

# Indoor Localization System for Patient Behavior Analysis in the Context of Connected Healthcare



## Wearable-based Fall Detection with Indoor Localization Context for Healthcare Environments

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# Update 1

# Project Setup & System Design

## Agenda

1. Motivation and Problem Definition
2. System-Level Design
3. Functional Pipeline
4. Sensing and Data Overview
5. Expected Outcomes

Time Scope: 22 Dec 2025 – 5 Jan 2026

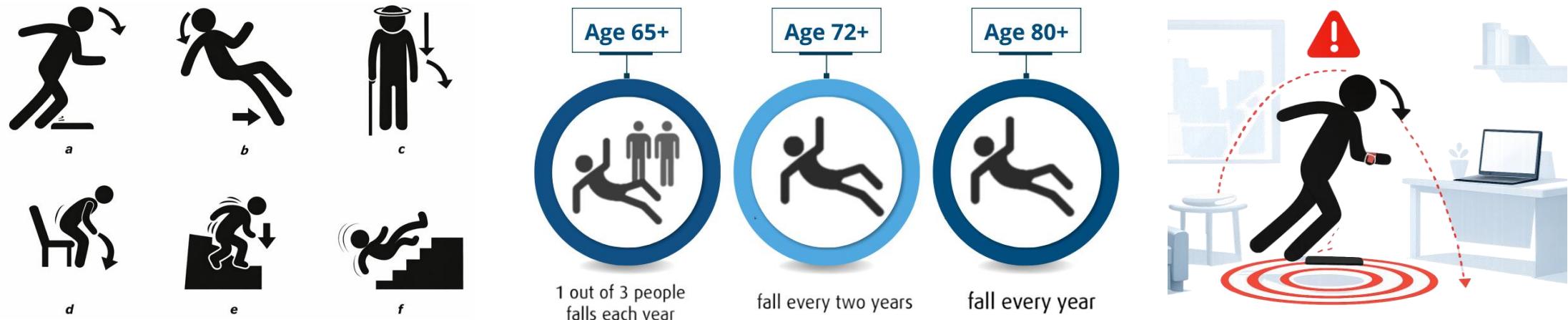
# 1.1 Motivation & Background

## Motivation

- Reliable and timely interpretation of patient behavior and location are essential to enable rapid medical intervention and reduce risks.

## Background

- Falls are among the most critical and time-sensitive patient behaviors.
- IPS\* are increasingly deployed in healthcare environments.
- Wearable devices (watch) are widely available and mature.



*IPS*: Indoor Positioning Systems (also referred to as Indoor Localization Systems)

# 1.2 Problem Statement

## Problem 1 – Fall Interpretation

- Falls and daily activities may exhibit similar movement patterns.
- Real-time and reliable interpretation of movements in real environments.
- Alert triggering and alert severity prioritization (professional decision support).

## Problem 2 – Indoor Localization

- Difficulty in determining the exact indoor location of a fall (e.g., room-level).
- Timeliness and reliability of indoor location information.
- Consistent and accurate representation of location information for alerting.

Fall detection is studied as a concrete instance of patient behavior analysis, with indoor localization used to determine the location of a fall event.

# 2 System-Level Design

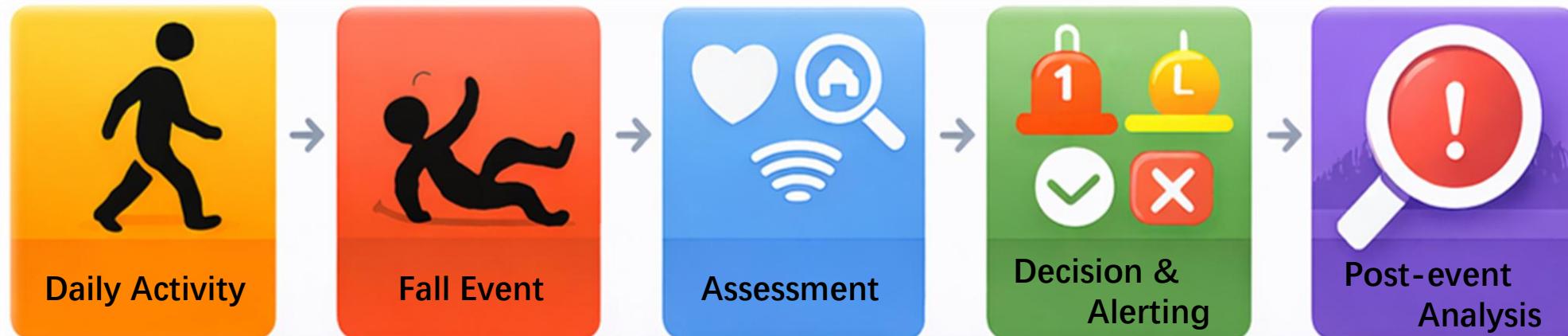
## Design Principles

- Wearable-first
- Low-intrusive & privacy-preserving
- Zone- / Room-level localization
- Modular and extensible system

## System Level

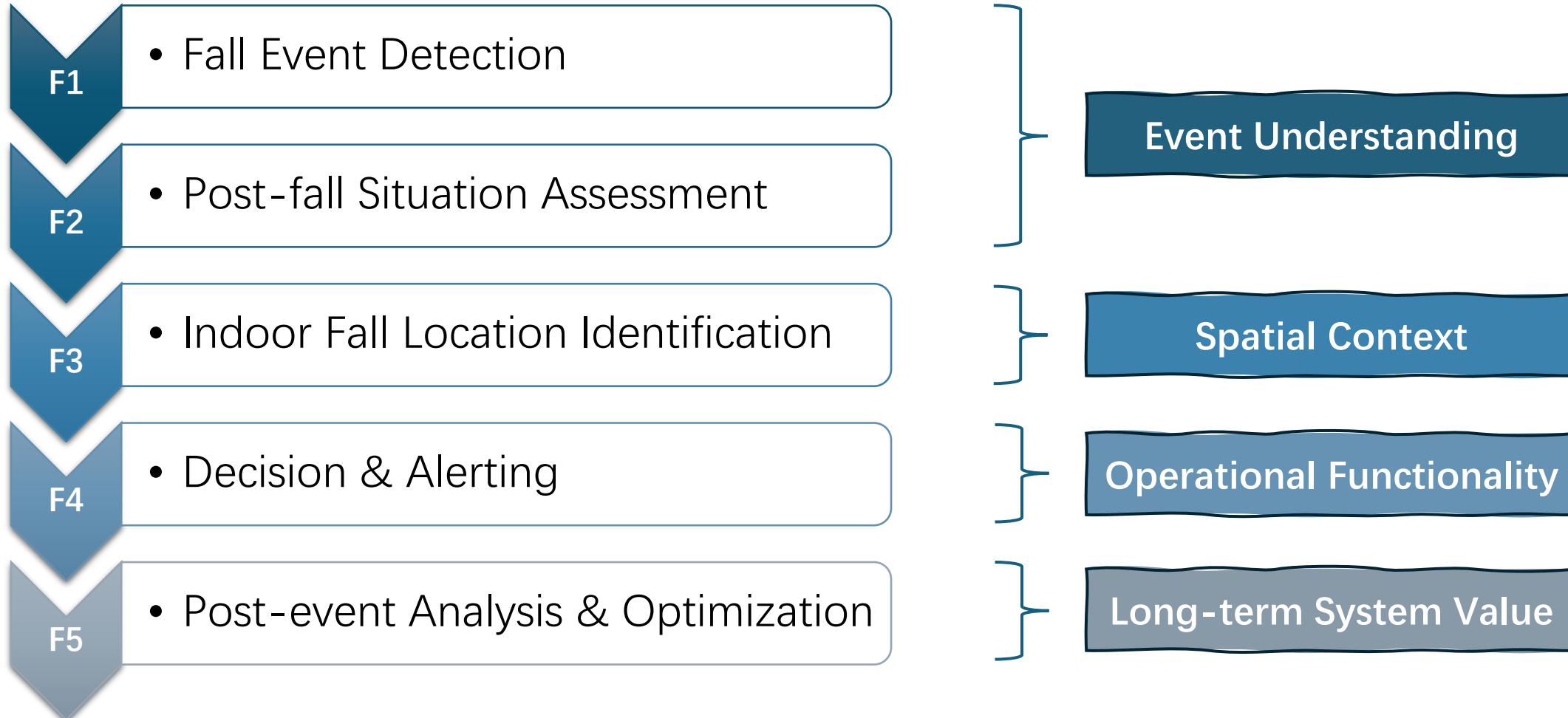
- Wearable sensing layer
- Indoor localization layer
- Processing & decision layer
- Alert & analysis layer

## End-to-End Fall Management Workflow



# 3 Functional Design Overview

## Functional Process Flow



# 3.1 F1-Fall Event Detection

## Purpose

- Distinguish daily activities vs. fall-related motion.
- Identify whether a fall event occurs and generate fall event candidates.

## Role

- Operates at the individual / event level.
- Provides the foundational event signal for subsequent functions.



## Devices & Data

- Device: wrist-worn wearable (IMU)
- Data: 3-axis acceleration, 3-axis angular velocity, timestamps



## Output

- Fall detection result (yes / no)
- Confidence / reliability indication (event-level)



# 3.2 F2-Post-fall Situation Assessment

## Purpose

- Assess whether the user can recover after the fall.
- Differentiate minor falls vs. critical / emergency falls.



## Role

- Refines risk and urgency level.
- Supports alert prioritization.

## Devices & Data

- Device: wrist-worn wearable (IMU)
- Data: 3-axis acceleration, 3-axis angular velocity, timestamps

## Output

- Post-fall motion status → recovery movements
- Estimated severity level of the fall.



# 3.3 F3-Indoor Fall Location Identification

## Purpose

- Determine where the fall event occurred (event-time location).

## Role

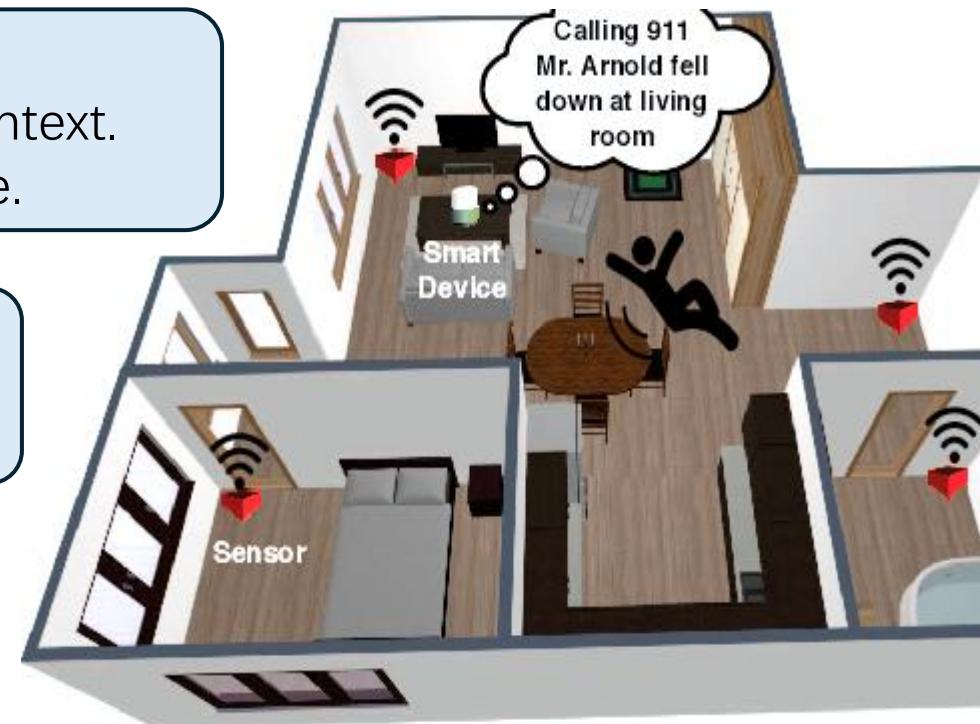
- Provides accurate spatial feedback.
- Embeds fall events into indoor spatial context.
- Supports navigation and rescue response.

## Devices & Data

- Devices: BLE beacons / Wi-Fi APs
- Data: RSSI signals, timestamps

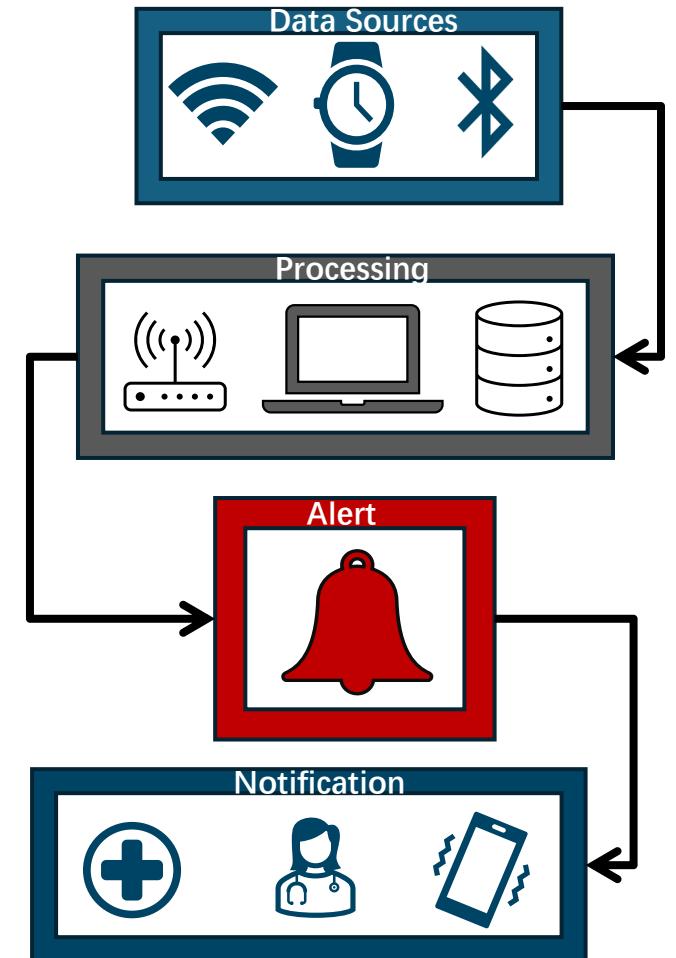
## Output

- Predicted zone / room of the fall
- Associated confidence level



# 3.4 F4-Decision & Alerting

Purpose	<ul style="list-style-type: none"> <li>Fuse information from F1, F2 and F3.</li> <li>Generate alerts with different priority levels.</li> </ul>
Role	<ul style="list-style-type: none"> <li>Transforms the system from event detection → to decision support &amp; operational response</li> </ul>
Devices & Data	<ul style="list-style-type: none"> <li>Devices: backend server / monitoring platform</li> <li>Data: structured outputs from F1-F3</li> </ul>
Output	<ul style="list-style-type: none"> <li>Structured alert message (event time, room / zone, severity)</li> </ul>



# 3.5 F5-Post-event Analysis & Optimization

## Purpose

- Long-term statistical analysis of fall frequency across locations / periods.
- Identify high-risk areas & high-risk periods.

## Role

- Extends system value from event handling  
→ to long-term knowledge and improvement



Spatial Risk



Temporal Risk



etc.

## Devices & Data

- Data source: accumulated event records from F1-F4
- Data types: location / time / severity / alert logs

## Output

- Long-term risk analysis reports.
- Spatial & temporal risk patterns.



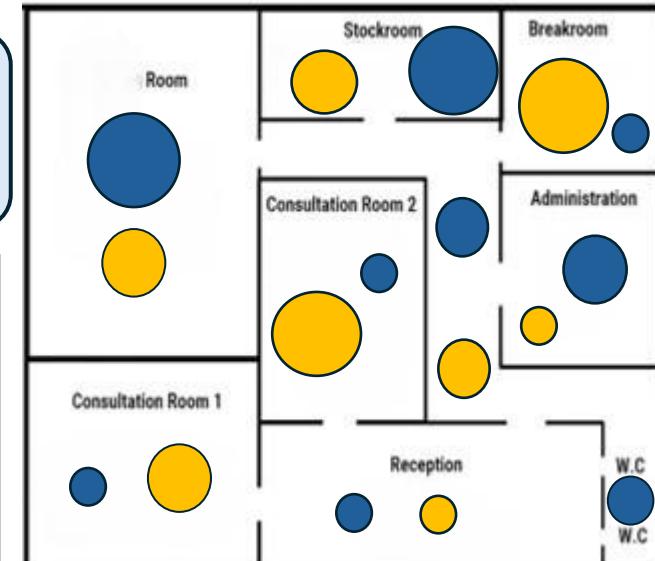
Low Risk



Medium Risk



High Risk



# 4.1 Sensing Overview

## 4.1.1 Fall-related motion sensing (wearable)

- Primary signal source (wrist-worn)

- Accelerometer: 3-axis acceleration ( $a_x, a_y, a_z$ )
- Gyroscope: 3-axis angular velocity ( $\omega_x, \omega_y, \omega_z$ )

- Effectiveness

- Acceleration captures impact / sudden change.
- Gyroscope captures rotation and posture transitions.
- Wrist-worn devices provide practical and effective signaling.

- Feasibility

- Each wearable device captures motion data independently.
- Typical wearable IMU\* streams are suitable for continuous monitoring.
- The resulting data follow a unified format suitable for common processing pipelines.

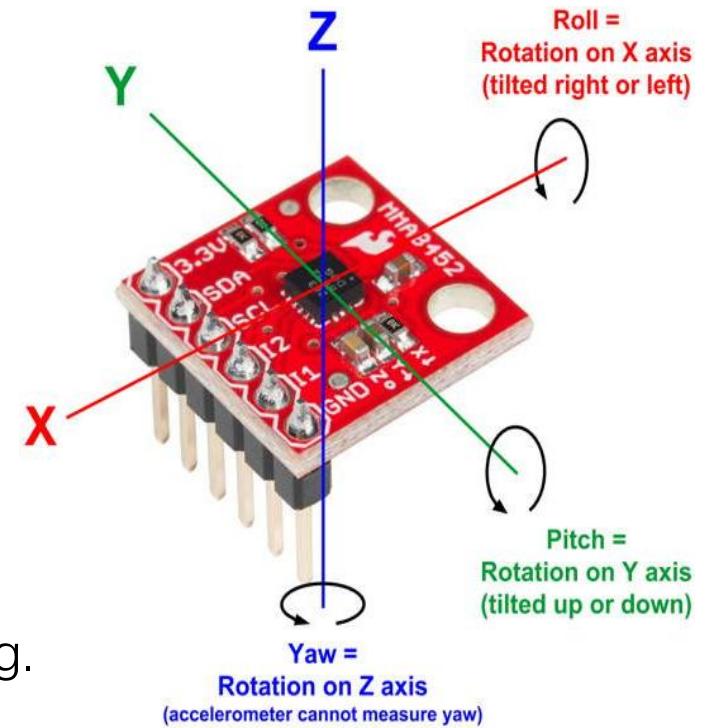


Fig. Sensor Coordinate System and Axes.

# 4.1 Sensing Overview

## 4.1.2 Indoor localization sensing (Event-driven)

- Primary signal source (environment-based)

- BLE-based signals: RSSI\*
- Wi-Fi-based signals: RSSI from APs\*

- Effectiveness

- BLE signals enable zone- / room-level localization (range 1-5 m).
- Wi-Fi signals support room-level localization (range 5-10 m).
- Event-driven sensing reduces unnecessary data acquisition.

- Feasibility

- BLE beacons and Wi-Fi infrastructure are widely available in indoor environments.
- Signal acquisition is lightweight and compatible with wearable devices.
- Room-level / Zone-level localization outputs can adopt a unified representation.

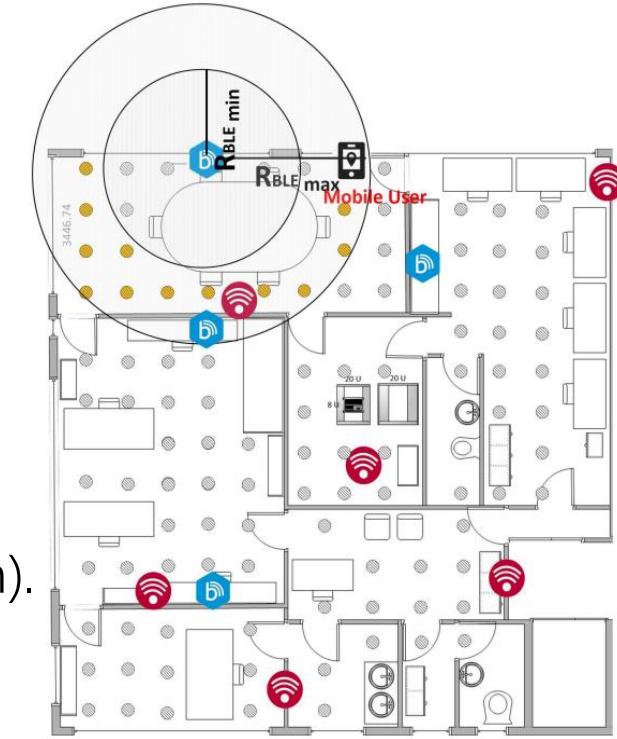


Fig. Combined BLE and Wi-Fi fingerprint based indoor positioning.

# 4.2 Data Overview

## 4.2.1 Motion Data for Fall Detection:

Acceleration vs. Angular Velocity (IMU)	Acceleration $a = (a_x, a_y, a_z)$	Angular Velocity $\omega = (\omega_x, \omega_y, \omega_z)$
Physical Meaning	Linear acceleration + Gravity	Rotational motion rate
Magnitude	$\ a\  = \sqrt{a_x^2 + a_y^2 + a_z^2}$	$\ \omega\  = \sqrt{\omega_x^2 + \omega_y^2 + \omega_z^2}$
Static State	$\ a\  \approx g$	$\ \omega\  \approx 0$
Orientation Sensitivity	High	Low
Impact Sensitivity	High (spikes at collision)	Low ~ Moderate
Posture Change Sensitivity	Low (indirect)	High

- **Complementarity for fall detection**

- Acceleration → impact detection
- Angular velocity → posture change
- Combined patterns → robust fall characterization

# 4.2 Data Overview

## 4.2.2 Indoor Localization Signals:

BLE vs. Wi-Fi	BLE RSSI	Wi-Fi RSSI
Signal Meaning	Proximity to beacon	Signal strength from APs
Battery Lifetime	High	Moderate
Sensitivity to Body Blocking	Moderate	High
Sensitivity to Multipath	Low ~ Moderate	High
Event-time Behavior	Local RSSI dominance	RSSI vector pattern
Infrastructure Density	High (dense beacons)	Low (sparse APs)

- **Complementarity for indoor localization**

- BLE → fine-grained local proximity
- Wi-Fi → stable spatial context
- Combined patterns → improves robustness

# 5 Expected Outcomes

## 1. Fall Event Detection

- Activity vs. fall discrimination
- Fall-related motion patterns
- Impact event detection

## 2. Indoor Location

- Event-time indoor location
- Room-level localization
- Zone-level context (if available)

## 3. Integrated Alerts

- Fall severity indication
- Predicted room / zone
- With event timestamp

## 4. Long-term Analysis

- High-risk fall-prone areas
- High-risk time periods
- Optimization suggestions

A complete fall detection and indoor localization alerting system.

# Thank You!