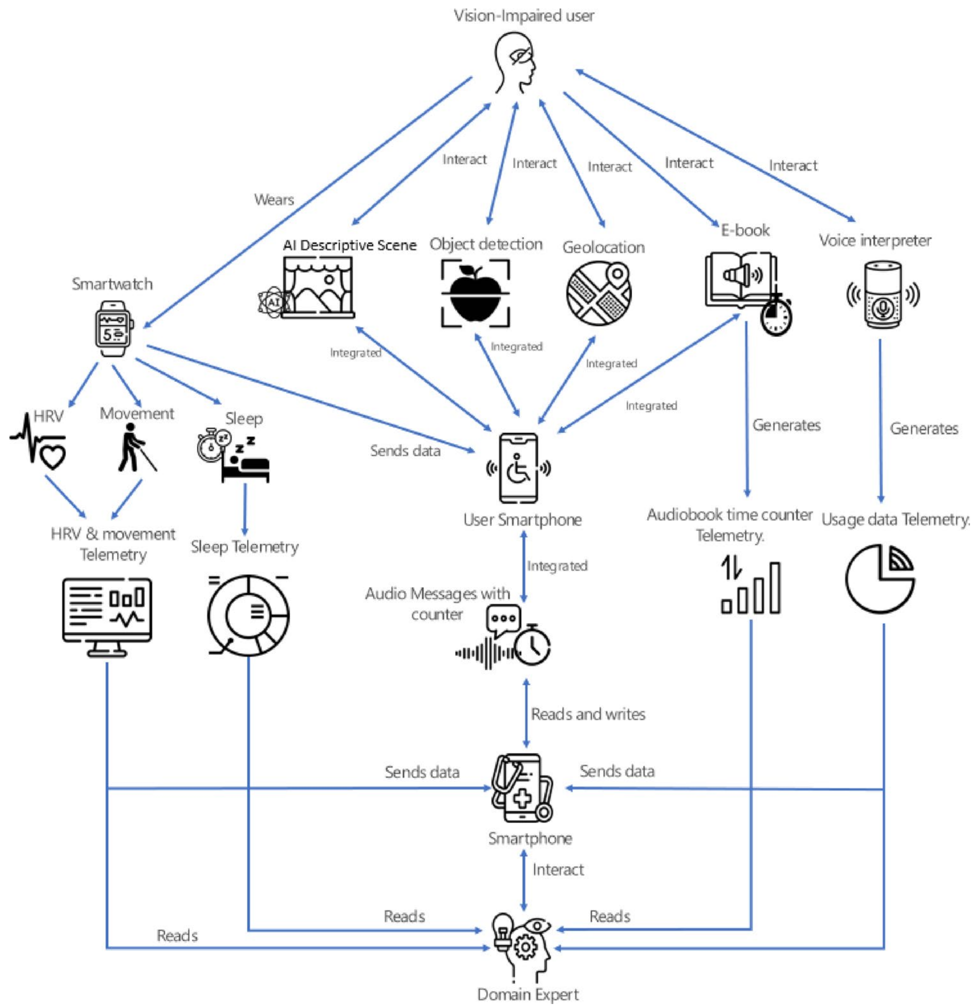


**Fig. 14** A data flow diagram illustrates the integration of IoT and AI components in a scenario tailored for individuals with vision impairments. It showcases device interactions and data generation processes

learning into MoSIoT enhances the system's ability to predict events tailored to individuals with vision impairments. For example, the system could predict environmental hazards and provide audible alerts for safety.

One of the scenario model's most important elements is patient access, which allows patients to interact with the devices in an accessible way. Specifically, this model establishes three patient accesses with the Smartphone device: AI Descriptive Scene, Object Detection, and Descriptive Geolocation. Their implementation has been specific for people with low vision and integrated into MoSIoT, which is described in detail in the following section.

#### 4.4.2 Empowering navigation and enhancing the object detection model

The need to utilize object detection arises from its ability to significantly enhance the QoL for individuals with visual impairments by providing them with a deeper understanding of their surroundings and enabling greater autonomy in navigation. Research has highlighted the importance of technologies like object detection in addressing mobility and safety challenges experienced by people with visual impairments [41]. Additionally, object detection serves as a patient access point that facilitates interaction between the user and their smartphone, further enhancing their ability to perceive and navigate their surroundings. In conjunction with object detection, AI Descriptive Scene and Geolocation supplement the user experience by offering detailed audio descriptions of the environment. For example, when users point their smartphone camera around, the AI system analyzes the visual input and provides comprehensive descriptions. Geolocation technology further aids navigation by using GPS to provide precise location data, guiding users with step-by-step directions and relevant information about nearby buildings. This approach enables the visually impaired to navigate complex urban environments independently.

In this scenario, the user launches the MoSIoT app and inputs the café's address. Geolocation technology kicks in, providing auditory directions: "Walk straight for 200 meters, then turn left onto Market Street." As the patient walks, his smartphone's camera detects obstacles. Object Detection alerts him to potential hazards: “Trash bin detected 2 meters ahead. Sidestep to the right to avoid.” Meanwhile, the patient points his phone towards a nearby park. AI Descriptive Scene technology provides descriptions: “You’re passing a park on your right. There are benches, trees, and people enjoying the sunshine.”

In the Dynamic Adjustments of All Technologies, geolocation provides real-time updates to keep the patient informed throughout their journey: “You’re halfway there. Stay on the current path.” Object detection maintains alertness: “Crosswalk ahead. Wait for the light.” As the patient approaches the coffee shop, Geolocation provides precise guidance: “The coffee shop is on your left in 50 meters.” AI Descriptive Scene enhances this with additional details: “The cafe has a red facade with outdoor seating.” Object detection remains active to promote safety: “Watch out for trash cans on the sidewalk.” The patient successfully reaches their destination, supported by the seamless integration of these technologies.

Building upon the scenario model outlined in Sect. 4.3, where the system integrates object detection, AI descriptive scene, and descriptive geolocation patient access components into mobile devices, to avoid making the article overly long, we delve only into the specific enhancements made to the object detection model.

The objective of this component evaluation is not to introduce a new object detection architecture, but to assess the feasibility of integrating YOLOv8 into the MoSIoT assistive workflow, where object recognition, distance estimation, and audio feedback operate together to support visually impaired users. The object detection component, for which we rely on the YOLOv8 convolutional neural network, is a cutting-edge architecture in computer vision and object detection. YOLO is known for its ability to perform real-time detections with a single pass through the image. It is especially suitable for applications where speed and accuracy are crucial, such as assisting visually impaired individuals. By systematically analyzing and enhancing the YOLOv8 object detection model, we aimed to refine the system’s ability to identify and describe surroundings in real-time. This improved model is crucial in improving patients’ overall well-being with vision impairment. In our approach to analyzing the YOLOv8 object detection model, we constructed a domain-specific annotated dataset of 400 original images covering 13 object classes: stairs, standing signs, crosswalks, road maintenance equipment, potholes, cones, trash cans, garbage, columns, planters, tree-pit, streetlight, and bollards. These objects were selected because they frequently appear in urban mobility scenarios and may represent relevant obstacles or orientation cues for individuals with visual impairments [42]. Although the original dataset is small for general-purpose object detection benchmarking, its purpose in this study was to support a feasibility evaluation of the object detection component within the MoSIoT assistive workflow. The dataset was divided into three subsets: 280 images (70%) for training, 88 images (22%) for validation, and 32 images (8%) for testing. This distribution allows the model to learn from diverse examples, verify its performance on unseen data, and effectively assess its generalization capabilities. After 30 epochs (iterations), the model’s performance metrics are depicted during the training and validation phases (Fig. 15).

Figure 15 shows the accuracy and proficiency of the YOLOv8 object detection model in detecting and classifying various objects without involving the generalization process. It provides insights into the model’s object detection and classification capability, offering information for further analysis and improving performance. The Train/box Loss Plot consistently shows an increasing mean average precision (mAP), indicating the model’s enhanced accuracy in predicting bounding boxes. Simultaneously, the Train/cls Loss Plot and Train/dfl Loss Plot reveal analogous trends, demonstrating the model’s proficiency in classifying objects and estimating depth during training. The Metrics/

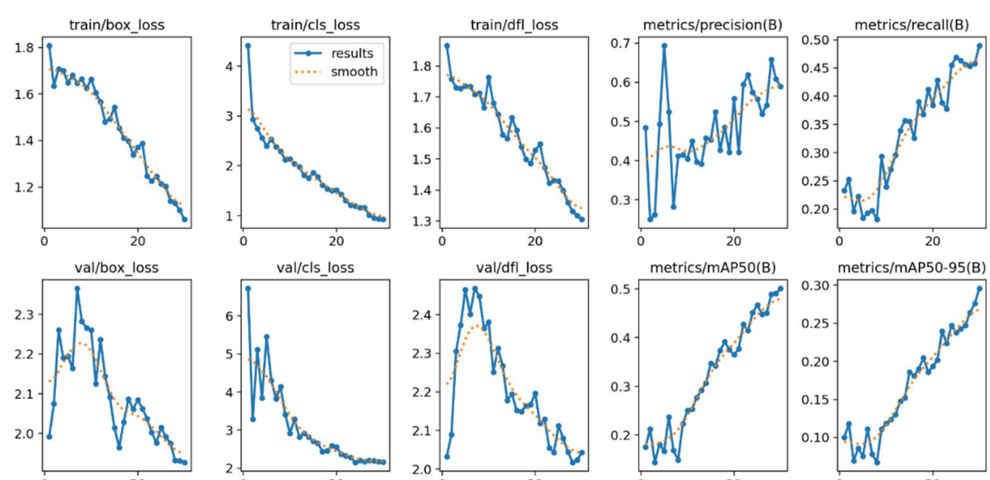


**Fig. 15** Performance metrics of YOLOv8 object detection model during training and validation phases

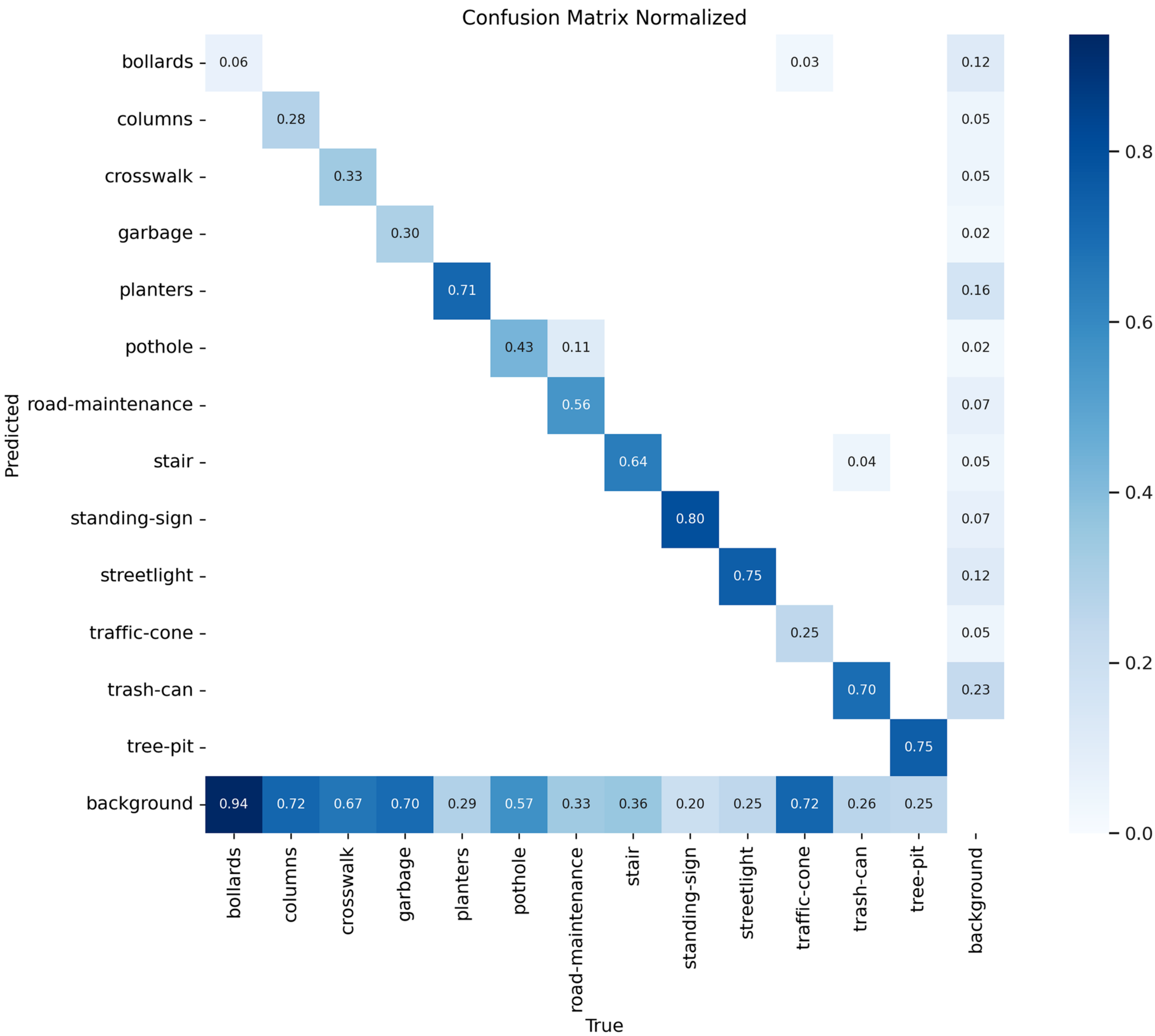


**Fig. 16** Confusion matrix of YOLOv8 model performance

Precision(B) and Metrics/Recall(B) plots further highlight the model's growing selectivity and improved detection proficiency.

Moving to the validation phase, the Val/box Loss Plot, Val/cls Loss Plot, and Val/dfl Loss Plot indicate slightly lower mAP on the validation dataset than training. This is a natural outcome as the model generalizes novel data. Finally, the Metrics/mAP50(B) and Metrics/mAP50-95(B) plots underscore the model's commendable performance in accurately detecting objects across varying IoU thresholds, validating its efficacy.

To conclude, Fig. 16 presents the confusion matrix, offering an overview of the YOLOv8 model's performance across thirteen diverse classes and contributing to the refinement of the object detection system.

Within this matrix, each normalized value represents the proportion of instances from an actual class predicted as each class, with diagonal values signifying true positives and off-diagonal values indicating misclassifications. The term "background" typically denotes the class representing the absence of any target or object of interest, encompassing elements the model is not trained to recognize as specific objects within most of the image in object detection tasks. Notable insights can be gleaned from the highest values in each row, revealing the predominant predicted class for a given true class. In contrast, lower values may suggest challenges in distinguishing certain classes, prompting


**Fig. 17** YOLOv8 object detection model predictions. The image showcases the model's accurate identification and classification of various objects and corresponding probabilities in a collage of photos

further exploration for potential model improvements or data augmentation strategies, and analyzing the provided normalized confusion matrix. Classes like "standing sign", "streetlight" and "tree-pit" exhibit relatively higher diagonal values, implying enhanced performance, with normalized accuracies of 0.80, 0.75, and 0.75, respectively. These values indicate the model's increased accuracy in predicting instances belonging to these specific classes.

Figure 17 depicts the predictions generated by the YOLOv8 object detection model on a collage of photos to represent the typical environment and objects that a visually impaired person might encounter daily, according to [42], demonstrating the model's capability to provide accurate and reliable object detection.

Using a diverse set of images reflects the model's ability to detect and classify various relevant objects. Each prediction is accompanied by information regarding the predicted class of the object and the corresponding probability, showcasing a diverse range of objects in the four images within the collage. This presentation offers a comprehensive overview of the model's proficiency in accurately identifying and classifying various items.

In addition, the object detection component was validated in real-world urban navigation situations involving stairs, trash bins, cones, bollards, crosswalks, streetlights, and pavement obstacles. These tests focused on verifying whether the trained model could operate within the MoSIoT mobile workflow and generate accessible audio feedback through the user application. The deployment validation confirmed the technical feasibility of combining object detection, distance estimation, and text-to-speech output in relevant navigation scenarios. At the same time, limitations were observed under lighting variation, partial occlusion, small-object appearance, and class imbalance, indicating the need for broader field testing and dataset expansion.

In the following, we applied several training methodologies and regularization techniques accessible at this reference [43] to address overfitting and improve generalization in our YOLOv8 model. Overfitting occurs when a model learns the training data too well, including its noise and outliers, leading to poor performance on new, unseen data. We employ Dropout, weight decay, L1 and L2 regularization, and Data Augmentation to mitigate this issue. Dropout introduces randomness during training to prevent neurons from relying too heavily on specific features or patterns. Weight decay, L1, and L2 regularization penalize large weights, encouraging the model to focus on essential features and reduce reliance on noisy or irrelevant information. Additionally, Data Augmentation diversifies the training data, exposing the model to a broader range of variations and improving its ability to generalize to unseen scenarios.

Furthermore, we discuss our analysis and evaluation, demonstrating the impact of these regularization techniques and Data Augmentation on model performance. Visualization of training curves, including loss, accuracy, and mean Average Precision (mAP) metrics, illustrates these techniques' convergence behavior and effectiveness. Comparisons against baseline models highlight the effectiveness of dropout, weight decay, L1/L2 regularization, and Data Augmentation in enhancing model robustness and generalization capacity. We also discuss the implications of these techniques in preventing overfitting, promoting model interpretability, and ultimately improving the model's ability to generalize to unseen data:

i. Dropout is a training technique that randomly sets a proportion of the nodes in the network to zero. We initialize the dropout probability to 0.5, indicating that each neuron has a 50% chance of being dropped out during training to prevent over-reliance on specific features.
ii. Weight Decay, also known as L2 regularization, adds a penalty term to the loss function proportional to the squared magnitude of the weights. We set Weight Decay to 0.0005, representing the strength of this penalty, encouraging the model to focus on essential features and reduce reliance on noisy or irrelevant information.
iii. Data Augmentation was used to expand the original dataset from 400 to 940 images and increase visual variability while preserving the domain-specific focus of the selected urban obstacles. The applied augmentation techniques included horizontal and vertical flipping, cropping with zoom levels ranging from 0% to 28%, rotation within a range of − 5° to +5°, horizontal and vertical shearing of up to ±14°, brightness adjustment up to ±25%, noise affecting up to 1.88% of pixels, and bounding box adjustments with horizontal and vertical shearing of ±10°. This augmentation process increased

**Table 4** Baseline comparison between non-regularized YOLOv8 and regularized YOLOv8 configurations

| Metric | Regularization model | Non-regularization model |
|---|---|---|
| Train/Box loss | Generally decreasing, stable (Range: 1.1921–1.7772) | Fluctuating, less stable (Range: 1.0608–1.8096) |
| Train/Cls loss | Generally decreasing, stable (Range: 1.3603–4.1065) | Fluctuating, less stable (Range: 0.92348–4.4143) |
| Train/Dfl loss | Generally decreasing, stable (Range: 1.3825–1.866) | Fluctuating, less stable (Range: 1.3053–1.866) |
| Val/Box loss | Generally decreasing, stable (Range: 1.8217–2.1929) | Fluctuating, less stable (Range: 1.9328–2.365) |
| Val/Cls loss | Generally decreasing, stable (Range: 2.1733–6.7251) | Fluctuating, less stable (Range: 2.3644–6.7251) |
| Val/Dfl loss | Generally decreasing, stable (Range: 1.9006–2.0323) | Fluctuating, less stable (Range: 2.0177–2.4652) |
| Metrics/Precision(B) | Increasing, stable (Range: 0.44044–0.71331) | Fluctuating, less stable (Range: 0.18196–0.69395) |
| Metrics/Recall(B) | Increasing, stable (Range: 0.34528–0.47427) | Fluctuating, less stable (Range: 0.1841–0.46906) |
| Metrics/mAP50(B) | Increasing, stable (Range: 0.44411–0.51809) | Fluctuating, less stable (Range: 0.14394–0.50088) |
| Metrics/mAP50-95(B) | Increasing, stable (Range: 0.24936–0.29586) | Fluctuating, less stable (Range: 0.06955–0.27607) |

the diversity of training examples and helped reduce the risk of overfitting in the YOLOv8 model.

To provide a baseline comparison within the implemented object detection component, we compared the regularized YOLOv8 configuration with a non-regularized YOLOv8 configuration trained under the same dataset conditions. The non-regularized configuration served as the baseline to evaluate the effects of dropout, weight decay, and data augmentation on training stability and detection performance. Table 4 summarizes comparisons across training and validation losses, precision, recall, and mAP. Through this comparison, we assess how regularization and data augmentation affect the stability and detection performance of the YOLOv8 component across several metrics.

The regularization model, incorporating dropout (0.5), weight decay (0.0005), and data augmentation, demonstrates stability throughout training and consistently improves performance metrics such as loss values, precision, recall, and mAP scores. This stability persists despite the increased diversity and quantity of training examples resulting from augmentation.

In contrast, the non-regularization model exhibits more significant fluctuations in metrics, indicating instability even with data augmentation. The absence of regularization techniques leads to less stable performance, with more substantial value variations across epochs.

The regularized configuration, incorporating dropout, weight decay, and data augmentation, showed more stable training and validation behavior than the non-regularized


**Fig. 18** The initial quality-of-life evaluation report, specifically designed for individuals with visual impairments, indicates a limited overall influence on their quality of life

baseline. In particular, precision, recall, mAP50, and mAP50-95 followed more consistent increasing trends, while validation losses showed lower fluctuation. These results suggest that regularization and augmentation improved the stability of the YOLOv8 component for the selected domain-specific urban obstacle dataset. However, this comparison should be interpreted as a baseline configuration analysis rather than a complete benchmark against alternative object detection architectures.

## 5 Results and analysis of QoL improvements for visually impaired in MoSIoT

This section presents the quantitative assessment of the QoL improvements achieved by the MoSIoT framework. The evaluation is based on pre-and post-intervention telemetry data collected from smartwatches and smartphones monitoring (1) Heart Rate Variability (HRV) as an indicator of physiological stress and emotional well-being, (2) Movement Count to reflect user engagement in mobility-related activities, (3) Sleep Quality Metrics to track sleep duration and patterns linked to emotional stability, (4) Audiobook Engagement to measure personal development through digital learning, and (5) Voice Interpreter Usage to assess digital accessibility and social interaction.

QoL assessment follows a structured approach. Initial assessments establish baseline scores, followed by an intervention phase in which MoSIoT's IoT and AI components are activated to improve the user experience. The post-intervention assessment generates updated scores that are analyzed for meaningful trends. Figure 18 illustrates the initial QoL assessment report, where different dimensions are visualized using a radar chart. This visualization helps domain experts identify areas for improvement.

As described in Sect. 4.3, domain experts configured the scenario model to enable all IoT and AI capabilities in response to these constraints. This configuration aligns with predefined goals from the care plan template or expert recommendations.

Progress is monitored through goal elements and telemetry data, including (1) communication time via a speech interpreter, (2) daily activities, (3) engagement with e-books, (4) interaction with the environment using AI features such as descriptive scene analysis, geolocation, and object recognition, and (5) consistent communication with caregivers monitored through audio message counter telemetry.

The application tracks and updates this data quantitatively, generating a comprehensive QoL assessment report visualized through a radar chart that facilitates precise identification of areas for improvement.

To measure the changes across QoL dimensions after the intervention, the improved value ( $D_{\text{improved}}$) is calculated using the following formula:

$$D_{\text{improved}} = D_{\text{initial}} + \frac{\sum_{i=1}^{n} \left[ \left( T_{i,current} - T_{i,initial} \right) W_i \Delta_i \right]}{\sum_{i=1}^{n} W_i} \quad (1)$$

where $D_{\text{initial}}$ represents the baseline score for each QoL dimension derived from previously established research and

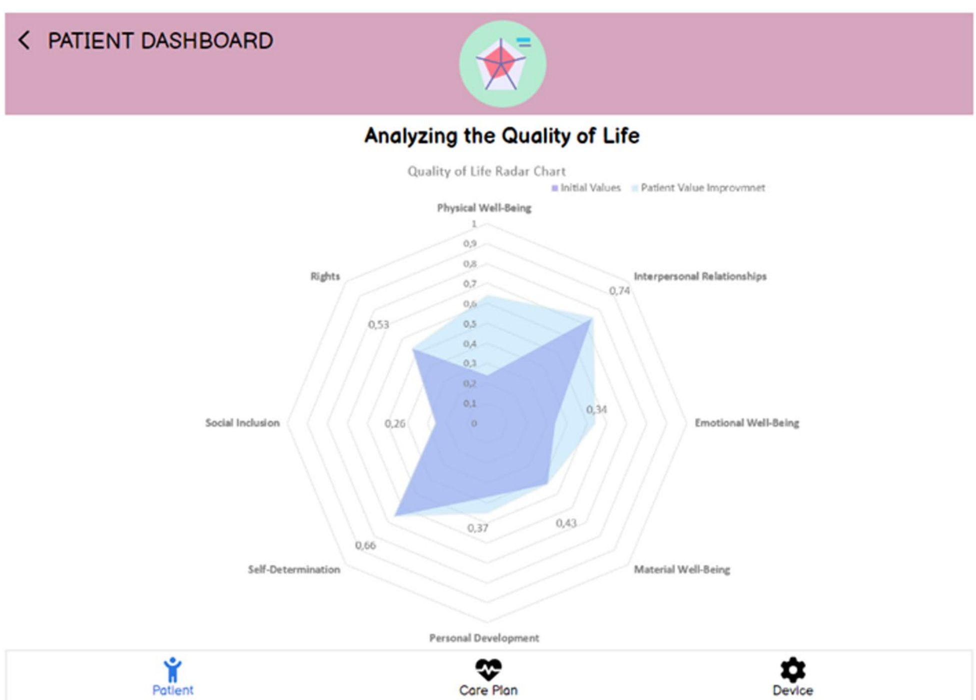


**Fig. 19** Post-intervention QoL report: increased engagement with IoT and AI devices and participation in the activities outlined in the care plan within the scenario model results in improved quality of life across multiple dimensions

**Table 5** Improvement in a patient's quality of life across various dimensions as a result of adhering to the activities outlined in the scenario model care plan

| Dimension | Initial values | Patient value improvements | Percentage improvement (%) | Explanation |
|---|---|---|---|---|
| Physical well-being | 0.24 | 0.64 | 52.63% | Significant improvement in physical well-being |
| Interpersonal relationships | 0.74 | 0.75 | 3.85% | Minimal improvement in interpersonal relationships |
| Emotional well-being | 0.34 | 0.54 | 30.30% | Greatly improved post-intervention |
| Material well-being | 0.43 | 0.43 | 0.00% | No improvement in material well-being |
| Personal development | 0.37 | 0.45 | 12.70% | Noticeable improvement in personal development. |
| Self-determination | 0.66 | 0.66 | 0.00% | No improvement in self-determination |
| Social inclusion | 0.26 | 0.26 | 0.00% | No improvement in social inclusion |
| Rights | 0.53 | 0.53 | 0.00% | No improvement in rights |

initial evaluations, as discussed in Sect. 4.1. The $T_{i,initial}$ values correspond to telemetry data recorded before the intervention begins, captured during an initial assessment phase using the MoSIoT system's sensors. These sensors measure factors such as movement, activity levels, biometric markers (e.g., HRV), and daily interactions with assistive technologies. The $T_{i,\ current}$ values represent telemetry data recorded after the intervention, reflecting changes due to the activities outlined in the care plan. The difference $T_{i,current} - T_{i,initial}$ quantifies the magnitude of improvement (or deterioration) in each contributing factor. Weights $(W_i)$ are assigned to each telemetry input, representing its relative importance to the specific QoL dimension, as informed by established frameworks like WHOQOL [44] and studies such as those by Chia et al. [45] and Misajon et al. [46]. Scaling factors $(\Delta_i)$ adjusts the impact of changes in telemetry inputs on the overall improvement of a QoL dimension. Normalization $\sum_{i=1}^{n} W_i$ scales the weighted contributions of all telemetry inputs, resulting in a meaningful and accurate improved value.

The post-intervention QoL report (Fig. 19) illustrates the significant progress made by a patient following the activities outlined in the scenario model's care plan. The radar chart visualizes baseline and patient value improvement across multiple dimensions of QoL, providing insight into the effectiveness of MoSIoT's assistive technologies. Notably, improvements are observed in Physical and Emotional Well-Being, while other areas, such as Interpersonal Relationships and Personal Development, show minimal progress, suggesting the need for further targeted interventions.

Motion counter data collected by MoSIoT telemetry evidence increased physical activity, indicating greater engagement in recommended activities. Improvements in emotional well-being are reflected in biometric markers such as HRV stability and sleep duration, further supported by AI-driven features such as descriptive scene analysis, geolocation, and object detection, which positively impact mood and overall emotional health. In addition, increased audiobook listening hours indicate progress in personal development, which aligns with care plan recommendations. Despite these improvements, minimal progress is observed in areas such as interpersonal relationships, suggesting the need for additional interventions to increase social engagement and support.

Table 5 presents a comparative analysis of the pre- and post-intervention QoL scores, highlighting percentage improvements across different dimensions.

The observed improvements were interpreted by linking each QoL dimension to the telemetry indicators, care-plan activities, and assistive services configured in the MoSIoT scenario. Physical well-being showed the largest increase, with a 52.63% improvement from 0.24 to 0.64. This change was associated with increased movement-related telemetry, smartwatch-based activity monitoring, and the use of mobility-support services such as object detection, distance estimation, and audio-based environmental feedback. Emotional well-being improved by 30.30%, from 0.34 to 0.54. This improvement was associated with more stable HRV and sleep indicators, together with assistive services such as descriptive scene analysis, geolocation support, and object recognition, which helped reduce uncertainty during environmental interaction. Personal development increased by 12.70%, from 0.37 to 0.45, mainly reflecting greater engagement with accessible e-book interaction and audio-based learning activities defined in the care plan. Interpersonal Relationships improved slightly by 3.85%, from 0.74 to 0.75, suggesting that assistive interaction alone may not be sufficient to substantially modify social participation patterns. Material Well-Being, Self-Determination, Social Inclusion, and Rights remained unchanged because the intervention primarily targeted mobility, environmental awareness, accessible interaction, and health-related monitoring, rather than economic, legal, or broader social participation factors. Therefore, the observed improvements should be understood as dimension-specific changes associated with the configured MoSIoT services and telemetry indicators, rather than as uniform improvement across all QoL dimensions. These reported QoL changes represent exploratory individual-level observations from a single participant and should not be interpreted as population-level effects.

## 6 Discussion

The framework represents a significant advancement in addressing the challenges that individuals with visual impairments face. However, some areas could be improved to enhance its effectiveness and usability. One such area is refining and optimizing the assistive technologies integrated into the framework.

Despite the advancements in AR geolocation, Object Detection Alert, and Audio Descriptive Scene Recognition Enhanced with AI, which offer solutions to many of the challenges identified in the study of Cushley et al. [42], there is room for improvement in accuracy, reliability, and real-time responsiveness. Continuous research and development efforts are necessary to fine-tune these technologies to meet diverse needs across various environments and scenarios.

As discussed in Sect. 2 (Background), previous research on assistive technologies for individuals with visual impairments has primarily focused on discrete functions such as mobility support, obstacle detection, and navigation assistance. While these solutions address key accessibility needs, they often lack integration with adaptive health monitoring systems or structured models for evaluating user well-being. For instance, McNicholl et al. [47] emphasize the importance of user-centered design in assistive technology development, noting that many existing solutions remain fragmented and fail to incorporate real-time user context. Similarly, Court et al. [48] highlight the complex physical and mental comorbidities frequently associated with visual impairment, underlining the need for comprehensive and personalized approaches. The MoSIoT framework builds upon these insights by combining IoT-based biometric data acquisition, AI-driven accessibility services, and a structured QoL assessment model. This integrative design enables not only assistive functionality but also proactive, individualized intervention grounded in the user's lived experience. Accordingly, our findings contribute to closing a critical gap in the literature by demonstrating the feasibility and potential impact of a holistic and intelligent assistive ecosystem.

The pattern of improvement across QoL dimensions is consistent with the intervention's scope. The greatest changes occurred in physical and emotional well-being and personal development, as these dimensions were directly targeted by the configured MoSIoT services, including mobility support, object detection, distance estimation, scene description, geolocation, smartwatch-based monitoring, and accessible e-book interaction. By contrast, dimensions such as material well-being, self-determination, social inclusion, and rights remained stable because they depend on broader socioeconomic, legal, personal autonomy, and community-level factors that were not directly addressed by the current intervention. This distinction helps explain why the proposed framework produced selective improvements in specific QoL dimensions rather than generalized progress across all parameters.

Additionally, while the MoSIoT framework prioritizes user-centric design, ongoing user feedback and iteration are needed to tailor the system to individual preferences and requirements. Furthermore, integrating assistive technologies into primary care practices and healthcare systems presents opportunities and challenges to address the challenges highlighted in the research by Court et al. [48] by offering proactive and integrated healthcare solutions.

Although remote monitoring and real-time data collection provide significant advantages for early detection and intervention, they also raise privacy, security, and ethical concerns. These issues are particularly relevant in AI-enabled assistive technologies because they may process sensitive details about the user's health, routines, and environment through visual data, location information, voice interactions, biometric signals, and behavioral telemetry. Addressing these risks requires careful consideration of informed consent, data minimization, transparency, potential algorithmic bias, and appropriate human oversight.

In addition, the reliance on stable Internet connectivity poses additional challenges, as interruptions or inconsistencies in network access could affect the real-time responsiveness and reliability of assistive technologies. This is particularly critical in rural or underserved regions where connectivity may be limited, hindering the system's ability to provide consistent and accurate support.

Scalability and affordability are critical to widespread adoption and accessibility. Reducing the cost of assistive technologies, improving device interoperability, and simplifying implementation processes are essential to expanding access and providing equitable support globally. These efforts must also address the challenges of varying levels of Internet infrastructure so that users in less connected regions can benefit from the Framework's capabilities.

As noted in the case-study methodology, the single-case design limits statistical generalization but is appropriate for exploratory and formative validation of a personalized assistive technology framework. In this study, the two-phase baseline/intervention structure, longitudinal telemetry collection, repeated monitoring, and QoL mapping enabled detailed individual-level analysis of physical and emotional well-being. Therefore, the observed changes should be interpreted as exploratory evidence of feasibility and potential impact, rather than as statistically generalizable proof of effectiveness. Accordingly, these findings reflect the experience of the individual participant and should not be extrapolated to the wider population without validation using a larger and more diverse sample.

Although statistical generalization is not feasible under this methodology, the richness of the data collected and the depth of analysis support the value of this approach in formative evaluations. Previous studies in assistive technology have successfully applied similar methodologies to evaluate system effectiveness in real-world contexts (Murray et al., [30]; Bould et al. [31]). As such, this work not only contributes to technological innovation but also strengthens the empirical foundation for assessing inclusive IoT-based interventions.

## 7 Conclusion and future work

Visual impairment affects at least 1 billion people worldwide, underscoring the need for innovative interventions. Traditional Assistive Technologies, while impactful, encounter limitations in cost, availability, and standardization. Assistive Technology, AI, and IoT convergence in MoSIoT empowers this demographic with personalized, inclusive solutions. Informed by a robust domain model and real-life IoT scenarios, this integration enhances environmental interaction and streamlines navigation for individuals with visual impairments. Additionally, this research extends the MoSIoT framework by emphasizing the critical role of remote monitoring through IoT devices, addressing broader healthcare needs. Integrating AI-driven solutions demonstrates a commitment to fostering communication skills and social interactions in this community.

Moving forward, our upcoming work involves integrating adaptable Audio IoT interfaces, AI-driven text readers, and customized Chatbots into the MoSIoT framework to cater to individuals with visual impairments. These additions aim to improve interaction and navigation capabilities for both indoor and outdoor environments. Additionally, we will explore how AI technologies can contribute to developing solutions for various disabilities. By integrating IoT systems with intelligent environments, such as smart homes or buildings, we aim to enhance the accessibility and usability of assistive technologies.

To ensure the efficacy of our developments, we will gather firsthand feedback from individuals with visual impairments through questionnaires and interviews. This direct input will guide us in refining our solutions to better align with their needs and preferences and overcome challenges such as standardization and interoperability among assistive technologies. In addition, future studies will include a larger and more diverse sample of participants, enabling the use of inferential statistical methods to evaluate the effectiveness of the MoSIoT framework more rigorously. This expansion will strengthen the generalizability of the findings and support the development of robust, evidence-based assistive technologies for individuals with visual impairments. In parallel, broader AI-component validation will be conducted using larger datasets, more diverse environmental conditions, and comparisons with alternative object detection models, such as YOLOv5 [49], SSD [50], or MobileNet-based models [51].

Future work will also explore adaptive personalization mechanisms that dynamically adjust interaction modalities, feedback levels, and assistive service configurations based on user preferences, context, and observed interaction patterns. Additionally, we will investigate large language model-based assistive services to support natural-language dialogue, contextual explanations, and personalized guidance. These extensions will require careful evaluation of reliability, privacy, transparency, and appropriate human oversight.

In conclusion, this article offers a comprehensive overview of the MoSIoT framework and its diverse components, aiming to contribute to the ongoing discourse on creating more inclusive and accessible technologies. The simulated scenarios and innovations presented within the framework highlight its potential to enhance the mobility, safety, and independence of individuals with visual impairments. In a world where digital interfaces predominantly cater to sighted individuals, the MoSIoT framework exemplifies a commitment to bridging the digital divide. Its adaptability, inclusivity, and emphasis on customization, aligned with established accessibility standards, make it a promising paradigm for future developments in assistive technologies. As technology evolves, embracing holistic solutions like MoSIoT becomes imperative in creating an equitable and accessible future for individuals with visual impairments.

**Author contributions** Conceptualization, S.N., and S.M.; Methodology, S.N., and S.M.; Software, S.N., and S.M.; Validation, S.N., S.M., B.L., and D.G.; Investigation, S.N., B.L., and D.G.; Resources, S.N., and S.M.; Writing – original draft preparation, S.N.; Writing – review and editing, S.N., S.M., B.L., and D.G.; Supervision, S.N., S.M., B.L., and D.G.; Project administration, S.M.; Funding acquisition, S.M. All authors have read and agreed to the published version of the manuscript.

**Funding** Open Access funding provided thanks to the CRUE-CSIC agreement with Springer Nature. This work was supported by the Spanish Ministry of Science and Innovation under Grant PID2023-149706OB-I00, "Design and application of a personalized and inclusive learning tool using artificial intelligence for students with Autism Spectrum Disorder."

**Data availability** No datasets were generated or analysed during the current study.

## Declarations

**Conflict of interest** The authors declare no competing interests.

**Informed consent** Not applicable.



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