# Early Detection and Analysis of Gait Disorders in the Elderly Using Innovative Sensor Technologies

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**The Research Evaluation Report is submitted**

**for the degree of**

**Master of Applied Artificial Intelligence (Professional)**

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**January 2024**

# DECLARATION

I hereby declare that this report represents my own work for the degree of Masters at Deakin University, and has not been previously included in a thesis or dissertation submitted to this or any other institution for a degree, diploma or other qualifications.

I have read the University's current research ethics guidelines, and accept responsibility for the conduct of the procedures following the University's Research Ethics Committee (REC). I have attempted to identify all the risks related to this research that may arise in conducting this research, obtained the relevant ethical and/or safety approval (where applicable), and acknowledged my obligations and the rights of the participants.

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# Abstract

This research focuses on leveraging cutting-edge sensor technologies to enable the early detection and in-depth analysis of gait disorders in the elderly population. By employing synthetic data generation and advanced algorithms, the study explores the interplay between gait dynamics and handrail reliance within smart pathways. The proposed solution integrates insights from gait analysis, handrail interaction, and user-specific details to develop robust algorithms for real-time monitoring. Through comprehensive visualizations and statistical analyses, the research aims to refine methodologies, enhance understanding, and contribute to advancements in healthcare interventions for elderly individuals facing gait challenges.

**Keywords:** Gait Disorders, Elderly Health, Sensor Technologies, Smart Pathways, Synthetic Data Generation, Algorithm Development, Handrail Reliance, Machine Learning, Early Detection, Healthcare Interventions.

# Acknowledgments

I extend my heartfelt appreciation to Dr Anuroop Gaddam and my peers for their invaluable guidance and support throughout this research project.

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# Integration of Solutions

## 1.1 Conceptual Solution Integration

Our approach is geared towards creating a sophisticated framework for the early detection of gait disorders in elderly individuals. By combining advanced technologies, such as LiDAR sensors, gait pattern analysis, and sensor fusion techniques, our model forms a sturdy foundation for accurate and non-intrusive monitoring of an individual's gait dynamics. Placing LiDAR sensors strategically in the environment, along with incorporating smart modules like the Smart Bench and Smart Path, facilitates comprehensive data collection. Sensor fusion techniques boost the reliability of gait pattern analysis by merging data from various sensors, offering a complete understanding of the user's movements. This integrated system not only captures subtle variations in gait patterns but also considers contextual factors through smart modules. The ultimate goal of our conceptual solution is to predictively model, using combined data to identify early indicators of gait disorders. This forward-thinking approach enables proactive intervention, aligning seamlessly with the overarching goal of personalized healthcare and establishing a foundation for empirically addressing the research questions effectively. (Please refer to Task 4.1 for more details).

## 1.2 Delivery Plan Implementation

### 1.2.1 Simulation Setup

The Smart Gait Monitoring System employs a structured delivery plan, initially utilizing simulations to test and validate its components. Simulated Smart Bench and Smart Path modules emulate real-world sensor data, employing NFC technology and sensor tiles for user identification and gait dynamics measurement.

### 1.2.2 Data Simulation and Processing

In the simulated environment, diverse sensors are emulated to capture user interaction data, including sit-to-stand exercises, landing coordinates, forces during landing, and foot pressure. Simulated pre-processing steps, such as noise reduction and calibration, are applied to the acquired data, which is then logged in tabular CSV format. This approach aligns with the system's initial development stages, allowing for rigorous testing before physical implementation.

### 1.2.3 Data Fusion and Integration

Data fusion is simulated by virtually integrating various sensor datasets into a unified stream, mimicking the enhancement of overall data quality. Simulated real-time communication between components, facilitated through predefined protocols, replicates the seamless interaction expected in a physical system.

### 1.2.4 Feature Extraction

During the simulated feature extraction phase, diverse methods are applied to emulate sensor data, extracting key parameters such as the centre of pressure (COP), gait speed, step length, foot pressures, touch duration, support level indicator, and spatial coordinates. This step serves as a foundational process for subsequent analysis in the Smart Gait Monitoring System.

### 1.2.5 Analytics and Insights

In the simulated analytics phase, a fundamental approach is taken, emphasizing data extraction techniques and straightforward visualizations (bar charts, line graphs, pie charts, and heat maps). The objective is to derive key insights from the processed and fused data, focusing on essential patterns, trends, and spatial correlations. The visualizations provide a comprehensive overview of critical metrics and variations over time. This approach ensures clarity and interpretability of results before physical implementation.

## 1.3 MVP Demonstration

We put together the MVP for the Smart Gait Monitoring System, with a focus on crucial functions in the Smart Bench and Smart Path components for gait analysis tailored to users in healthcare. Noteworthy features include NFC-based user identification, capturing sit-to-stand exercise data, analyzing landing dynamics, providing gait metrics on the Smart Path, and assessing real-time handrail reliance. To handle limitations and make trade-offs, we followed an iterative development plan that prioritized features. The implementation of simulated features was designed to showcase core functionalities, and our iterative approach involved incorporating user feedback and testing to continually improve. The evaluation of the MVP showcases successful performance, recognizes challenges, and outlines plans for an extensive testing phase.(Please refer to Task 4.3 for more details).

## 1.4 Unified Framework

The framework (see Appendix B) was successfully simulated on software as a compelling proof of concept for potential stakeholders, laying the groundwork for real-world testing. While time constraints led to a focused simulation, specific aspects of the initially proposed solution were effectively showcased.

### 1.4.1 Smart Bench Module Simulation

#### NFC-Based User Identification

```
import pandas as pd
import uuid
import random

# Constants
num_users = 10  # Number of users

# Create an array to store the datasets for each user
users_datasets = []

for user_id in range(1, num_users + 1):
    # Simulate user information

    user_name = f"User_{user_id}"
    user_age = random.randint(50, 90)  # Age range
    user_gender = random.choice(['Male', 'Female']) #Gender
    user_height = round(random.uniform(150, 190), 2)  # Height in centimeters
    user_weight = round(random.uniform(50, 90), 2)   # Weight in kilograms

    # Simulate a unique NFC identifier for each user
    nfc_id = str(uuid.uuid4())

    # Create a DataFrame for each user's information
    user_data = pd.DataFrame({
        'User_ID': [user_id],
        'User_Name': [user_name],
        'User_Age': [user_age],
        'User_Gender': [user_gender],
        'User_Height_cm': [user_height],
        'User_Weight_Kg': [user_weight],
        'NFC_ID': [nfc_id]
    })

    users_datasets.append(user_data)

# Combine datasets for all users into a single DataFrame
users_dataset = pd.concat(users_datasets, ignore_index=True)

# Save the user dataset to a CSV file
users_dataset.to_csv('nfc_users_dataset.csv', index=False)
```

Figure 1.1: NFC Users Identification Simulation Code

The code simulates real-life NFC identification by generating unique NFC identifiers for users. It utilizes the uuid module to create universally unique identifiers (UUIDs) in a loop over user IDs. The UUIDs act as digital markers, mimicking NFC technology's unique identification capability. In practical scenarios, this process mirrors a user with an NFC tag approaching an NFC-enabled smart bench. These synthetic NFC identifiers enable secure, contactless communication between devices, crucial for data collection and analysis in diverse applications. The simulated dataset thus contains unique identifiers for each user, emulating the functionality of NFC technology.

| | A | B | C | D | E | F | G | H | I | J |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | User_ID | User_Nam | User_Age | User_Genc | User_Heig | User_Weig | NFC_ID | | | |
| 2 | 1 | User_1 | 88 | Male | 156.25 | 56.53 | 19c50d99-b22a-455e-9420-dbdc6ccd7623 | | | |
| 3 | 2 | User_2 | 50 | Male | 152.47 | 78.12 | 05bfb6c6-2252-4209-8e58-3e06b00c1c68 | | | |
| 4 | 3 | User_3 | 63 | Female | 150.97 | 63.32 | 774b9e1e-b666-4ad9-8520-9d68d6a0ed2f | | | |
| 5 | 4 | User_4 | 59 | Male | 181.41 | 89.76 | ff9d6787-b67c-4ee0-be06-f7de94baf416 | | | |
| 6 | 5 | User_5 | 78 | Female | 162.78 | 81.79 | 3cd9f993-0aaf-41ec-bff2-309b1a9c1b31 | | | |
| 7 | 6 | User_6 | 72 | Female | 175.92 | 57.78 | 91e2db21-5704-45f9-af3d-74ea59f92bea | | | |
| 8 | 7 | User_7 | 50 | Male | 185.12 | 51.5 | 4cbc9edf-b24f-4511-8a64-63f418b7b8f1 | | | |
| 9 | 8 | User_8 | 58 | Male | 185.78 | 51.17 | 9576133c-f67a-4d38-b8cf-5461582f2ddd | | | |
| 10 | 9 | User_9 | 65 | Male | 164.98 | 56.54 | 1fb631e3-1f79-4fd4-81b1-89b89282a3c5 | | | |
| 11 | 10 | User_10 | 62 | Female | 158.94 | 77.36 | 2abe368d-5092-4449-b4e0-88c3659efeda | | | |

Figure 1.2: NFC Users Identification Dataset

The dataset contains information for 10 users, where each user is assigned a unique identifier User ID. The User Name column represents the name of each user. User Age indicates the age of the user in years. User Gender specifies the gender of the user, and it can be either 'Male' or 'Female.' User Height cm provides the height of the user in centimeters as a floating-point number, and User Weight Kg represents the weight of the user in kilograms. Finally, the NFC ID column contains unique identifiers in UUID format, simulating NFC tags associated with each user for identification purposes.

The simulated dataset collected in CSV format includes the following columns with corresponding data types:

- **User_ID:** Integer
- **User_Name:** String
- **User_Age:** Integer
- **User_Gender:** String (can be "Male" or "Female")
- **User_Height_cm:** Float
- **User_Weight_Kg:** Float
- **NFC_ID:** String (UUID format)

### Daily Attendance of Users

```
import pandas as pd
import numpy as np
from datetime import datetime, timedelta

# Load the NFC users dataset
nfc_users_dataset = pd.read_csv('nfc_users_dataset.csv')

# Constants
num_entries = 1  # Number of entries per user
consecutive_days_threshold = 3  # Number of consecutive days to be considered a frequent visitor

# Adjusted probability values
probability_yes = 0.6  # Probability of having an entry on the current day
probability_no = 1 - probability_yes  # Probability of not having an entry on the current day

# Create an array to store the datasets for each entry
attendance_datasets = []

for index, user_row in nfc_users_dataset.sample(frac=1).iterrows():
    user_id = user_row['User_ID']
    user_name = user_row['User_Name']
    nfc_id = user_row['NFC_ID']

    consecutive_days = 0  # Counter for consecutive days
    for _ in range(num_entries):
        # Simulate random entry date within the last 30 days
        entry_date = datetime.now() - timedelta(days=np.random.randint(1, 30))
        random_time = datetime.strptime(np.random.choice(['09:00', '12:30', '15:45', '18:20', '21:10']), '%H:%M').time()


        # Determine if the user has an entry on the current day
        has_entry = np.random.choice([True, False], p=[probability_yes, probability_no])

        if has_entry:
            # Update consecutive days counter
            consecutive_days += 1
        else:
            # Reset consecutive days counter if no entry on the current day
            consecutive_days = 0
```

```
        # Create a DataFrame for each entry
        entry_data = pd.DataFrame({
            'Date': [entry_date.date()],
            'Time': [random_time],
            'User_ID': [user_id],
            'User_Name': [user_name],
            'NFC_ID': [nfc_id],
            'Frequent_Visitor': ['Yes' if consecutive_days > consecutive_days_threshold or consecutive_days == num_entries
                                 else 'No']
        })

        attendance_datasets.append(entry_data)

# Combine datasets for all entries into a single DataFrame
attendance_dataset = pd.concat(attendance_datasets, ignore_index=True)

# Save the attendance dataset to a CSV file
attendance_dataset.to_csv('attendance_data_with_frequent_visitor.csv', index=False)
```

Figure 1.3: Daily User Attendance Simulation Code

The provided code simulates the collection of attendance data for users using NFC technology. It generates random entries for users over the past 30 days, with each user having a probability of having an entry on a given day. For each entry, a date and time are simulated, and the code determines whether the user is a frequent visitor based on consecutive days of attendance. If a user has entries on more than the specified consecutive day's threshold or has attended all specified entries, they are labelled as a "Frequent Visitor," otherwise labelled as "Not Frequent." The resulting attendance data, including date, time, user information, and the frequent visitor label, is saved to a CSV file named 'attendance_data_with_frequent_visitor.csv'. This simulated dataset can be used for analyzing user attendance patterns and identifying frequent visitors.

| | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| 1 | Date | Time | User_ID | User_Nam | NFC_ID | Frequent_Visitor | |
| 2 | 12/30/2023 | 21:10:00 | 9 | User_9 | 1fb631e3-1f79-4fd4-81b1-89b89282a3c5 | Yes | |
| 3 | 1/18/2024 | 21:10:00 | 4 | User_4 | ff9d6787-b67c-4ee0-be06-f7de94baf416 | Yes | |
| 4 | 1/7/2024 | 21:10:00 | 3 | User_3 | 774b9e1e-b666-4ad9-8520-9d68d6a0ed2f | No | |
| 5 | 12/25/2023 | 9:00:00 | 6 | User_6 | 91e2db21-5704-45f9-af3d-74ea59f92bea | Yes | |
| 6 | 12/24/2023 | 12:30:00 | 5 | User_5 | 3cd9f993-0aaf-41ec-bff2-309b1a9c1b31 | No | |
| 7 | 12/29/2023 | 12:30:00 | 1 | User_1 | 19c50d99-b22a-455e-9420-dbdc6ccd7623 | No | |
| 8 | 1/12/2024 | 21:10:00 | 7 | User_7 | 4cbc9edf-b24f-4511-8a64-63f418b7b8f1 | Yes | |
| 9 | 1/17/2024 | 12:30:00 | 8 | User_8 | 9576133c-f67a-4d38-b8cf-5461582f2ddd | Yes | |
| 10 | 1/12/2024 | 18:20:00 | 10 | User_10 | 2abe368d-5092-4449-b4e0-88c3659efeda | No | |
| 11 | 12/29/2023 | 18:20:00 | 2 | User_2 | 05bfb6c6-2252-4209-8e58-3e06b00c1c68 | Yes | |

Figure 1.4: Daily User Attendance Dataset

The simulated dataset consists of attendance data with the following columns:

- **Date** (`object`): The date of the entry in MM/DD/YYYY format.
- **Time** (`object`): The time of the entry in HH:MM:SS format.
- **User_ID** (`int64`): Unique identifier for each user.
- **User_Name** (`object`): User's name.
- **NFC_ID** (`object`): Unique identifier for NFC communication.
- **Frequent Visitor** (`object`): Indicates whether the user is a frequent visitor, labelled as "Yes" or "No."

The dataset represents a log of attendance entries for different users, capturing the date and time of each entry along with user-specific information and a label indicating whether the user is considered a frequent visitor based on consecutive attendance days.

### Capture of Sit-to-Stand Exercise Data

```python
import pandas as pd
import numpy as np
from datetime import datetime, timedelta

# Load the NFC users dataset
nfc_users_dataset = pd.read_csv('nfc_users_dataset.csv')

# Constants
num_exercises = 1  # Number of exercises
exercise_duration = 30  # Duration of exercise in seconds

# Create an array to store the datasets for each exercise
exercise_datasets = []

for index, user_row in nfc_users_dataset.sample(frac=1).iterrows():
    user_id = user_row['User_ID']
    user_name = user_row['User_Name']
    nfc_id = user_row['NFC_ID']

    # Simulate multiple exercises for each user
    for _ in range(num_exercises):
        # Simulate random exercise date and time within the last 30 days
        random_date = datetime.now() - timedelta(days=np.random.randint(1, 30))
        random_time = datetime.strptime(np.random.choice(['09:00', '12:30', '15:45', '18:20', '21:10']), '%H:%M').time()

        # Simulate sit-to-stand transitions in a 30-second interval
        sit_stand_transitions = np.random.randint(5, 20)

        # Create a DataFrame for each exercise
        exercise_data = pd.DataFrame({
            'User_ID': [user_id],
            'User_Name': [user_name],
            'NFC_ID': [nfc_id],
            'Date': [random_date.date()],
            'Time': [random_time],
            'Sit_Stand_Transitions_30s': [sit_stand_transitions]
        })

        exercise_datasets.append(exercise_data)

# Combine datasets for all exercises into a single DataFrame
exercise_dataset = pd.concat(exercise_datasets, ignore_index=True)
```

Figure 1.5: Sit-to-Stand Exercise Simulation Code

This code simulates the collection of data related to sit-to-stand exercises performed by users on a smart bench. It utilizes a dataset of NFC users and generates exercise data for each user, including the number of sit-to-stand transitions performed in a 30-second interval. The code iterates through each user, simulating multiple exercises for them.

For each exercise, it randomly selects a date and time within the last 30 days, simulates a random number of sit-to-stand transitions in a 30-second interval, and creates a DataFrame entry with relevant information. The resulting dataset, named 'sit_stand_exercise_data_random.csv,' contains columns such as User_ID, User_Name, NFC_ID, Date, Time, and Sit_Stand_Transitions_30s, providing insights into users' exercise activities on the smart bench.

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | User_ID | User_Nam | NFC_ID | Date_of_Ex | Time_of_E | Sit_Stand_Transitions_30s |
| 2 | 1 | User_1 | 19c50d99-b22a-455e-9420-dbdc6ccd7623 | 1/22/2024 | 37:06.5 | 13 |
| 3 | 2 | User_2 | 05bfb6c6-2252-4209-8e58-3e06b00c1c68 | 1/22/2024 | 37:06.5 | 9 |
| 4 | 3 | User_3 | 774b9e1e-b666-4ad9-8520-9d68d6a0ed2f | 1/22/2024 | 37:06.5 | 19 |
| 5 | 4 | User_4 | ff9d6787-b67c-4ee0-be06-f7de94baf416 | 1/22/2024 | 37:06.5 | 11 |
| 6 | 5 | User_5 | 3cd9f993-0aaf-41ec-bff2-309b1a9c1b31 | 1/22/2024 | 37:06.5 | 16 |
| 7 | 6 | User_6 | 91e2db21-5704-45f9-af3d-74ea59f92bea | 1/22/2024 | 37:06.5 | 10 |
| 8 | 7 | User_7 | 4cbc9edf-b24f-4511-8a64-63f418b7b8f1 | 1/22/2024 | 37:06.5 | 6 |
| 9 | 8 | User_8 | 9576133c-f67a-4d38-b8cf-5461582f2ddd | 1/22/2024 | 37:06.5 | 7 |
| 10 | 9 | User_9 | 1fb631e3-1f79-4fd4-81b1-89b89282a3c5 | 1/22/2024 | 37:06.5 | 16 |
| 11 | 10 | User_10 | 2abe368d-5092-4449-b4e0-88c3659efeda | 1/22/2024 | 37:06.5 | 8 |

Figure 1.6: Sit-to-Stand Exercise Dataset

- **User_ID:** Integer
- **User_Name:** String
- **NFC_ID:** String
- **Date_of_Exercise:** String (representing the date)
- **Time_of_Exercise:** String (representing the time)
- **Sit_Stand_Transitions_30s:** Integer

This dataset simulates sit-to-stand exercises recorded on a smart bench, with each entry corresponding to a simulated exercise session for a specific user. Key columns include 'User_ID' for user identification, 'User_Name' for the user's name, 'NFC_ID' as the NFC identifier, 'Date_of_Exercise,' and 'Time_of_Exercise.' The column 'Sit_Stand_Transitions_30s' quantifies the number of sit-to-stand transitions in a 30-second interval during the exercise session.

In a real-world scenario, such data could be collected by a sensor-equipped smart bench, providing insights into users' physical activities. The 'Sit_Stand_Transitions_30s' column offers valuable information for health monitoring, exercise tracking, and understanding smart bench usage patterns in public spaces. This dataset facilitates the analysis of user behaviour and engagement, supporting initiatives to promote a healthy lifestyle in urban environments.

### Recording Landing Coordinates & Forces

```python
# Load the NFC users dataset
nfc_users_dataset = pd.read_csv('nfc_users_dataset.csv')

# Constants
num_landings = 1  # Number of landing recordings per user
force_factor_range = (1.5, 3.0)  # Assuming the force generated by foot is between 1.5 and 3 times the body weight
square_side_length = 1  # Assume a square with a side length of 1 meters

# Create an array to store the datasets for each landing
landing_datasets = []

for index, user_row in nfc_users_dataset.sample(frac=1).iterrows():
    user_id = user_row['User_ID']
    user_name = user_row['User_Name']
    nfc_id = user_row['NFC_ID']
    user_weight = user_row['User_Weight_Kg']

    # Simulate multiple landings for each user
    for _ in range(num_landings):
        # Simulate random landing date and time within the last 30 days
        landing_date = datetime.now() - timedelta(days=np.random.randint(1, 30))
        landing_time = datetime.strptime(np.random.choice(['09:00', '12:30', '15:45', '18:20', '21:10']), '%H:%M').time()

        # Simulate landing coordinates within the square
        landing_coordinates_x = np.random.uniform(-square_side_length/2, square_side_length/2)
        landing_coordinates_y = np.random.uniform(-square_side_length/2, square_side_length/2)

        # Multiply the user weight by a factor between 1.5 and 3 to represent landing force
        force_factor = np.random.uniform(*force_factor_range)
        landing_force = user_weight * force_factor

        # Create a DataFrame for each landing
        landing_data = pd.DataFrame({
            'User_ID': [user_id],
            'User_Name': [user_name],
            'NFC_ID': [nfc_id],
            'Date': [landing_date.date()],
            'Time': [landing_time],
            'Landing_Coordinates_X': [landing_coordinates_x],
            'Landing_Coordinates_Y': [landing_coordinates_y],
            'Landing_Forces_Kg': [landing_force]
        })

        landing_datasets.append(landing_data)

# Combine datasets for all landings into a single DataFrame
landing_dataset = pd.concat(landing_datasets, ignore_index=True)
```

Figure 1.7: Landing Co-ordinates & Forces Simulation Code

The provided Python code simulates the collection of landing details from users standing up from a smart bench with a landing pad in a real-life environment. The code generates multiple landing events for each user, incorporating factors such as landing date, time, coordinates within a square landing pad, and the estimated landing force. It leverages a dataset containing NFC user information, simulating diverse scenarios by randomizing landing parameters. The resulting dataset, saved as 'landing_coordinate_forces_data_with_square.csv,' represents a simulated record of user landings, providing insights into the spatial and force dynamics associated with standing up from the smart bench. In a real-world context, such data could be instrumental for assessing user interactions, optimizing smart bench designs, and understanding the bio mechanics of standing transitions.

| | A | B | C | D | E | F | G | H |
|---|---|---|---|---|---|---|---|---|
| 1 | User_ID | User_Nam | NFC_ID | Date | Time | Landing_Coordinates_X | Landing_Coordinates_Y | Landing_Forces_Kg |
| 2 | 10 | User_10 | 2abe368d-5092-4449-b4e0-88 | 12/29/2023 | 12:30:00 | 0.294218737 | 0.45627948 | 222.9291757 |
| 3 | 3 | User_3 | 774b9e1e-b666-4ad9-8520-9d | 1/12/2024 | 18:20:00 | 0.025192515 | -0.05248117 | 176.5152966 |
| 4 | 2 | User_2 | 05bfb6c6-2252-4209-8e58-3e | 1/21/2024 | 21:10:00 | -0.352162752 | -0.437681824 | 185.7667599 |
| 5 | 7 | User_7 | 4cbc9edf-b24f-4511-8a64-63f | 1/17/2024 | 12:30:00 | 0.180648847 | 0.21776892 | 102.3758239 |
| 6 | 4 | User_4 | ff9d6787-b67c-4ee0-be06-f7d | 1/2/2024 | 12:30:00 | 0.339083511 | 0.054921415 | 253.2756639 |
| 7 | 5 | User_5 | 3cd9f993-0aaf-41ec-bff2-309 | 12/24/2023 | 9:00:00 | 0.031821473 | -0.428851472 | 242.5164053 |
| 8 | 6 | User_6 | 91e2db21-5704-45f9-af3d-74e | 1/17/2024 | 18:20:00 | 0.414429619 | 0.13826338 | 131.8925769 |
| 9 | 9 | User_9 | 1fb631e3-1f79-4fd4-81b1-89b | 1/1/2024 | 12:30:00 | -0.36304645 | 0.086617243 | 123.7144036 |
| 10 | 1 | User_1 | 19c50d99-b22a-455e-9420-db | 1/16/2024 | 9:00:00 | 0.169844188 | -0.184136422 | 161.8247923 |
| 11 | 8 | User_8 | 9576133c-f67a-4d38-b8cf-546 | 12/31/2023 | 15:45:00 | -0.246208001 | 0.470074175 | 97.82532722 |

Figure 1.8: Landing Co-ordinates & Forces Dataset

The dataset `landing_coordinates_forces_data_with_square.csv` contains the following data types:

- **User_ID:** Integer
- **User_Name:** String
- **NFC_ID:** String (UUID format)
- **Date:** The date of the entry in MM/DD/YYYY format.
- **Time:** The time of the entry in HH:MM:SS format.
- **Landing_Coordinates_X:** Float
- **Landing_Coordinates_Y:** Float
- **Landing_Forces_Kg:** Float

In the simulated landing dataset, user identification includes an integer User_ID, a string User_Name, and a unique NFC_ID in UUID format. Temporal aspects are represented by Date and Time, while spatial details are captured through Landing_Coordinates_X and Landing_Coordinates_Y. The dataset quantifies landing forces in kilograms in the Landing_Forces_Kg column. In a real-world context, this dataset mirrors the recording of users' landing forces when interacting with a smart bench. The Landing_Forces_Kg values offer insights into the impact during activities like standing up or sitting down, contributing to understanding user interactions.

## Data Fusion

```python
import pandas as pd

# Load the datasets
nfc_users_dataset = pd.read_csv('nfc_users_dataset.csv')
attendance_dataset = pd.read_csv('attendance_data_with_frequent_visitor.csv')
exercise_dataset = pd.read_csv('sit_stand_exercise_data_random.csv')
landing_dataset = pd.read_csv('landing_coordinates_forces_data_with_square.csv')

# Merge the datasets based on User_ID, Date, and Time
merged_dataset = pd.merge(nfc_users_dataset, attendance_dataset, on=['User_ID', 'User_Name', 'NFC_ID'], how='left',
                          suffixes=('_nfc', '_attendance'))
merged_dataset = pd.merge(merged_dataset, exercise_dataset, on=['User_ID', 'User_Name', 'NFC_ID'], how='left',
                          suffixes=('_merged', '_exercise'))
merged_dataset = pd.merge(merged_dataset, landing_dataset, on=['User_ID', 'User_Name', 'NFC_ID'], how='left',
                          suffixes=('_merged', '_landing'))

# Save the merged dataset to a CSV file
merged_dataset.to_csv('smart_bench_combined_dataset.csv', index=False)
```

Figure 1.9: Sensors Data Fusion - Smart Bench Module Simulation Code

The code exemplifies a data fusion process for a smart bench, merging information from various sensors. In real-world scenarios, this technique enhances user identification, attendance tracking, exercise monitoring, and landing force recording. By unifying datasets based on common user identifiers, the code facilitates a thorough analysis of user interactions. This consolidated dataset is essential for understanding user behaviours and preferences. Additionally, it aids in optimizing smart bench functionalities, improving user experiences, and gaining insights into public space utilization. The showcased data fusion approach reflects a practical application, deriving actionable insights for enhanced urban infrastructure management.

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | User_I | User_Nam | User_Ag | User_Gende | User_Height | User_Weigh | NFC_ID | Date_merged | Time_merg | Frequent_Visito | Date_exercise | Time_exercis | Sit_Stand_Transition | Date | Time | Landing_Coordinates_X | Landing_Coordinates_ | Landing_Forces_Kg |
| 2 | 1 | User_1 | 88 | Male | 156.25 | 56.53 | 19c50d9 | 12/29/2023 | 12:30:00 | No | 12/30/2023 | 18:20:00 | 15 | 1/16/2024 | 9:00:00 | 0.169844188 | -0.184138422 | 161.8247923 |
| 3 | 2 | User_2 | 50 | Male | 152.47 | 78.12 | 05bfb6c6 | 12/29/2023 | 18:20:00 | Yes | 12/28/2023 | 18:20:00 | 11 | 1/21/2024 | 21:10:00 | -0.352162752 | -0.437681824 | 185.7667599 |
| 4 | 3 | User_3 | 63 | Female | 150.97 | 63.32 | 774b9e1e | 1/7/2024 | 21:10:00 | No | 1/9/2024 | 12:30:00 | 8 | 1/12/2024 | 18:20:00 | 0.025192515 | -0.05248117 | 176.5152966 |
| 5 | 4 | User_4 | 59 | Male | 181.41 | 89.76 | ff9d6787- | 1/18/2024 | 21:10:00 | Yes | 1/16/2024 | 15:45:00 | 19 | 1/2/2024 | 12:30:00 | 0.339083511 | 0.054921415 | 253.2756639 |
| 6 | 5 | User_5 | 78 | Female | 162.78 | 81.79 | 3cd9f993 | 12/24/2023 | 12:30:00 | No | 1/15/2024 | 9:00:00 | 11 | 12/24/2023 | 9:00:00 | 0.031821473 | -0.428851472 | 242.5164053 |
| 7 | 6 | User_6 | 72 | Female | 175.92 | 57.78 | 91e2db21 | 12/25/2023 | 9:00:00 | Yes | 1/19/2024 | 15:45:00 | 10 | 1/17/2024 | 18:20:00 | 0.414429619 | 0.13826338 | 131.8925769 |
| 8 | 7 | User_7 | 50 | Male | 185.12 | 51.5 | 4cbc9edf- | 1/12/2024 | 21:10:00 | Yes | 12/25/2023 | 18:20:00 | 10 | 1/17/2024 | 12:30:00 | 0.180648847 | 0.21776892 | 102.3758239 |
| 9 | 8 | User_8 | 58 | Male | 185.78 | 51.17 | 9576133c | 1/17/2024 | 12:30:00 | Yes | 1/8/2024 | 15:45:00 | 5 | 12/31/2023 | 15:45:00 | -0.246208001 | 0.470074175 | 97.82532722 |
| 10 | 9 | User_9 | 65 | Male | 164.98 | 56.54 | 1fb631e3 | 12/30/2023 | 21:10:00 | Yes | 1/11/2024 | 15:45:00 | 5 | 1/1/2024 | 12:30:00 | -0.36304645 | 0.086617243 | 123.7144036 |
| 11 | 10 | User_10 | 62 | Female | 158.94 | 77.36 | 2abe368d | 1/12/2024 | 18:20:00 | No | 12/26/2023 | 12:30:00 | 17 | 12/29/2023 | 12:30:00 | 0.294218737 | 0.45627948 | 222.9291757 |

Figure 1.10: Sensors Data Fusion - Smart Bench Module Dataset

The merged dataset, combining NFC interactions, attendance records, exercise routines, and landing forces (18 columns in total), provides a holistic view of users' behaviours and physical activities. This compilation is vital for the early detection of gait disorders in the elderly. Analyzing mobility patterns, exercise routines, and landing forces enables insights into gait dynamics. Including Frequent_Visitor status and temporal aspects allows a thorough examination of consistent behavioural patterns over time.

This diverse dataset facilitates the development of predictive models, aiding in the early identification of potential gait disorders in the ageing population. It stands as a valuable resource for understanding and addressing mobility-related issues in elderly individuals.

### Data Pre-Processing & Cleaning

```python
import pandas as pd

# Load the combined dataset
combined_dataset = pd.read_csv('smart_bench_combined_dataset.csv')

# Drop columns
columns_to_drop = ['Date', 'Time', 'Date_exercise', 'Time_exercise']
combined_dataset = combined_dataset.drop(columns=columns_to_drop)

# Rename columns
combined_dataset = combined_dataset.rename(columns={'Date_merged': 'Date', 'Time_merged': 'Time'})

# Save the modified dataset to a new CSV file
combined_dataset.to_csv('smart_bench_combined_dataset_cleaned.csv', index=False)
```

Figure 1.11: Data Cleaning Code - Smart Bench

The code snippet performs data cleaning on a merged smart bench dataset, dropping redundant date and time columns and renaming others for clarity. The resulting cleaned dataset is saved to 'smart_bench_combined_dataset_cleaned.csv,' ensuring its readiness for analysis. This process enhances dataset quality, making it well-prepared for applications such as monitoring and early detection of gait disorders in elderly individuals using a smart bench.

### Visualizations & Insights

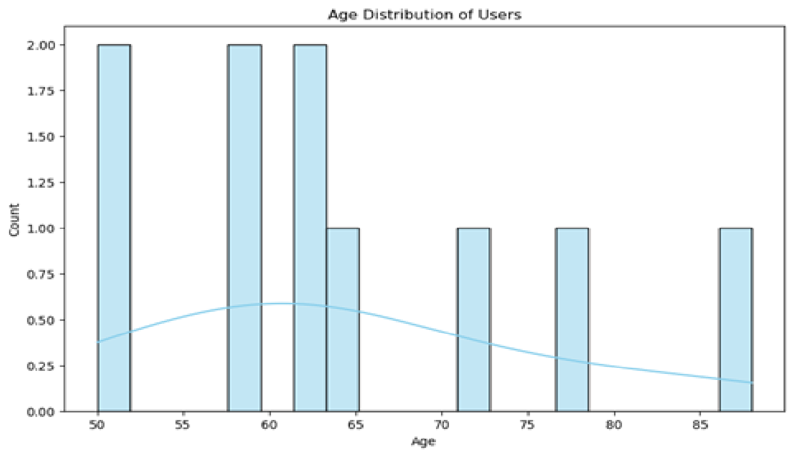


Figure 1.12: Age Distribution of Users

The histogram displays user frequency across age groups, providing insights into the demographic composition. Analyzing age distribution aids in tailoring interventions for effective early detection among age groups susceptible to gait disorders. By utilizing a histogram with a kernel density estimate, we can identify patterns, concentrations, or trends in specific age ranges.

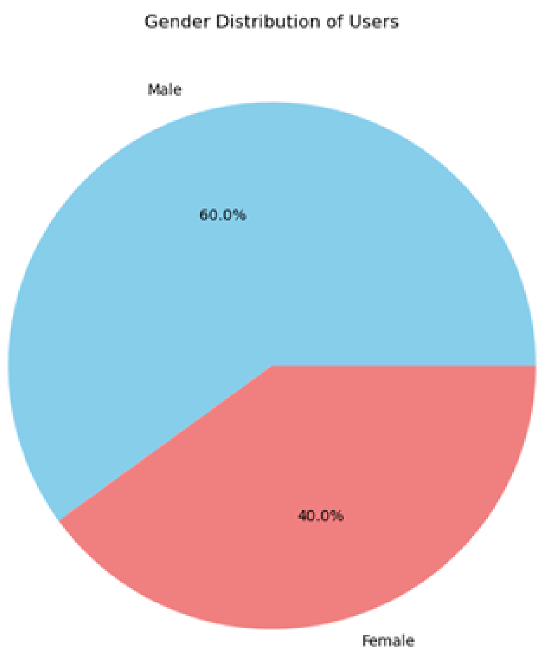


Figure 1.13: Gender Distribution of Users

The gender distribution visualization offers a snapshot of the diverse smart bench user population, aiding in understanding potential gender-specific patterns related to gait disorders. Recognizing these patterns contributes valuable insights for tailoring interventions and strategies for early detection, considering gender-related variations in certain gait disorders.

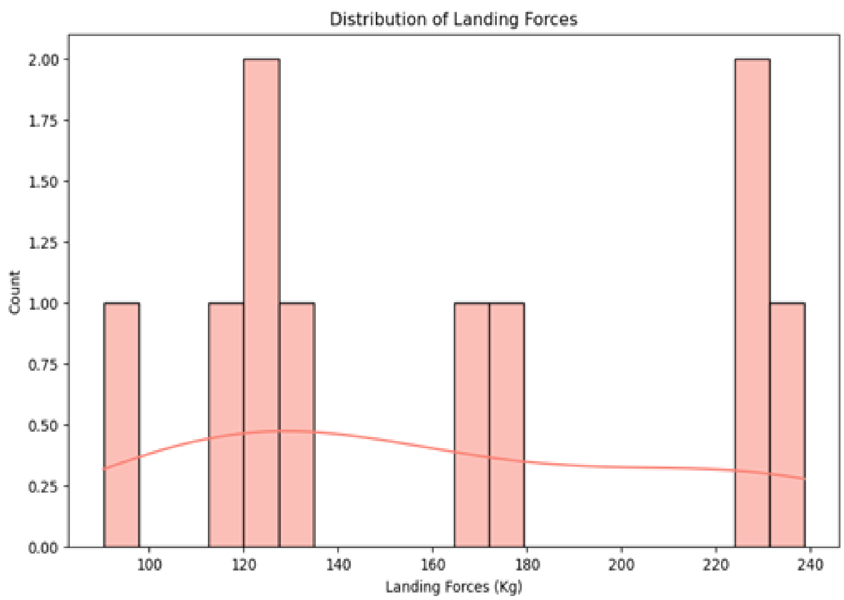


Figure 1.14: Distribution of Landing Forces

The landing forces distribution visualization uncovers patterns in forces exerted during recorded landings by the smart bench, offering insights into potential irregular gait or balance issues. Analyzing this histogram helps researchers identify outliers, providing a better understanding of typical landing force ranges and detecting deviations indicative of gait disorders.

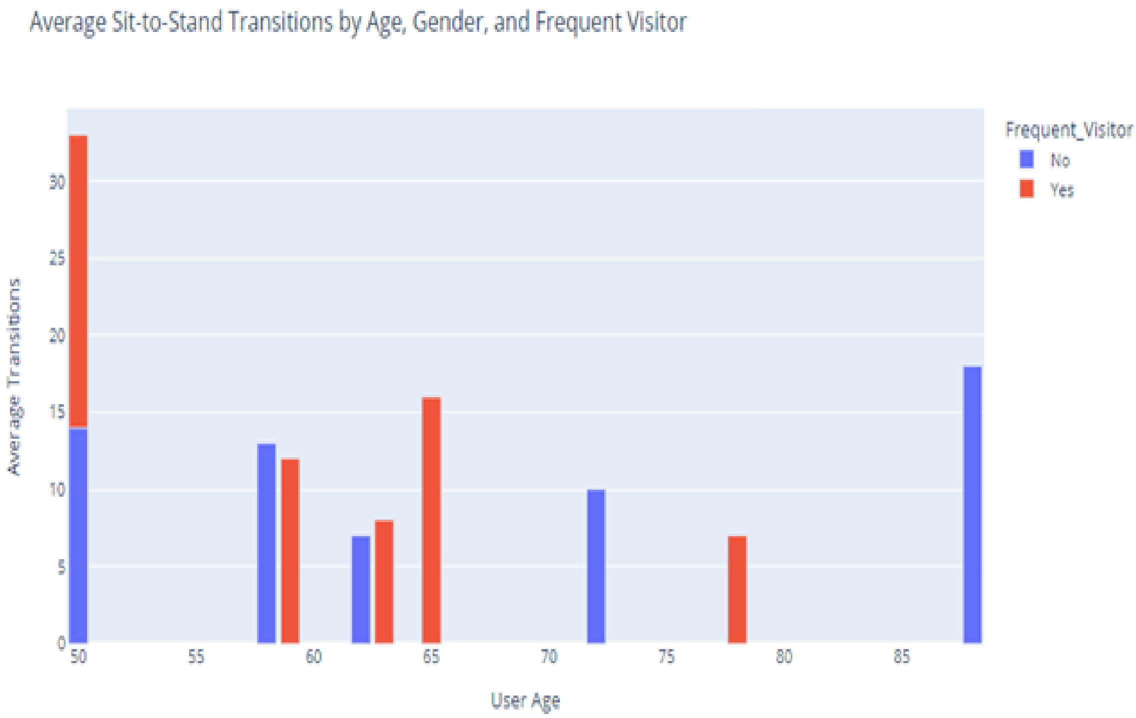


Figure 1.15: Average Sit-to-Stand Transitions by Gender, Age & Frequent Visitor

This visualization provides comprehensive insights into average sit-to-stand transitions, considering factors like age, gender, and frequent visitor status. Interactive plots offer a nuanced perspective, enabling researchers to understand how these variables contribute to variations in user behavior and mobility across diverse demographic groups.

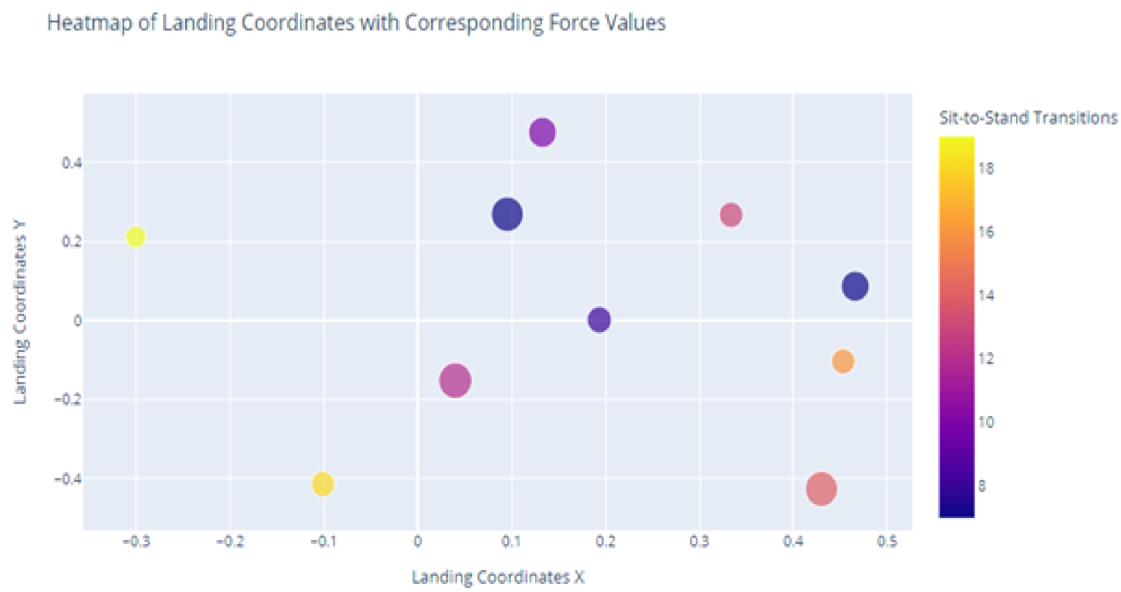


Figure 1.16: Heatmap of Landing Coordinates with Corresponding Force Values

The heatmap illustrates landing coordinates and corresponding force values during sit-to-stand transitions, offering insights into spatial distribution and weight distribution patterns on the smart bench. The color-coded representation aids in identifying patterns and irregularities, contributing to a deeper understanding of spatial dynamics crucial for gait analysis and early detection of gait-related issues.

### 1.4.2 Smart Path Module Simulation

#### Gait Dynamics Data

```python
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from datetime import datetime, timedelta

# Load the NFC users dataset
nfc_users_dataset = pd.read_csv('nfc_users_dataset.csv')

# Create a dataset for 10 users
np.random.seed(42)

# Constants
num_users = 10
num_measurements = 1

# Generate synthetic data
user_ids = np.arange(1, num_users + 1)
nfc_ids = nfc_users_dataset['NFC_ID'].sample(num_users).tolist()  # Match NFC IDs with the provided dataset
speeds = np.random.uniform(1.0, 2.5, num_users)
step_lengths = np.random.uniform(0.5, 1.2, num_users)
stride_lengths = speeds * np.random.uniform(1.2, 1.5, num_users)
cadences = np.random.uniform(80, 120, num_users)  # Steps per minute
double_support_times = np.random.uniform(0.1, 0.3, num_users)  # Percentage of gait cycle
step_times = 60 / cadences  # Time per step in seconds

# Generate dates and times for the measurements (within the past month)
start_date = datetime.now() - timedelta(days=30)
measurement_dates = [start_date + timedelta(days=i) for i in range(num_measurements)]
measurement_times = [start_date + timedelta(minutes=i) for i in range(num_measurements * num_users)]

# Create the gait dynamics dataset
gait_data = pd.DataFrame({
    'User_ID': np.repeat(user_ids, num_measurements),
    'User_Name': np.repeat(nfc_users_dataset.loc[nfc_users_dataset['NFC_ID'].isin(nfc_ids), 'User_Name'].tolist(),
                           num_measurements),
    'NFC_ID': np.repeat(nfc_ids, num_measurements),
    'Date': np.tile([d.date() for d in measurement_dates], num_users),
    'Time': [t.time().strftime('%H:%M:%S') for t in measurement_times],
    'Speed_m_s': np.repeat(speeds, num_measurements),
    'Step_Length_m': np.repeat(step_lengths, num_measurements),
    'Stride_Length_m': np.repeat(stride_lengths, num_measurements),
    'Cadence_steps_min': np.repeat(cadences, num_measurements),
    'Double_Support_Time_percent': np.repeat(double_support_times, num_measurements),
    'Step_Time_sec': np.repeat(step_times, num_measurements)
})

# Correct NFC_IDs based on User_Name
gait_data['NFC_ID'] = gait_data['User_Name'].map(nfc_users_dataset.set_index('User_Name')['NFC_ID'])

gait_data.to_csv('Gait_Dynamics.csv', index=False)

# Display the corrected gait_data
gait_data
```

Figure 1.17: Gait Dynamics Simulation Code

The script employs synthetic data generation to replicate datasets from sophisticated sensors in smart pathways. By mimicking critical biomechanical parameters such as walking speed, step length, cadence, and double support time, the 'Gait_dynamics.csv' dataset is a controlled surrogate for analyzing nuanced relationships among gait parameters.

The synthetic data generation process reproduces the precise gait information collected by real-life sensors— LiDARs, Touch Sensors, and pressure sensors integral to smart pathways. These sensors capture authentic datasets from individuals navigating these pathways in real-world scenarios. The synthetic dataset proves valuable for initial algorithm development to refine methodologies before transitioning to real-life data acquisition processes.

| | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | User_ID | User_Nam | NFC_ID | Date | Time | Speed_m_s | Step_Length_m | Stride_Length_m | Cadence_steps_min | Double_Support_Time_ | Step_Time_sec |
| 2 | 1 | User_1 | 19c50d99- | 12/24/2023 | 13:50:17 | 1.23399178 | 0.628383157 | 1.771460341 | 112.3358939 | 0.232504457 | 0.534112454 |
| 3 | 2 | User_2 | 05bfb6c6-: | 12/24/2023 | 13:51:17 | 1.08712542 | 0.71296957 | 1.369671635 | 92.18455077 | 0.162342215 | 0.65086828 |
| 4 | 3 | User_3 | 774b9e1e- | 12/24/2023 | 13:52:17 | 2.29926422 | 0.867329502 | 3.113825316 | 83.90688456 | 0.204013604 | 0.715078391 |
| 5 | 4 | User_4 | ff9d6787-b | 12/24/2023 | 13:53:17 | 1.90167252 | 0.802361513 | 2.619980573 | 107.3693211 | 0.209342056 | 0.558818845 |
| 6 | 5 | User_5 | 3cd9f993-( | 12/24/2023 | 13:54:17 | 2.06210887 | 0.703860398 | 2.503266382 | 97.60609975 | 0.136970891 | 0.61471568 |
| 7 | 6 | User_6 | 91e2db21- | 12/24/2023 | 13:55:17 | 1.03087674 | 0.928297026 | 1.424943247 | 84.88152939 | 0.293916926 | 0.706867565 |
| 8 | 7 | User_7 | 4cbc9edf-l | 12/24/2023 | 13:56:17 | 2.45486478 | 0.597645702 | 3.071421833 | 99.8070764 | 0.255026565 | 0.601159779 |
| 9 | 8 | User_8 | 9576133c- | 12/24/2023 | 13:57:17 | 2.24866396 | 0.704501254 | 2.742280505 | 81.37554084 | 0.287899788 | 0.737322288 |
| 10 | 9 | User_9 | 1fb631e3-: | 12/24/2023 | 13:58:17 | 1.31850867 | 0.75645329 | 1.95754454 | 116.3728161 | 0.27896547 | 0.515584326 |
| 11 | 10 | User_10 | 2abe368d- | 12/24/2023 | 13:59:17 | 1.27273745 | 0.819248989 | 1.895983757 | 90.35119926 | 0.219579996 | 0.664075303 |

Figure 1.18: Gait Dynamics Dataset

The dataset 'Gait_dynamics.csv' contains the following data types:

- **User_ID:** Integer
- **User_Name:** String
- **NFC_ID:** String
- **Date:** Date
- **Time:** Time
- **Speed_m_s:** Float
- **Step_Length_m:** Float
- **Stride_Length_m:** Float
- **Cadence_steps_min:** Float
- **Double_Support_Time_percent:** Float
- **Step_Time_sec:** Float

The dataset, comprising user IDs, names, NFC IDs, and temporal details, serves for gait analysis. It includes biomechanical parameters like walking speed, step length, and cadence, crucial for refining algorithms in early gait disorder detection. This controlled surrogate mimics real-world smart pathways data, enabling researchers to enhance methodologies before real-life data collection, advancing healthcare interventions for elderly individuals with gait challenges.

### Handrail Reliance Evaluation

```python
import pandas as pd
import numpy as np

# Constants
num_users = 10
num_measurements = 1

# Generate synthetic data for handrail reliance evaluation
np.random.seed(42)

user_ids = np.tile(np.arange(1, num_users + 1), num_measurements)
user_names = np.repeat(['User_' + str(i) for i in range(1, num_users + 1)], num_measurements)
timestamps = pd.date_range('2023-12-24', periods=num_users * num_measurements, freq='5T')


# Simulate activation duration (in seconds) for handrail reliance (adjusted range: 10 to 60 seconds)
activation_duration = np.random.uniform(low=7.0, high=80.0, size=num_users * num_measurements)

# Simulate frequently used sides ('Left' or 'Right')
frequently_used_sides = np.random.choice(['Left', 'Right'], size=num_users * num_measurements)

# Simulate handrail pressure
handrail_pressure = np.random.uniform(low=5.0, high=25.0, size=num_users * num_measurements)

# Simulate grip type ('Full Grip' or 'Fingertips')
grip_type = np.random.choice(['Full Grip', 'Fingertips'], size=num_users * num_measurements)

# Simulate hand orientation ('Vertical' or 'Horizontal')
hand_orientation = np.random.choice(['Vertical', 'Horizontal'], size=num_users * num_measurements)

# Create the dataset
handrail_dataset = pd.DataFrame({
    'User_ID': user_ids,
    'User_Name': user_names,
    'Timestamp': timestamps,
    'Activation_Duration_sec': activation_duration,
    'Frequently_Used_Side': frequently_used_sides,
    'Handrail_Pressure': handrail_pressure,
    'Grip_Type': grip_type,
    'Hand_Orientation': hand_orientation,
})

# Convert 'Timestamp' column to object type
handrail_dataset['Timestamp'] = handrail_dataset['Timestamp'].astype(str)

handrail_dataset['Reliance_Category'] = pd.cut(handrail_dataset['Activation_Duration_sec'],
                                               bins=[-np.inf, 10, 30, 60, np.inf],
                                               labels=['No Support', 'Low Support', 'Moderate Support', 'High Support'])

handrail_dataset.to_csv('Handrail_Reliance.csv', index=False)

# Display the first few rows of the dataset
handrail_dataset
```

Figure 1.19: Handrail Reliance Simulation Code

The Python code generates a synthetic dataset ('Handrail_Reliance.csv') simulating handrail reliance on a smart path with touch sensors. It mimics real-world scenarios, capturing activation duration, frequently used sides, handrail pressure, grip type, and hand orientation.

For each user and timestamp, the activation duration reflects the time a user relies on the handrail. The 'Reliance_Category' column categorizes users based on their activation duration, providing insights into the level of support needed: 'No Support,' 'Low Support,' 'Moderate Support,' or 'High Support.' This dataset serves as a valuable resource for developing and testing algorithms related to assessing handrail reliance, which is crucial for understanding user mobility patterns.

| User_ID | User_Name | Timestamp | Activation | Frequently_Used_Side | Handrail_Pressure | Grip_Type | Hand_Orientation | Reliance_Category |
|---|---|---|---|---|---|---|---|---|
| 1 | User_1 | 12/24/2023 0:00 | 34.34143 | Right | 8.668090197 | Full Grip | Vertical | Moderate Support |
| 2 | User_2 | 12/24/2023 0:05 | 76.40214 | Left | 11.08484486 | Fingertips | Vertical | High Support |
| 3 | User_3 | 12/24/2023 0:10 | 60.43556 | Right | 15.49512863 | Full Grip | Vertical | High Support |
| 4 | User_4 | 12/24/2023 0:15 | 50.70207 | Right | 13.63890037 | Fingertips | Vertical | Moderate Support |
| 5 | User_5 | 12/24/2023 0:20 | 18.38936 | Right | 10.8245828 | Full Grip | Vertical | Low Support |
| 6 | User_6 | 12/24/2023 0:25 | 18.3876 | Right | 17.23705789 | Fingertips | Horizontal | Low Support |
| 7 | User_7 | 12/24/2023 0:30 | 11.2401 | Right | 7.789877213 | Fingertips | Horizontal | Low Support |
| 8 | User_8 | 12/24/2023 0:35 | 70.23086 | Right | 10.84289297 | Full Grip | Vertical | High Support |
| 9 | User_9 | 12/24/2023 0:40 | 50.8814 | Right | 12.32723687 | Full Grip | Horizontal | Moderate Support |
| 10 | User_10 | 12/24/2023 0:45 | 58.6893 | Right | 14.12139968 | Full Grip | Horizontal | Moderate Support |

Figure 1.20: Handrail Reliance Dataset

The dataset `Handrail_Reliance.csv` contains the following data types:

- **User_ID:** Integer
- **User_Name:** String
- **Timestamp:** DateTime
- **Activation_Duration_sec:** Float
- **Frequently_Used_Side:** String
- **Handrail_Pressure:** Float
- **Grip_Type:** String
- **Hand_Orientation:** String
- **Reliance_Category:** Category

The dataset 'Handrail_Reliance.csv' simulates user interactions with a smart path featuring touch sensors on handrails. Entries include User_ID, User_Name, Timestamp, Activation_Duration_sec, Frequently_Used_Side, Handrail_Pressure, Grip_Type, Hand_Orientation, and Reliance_Category. This dataset is crucial for evaluating handrail reliance in controlled environments, aiding in smart path optimization. It supports algorithm refinement and analysis of handrail interaction parameters, fostering advancements in assistive technologies for diverse mobility needs.

## Data Fusion

```python
# Merge handrail_dataset and gait_data on common columns
Smart_path_merged_data = pd.merge(handrail_dataset, gait_data, on=['User_ID', 'User_Name'])
Smart_path_merged_data = Smart_path_merged_data.drop(['Date', 'Time'], axis=1)

# Save the merged dataset to a CSV file
Smart_path_merged_data.to_csv('Smart_Path_Merged_Data.csv', index=False)

# Display the merged dataset
Smart_path_merged_data
```

Figure 1.21: Data Fusion Simulation Code - Smart Path

The code integrates handrail assessment and gait dynamics data within the smart path module, creating a unified dataset ('Smart_Path_Merged_Data.csv') by merging 'handrail_dataset' and 'gait_data' excluding redundant 'Date' and 'Time' columns streamlines the representation. This consolidated dataset is valuable for comprehensive analyses and algorithm development, offering a holistic understanding of user interactions within the smart path environment in gait-related research.

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | User_ID | User_Name | Timestamp | Activation_Duration_sec | Frequently_Used_Sid | Handrail_Pressure | Grip_Type | Hand_Orientation | Reliance_Category | NFC_ID | Speed_m_s | Step_Length_m | Stride_Length_m | Cadence_steps_mi | Double_Support_Time | Step_Time_sec |
| 2 | 1 | User_1 | 12/24/2023 0:00 | 34.34142868 | Right | 8.668090197 | Full Grip | Vertical | Moderate Support | 19c50d99-b22a-455 | 1.23399178 | 0.628383157 | 1.779460341 | 112.3358939 | 0.232504457 | 0.534112454 |
| 3 | 2 | User_2 | 12/24/2023 0:05 | 78.40214437 | Left | 11.08484486 | Fingertips | Vertical | High Support | 05bfb6c6-2252-420 | 1.08712542 | 0.71290957 | 1.369671635 | 92.18455077 | 0.162342215 | 0.65086828 |
| 4 | 3 | User_3 | 12/24/2023 0:10 | 60.43555775 | Right | 15.49512863 | Full Grip | Vertical | High Support | 774b9e1e-b666-4a | 2.29926422 | 0.867129502 | 3.113825316 | 83.90688456 | 0.204013604 | 0.715078391 |
| 5 | 4 | User_4 | 12/24/2023 0:15 | 50.70200915 | Right | 13.63890037 | Fingertips | Vertical | Moderate Support | ff9d6787-b67c-4ee | 1.90167252 | 0.802361513 | 2.619980573 | 107.3693211 | 0.209342056 | 0.558818845 |
| 6 | 5 | User_5 | 12/24/2023 0:20 | 18.18936075 | Right | 10.8245828 | Full Grip | Vertical | Low Support | 3cd9f993-0aaf-41e | 2.06210887 | 0.703860398 | 2.503266382 | 97.60609975 | 0.136970891 | 0.61471568 |
| 7 | 6 | User_6 | 12/24/2023 0:25 | 18.18759998 | Right | 17.23705789 | Fingertips | Horizontal | Low Support | 91e2db21-5704-45f | 1.03087674 | 0.928297026 | 1.424943247 | 84.88152939 | 0.293910926 | 0.706867565 |
| 8 | 7 | User_7 | 12/24/2023 0:30 | 11.24010369 | Right | 7.789877213 | Fingertips | Horizontal | Low Support | 4cbc9edf-b24f-451 | 2.45486478 | 0.597645702 | 3.07421833 | 99.8070764 | 0.255026565 | 0.601159779 |
| 9 | 8 | User_8 | 12/24/2023 0:35 | 70.23085864 | Right | 10.84289297 | Full Grip | Vertical | High Support | 9576133c-f67a-4d3 | 2.24866396 | 0.704501254 | 2.742280505 | 81.37554084 | 0.287899788 | 0.737122288 |
| 10 | 9 | User_9 | 12/24/2023 0:40 | 50.88139586 | Right | 12.32723687 | Full Grip | Horizontal | Moderate Support | 1fb631e3-1f79-4fd | 1.31850867 | 0.75645329 | 1.95754454 | 116.3728161 | 0.27896547 | 0.515584326 |
| 11 | 10 | User_10 | 12/24/2023 0:45 | 58.68929818 | Right | 14.12139968 | Full Grip | Horizontal | Moderate Support | 2aba168d-5092-44 | 1.27271745 | 0.819248989 | 1.895983757 | 90.35119926 | 0.219579996 | 0.664075303 |

Figure 1.22: Data Fusion Merged Dataset - Smart Path

The unified dataset, combining handrail assessment and gait dynamics data, advances research on early gait disorder detection in the elderly. This consolidated dataset offers a multifaceted perspective on user mobility in a smart path environment, revealing potential correlations between handrail reliance patterns and specific gait dynamics. The dataset is crucial for developing sophisticated algorithms to discern subtle patterns indicative of gait irregularities. Its holistic nature facilitates a deeper exploration of the complex relationship between handrail interaction and gait patterns.

### Visualizations & Insights

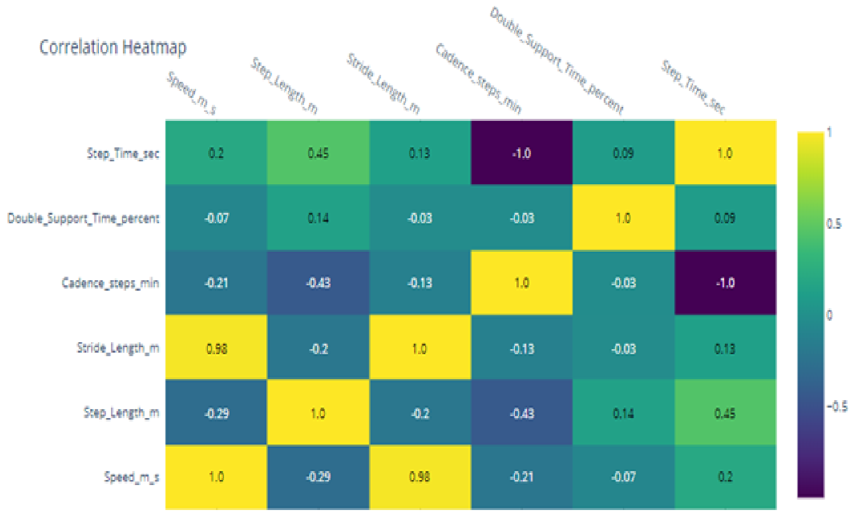


Figure 1.23: Correlation Heatmap - Gait Parameters

Analyzing the correlation matrix through a heatmap is crucial as it visually represents the relationships between different gait parameters. This helps identify interdependencies, providing insights into how changes in one parameter correlate with changes in others. Understanding these correlations is essential for refining algorithms and models in the early detection of gait disorders.

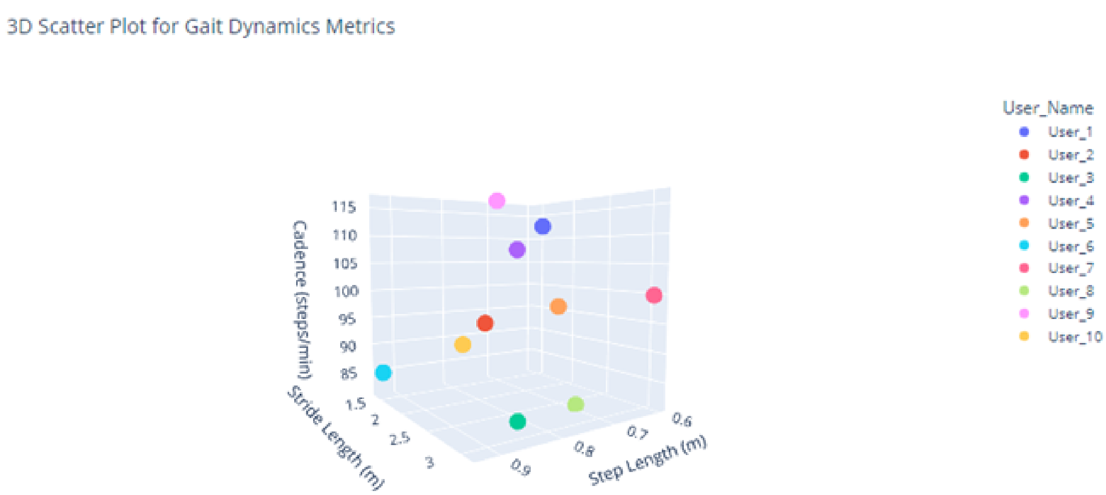


Figure 1.24: 3D Scatter Plot for Gait Parameters

Visualizing gait dynamics in a 3D scatter plot is crucial for comprehensive insights into relationships among key metrics. This representation aids in understanding individual variations, identifying patterns, and refining algorithms for targeted interventions based on specific gait patterns.

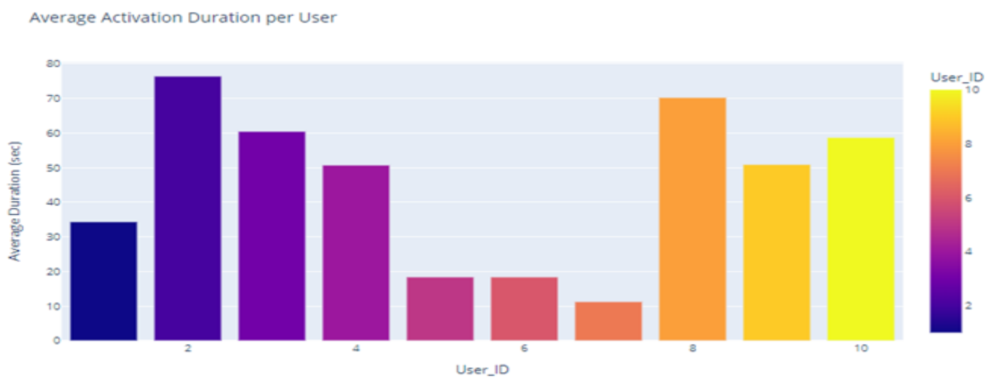


Figure 1.25: Average Activation Duration per User

The average activation duration per user, depicted in a bar chart, provides a clear comparison of handrail usage patterns among different users. This insight is crucial for understanding user-specific reliance behaviours, contributing to personalized interventions.

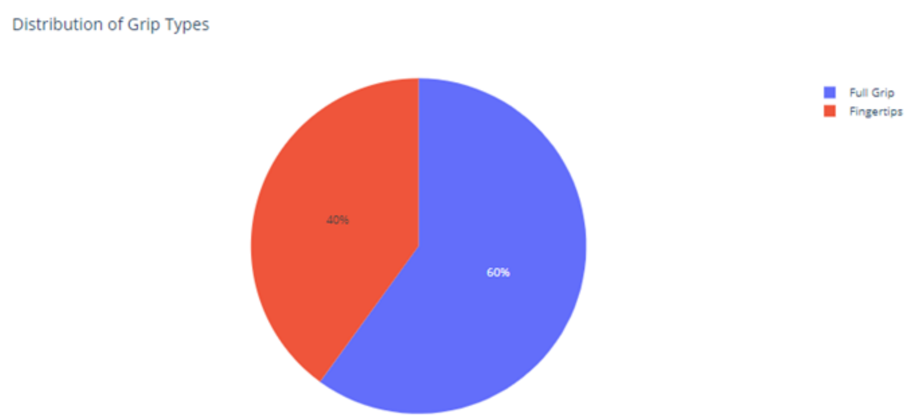


Figure 1.26: Distribution of Grip Types

The pie chart illustrating the distribution of grip types offers a quick overview of the prevalent handrail gripping techniques. This visualization aids researchers in identifying the dominant grip types, influencing the design of handrails for optimal user interaction and support.


Figure 1.27: Distribution of Support Levels

The bar chart presenting the distribution of support levels provides insight into the frequency of various support categories. Understanding the prevalence of different support levels is vital for tailoring interventions and designing supportive environments based on users' reliance on handrails.

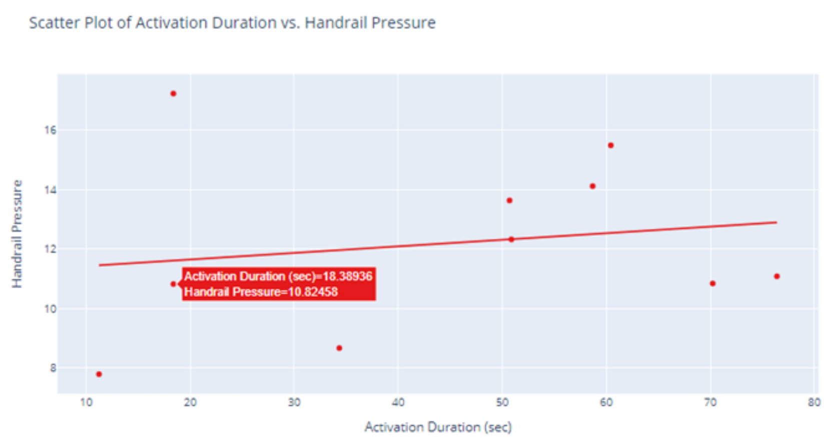


Figure 1.28: Scatter Plot of Activation Duration vs. Handrail Pressure

The scatter plot illustrating the correlation between activation duration and handrail pressure serves to uncover potential relationships between the time of handrail usage and the pressure exerted. This visualization aids in exploring patterns and trends that may influence handrail reliance, contributing to a more nuanced understanding of user behaviour in smart pathways.

# Chapter 2

# Alignment with Research Questions

## 2.1 Refinement of Research Questions

**Original Research Question 1**

The initial research question aimed to explore the optimization of machine learning algorithms for real-time analysis of gait patterns in outdoor environments using IoT data. This inquiry recognized the significance of leveraging advanced analytics to gain insights into human mobility, with a focus on the dynamic conditions present in outdoor settings. The overarching goal was to enhance the efficiency and accuracy of algorithms designed for gait analysis, particularly in scenarios where immediate feedback or interventions based on real-time data are essential.

**Refined Question & Solution 1**

Refining the research question, the focus shifted to the development and application of machine learning algorithms to a proof-of-concept dataset, encompassing gait dynamics, handrail reliance, and user-specific details. The refined question centres on how machine learning algorithms can be effectively trained and implemented using this dataset to analyze gait patterns and derive meaningful insights.

The solution involves utilizing the rich IoT data, and exploring features such as speed, step length, stride length, and more, to optimize algorithms for accurate and real-time gait analysis. This approach lays the groundwork for future implementations, demonstrating the feasibility of using machine learning to enhance our understanding of gait dynamics in diverse outdoor environments, with potential applications in healthcare, assistive technologies, and infrastructure design.

**Original Research Question 2**

The original research question sought to investigate how the IoT framework could integrate with clinical correlations to detect early signs of gait disorders. This inquiry aimed to explore the synergy between IoT technology and clinical knowledge for proactive identification of potential gait-related issues.

**Refined Research Question & Solution 2**

Refining the research question considering having foundational data for the proof of concept, the focus narrows to: "Given the existing foundational gait pattern data from IoT devices, how can future implementations correlate this data with clinical indicators to enhance the early detection of gait disorders?" The solution involves leveraging the already available dataset to develop advanced algorithms for a more nuanced analysis of gait patterns. This refined approach aligns with the research objectives, emphasizing the need to correlate foundational IoT-derived gait patterns with established clinical knowledge. The existing data serves as a crucial asset for future implementations, providing a basis to uncover correlations and insights that contribute to a seamless integration of technological advancements and clinical applications in the detection of early signs of gait disorders.

# Chapter 3

# Benchmarking Against Existing Literature

## 3.1 Bench marking

**Paper 1 - Development and Validation of 2D-LiDAR-Based Gait Analysis (Yoon, S et al., 2021)**

[1] While the study utilizes 2D LiDAR for gait analysis, our proposed solution diverges in focus, emphasizing early detection of gait disorders in the elderly. Paper 1 primarily targets young, healthy participants, validating 2D LiDAR's accuracy in tracking gait parameters. In contrast, our research involves a proof-of-concept phase for individuals with various gait disorders, ensuring relevance to clinical scenarios.

**Paper 2 - Gait-Based Person Identification using 3D LiDAR & LSTM Networks (Yamada, H. et al., 2020)**

[2] Both studies involve LiDAR technology, but our proposed solution opts for 2D LiDAR to create three-dimensional point cloud models, addressing the computational burden associated with 3D LiDARs. Paper 2 focuses on person identification through gait recognition using a multi-line 3D LiDAR system and LSTM, while our study places specific emphasis on gait features (step length, stride length, cadence) and the early detection of gait disorders in the elderly.

**Paper 3: Developing a Mixed Sensor Smart Chair System for Real-Time Posture Classification (Haeseok, J.; Woojin, P., 2021)**

[3] **Smart Path Module vs. Smart Chair System:** While Paper 3 focuses on a sensor-equipped smart chair for real-time posture classification, our research introduces a smart path module for gait analysis in outdoor environments. This distinction highlights the versatility of our proposed solution, catering specifically to gait disorders and dynamic outdoor scenarios.

**Holistic Evaluation of Body Dynamics:** Our study surpasses Paper 3's emphasis on sitting posture by evaluating body dynamics comprehensively, including parameters like force exertion and strength during specific movements. This expansion ensures a more holistic understanding of human posture dynamics, addressing a gap identified in the existing literature.

**Paper 4: Designing a Testing Device for Athletes Assessing Trunk Control in Seated Environments (Rosso, V. et al., 2017)**

[4] **Gait Dynamics vs. Trunk Control:** Our research, focusing on gait dynamics in outdoor environments, differs significantly from Paper 4, which evaluates trunk control in seated environments for athletes. This distinction underscores the specificity of our approach, contributing to the field of gait analysis and disorders.

**Inclusive Participant Pool and Statistical Analyses:** Unlike Paper 4, which involves a small sample size without statistical analyses, our study addresses this limitation by expanding the participant pool to individuals with diverse impairment levels and incorporating rigorous statistical analyses.

**Paper 5: Gait Phase Estimation of Unsupervised Outdoors Walking Using IMUs and a Linear Regression (Ahmed, S., et al., 2022)**

[5] **Comparison in Gait Phase Estimation:** While Paper 5 focuses on unsupervised outdoor gait phase estimation using IMUs, it contrasts with Paper 3's emphasis on real-time posture classification in seated environments. Our research diverges by addressing the complexities of gait dynamics outdoors, showcasing the adaptability of IMUs for assessing dynamic activities beyond static postures.

**Application Scope:** Paper 5 widens the scope of applications to controlling human-assistive devices, rehabilitation tools, and clinical gait analysis outdoors. This extends beyond the confined setting addressed by Paper 3, showcasing the versatility of IMUs for real-world scenarios and human mobility. Our research aligns with this broad application focus, emphasizing Lidar sensors and machine learning for gait analysis in outdoor environments.

## 3.2 Unique Contributions and Advantages of Our Solution

**Paper 1 - Development and Validation of 2D-LiDAR-Based Gait Analysis (Yoon, S et al., 2021)**

[1] **Inclusive Demographic Focus:** Our proposed solution builds upon Paper 1 by extending its demographic focus. While Paper 1 primarily targets young, healthy participants, our research specifically addresses the elderly population, acknowledging the unique gait challenges faced by this demographic.

**Clinical Relevance:** While Paper 1 focuses on protocol development and validation, our study goes further by incorporating a proof-of-concept phase surveying individuals with various gait disorders. This approach establishes clinical relevance, ensuring that our findings apply to real-world scenarios involving individuals with diverse gait conditions.

**Paper 2 - Gait-Based Person Identification using 3D LiDAR & LSTM Networks (Yamada, H. et al., 2020)**

[2] **Comprehensive Gait Feature Extraction:** Our proposed solution extends beyond the scope of Paper 2, which focuses on overall person identification through gait recognition. In contrast, our study places specific emphasis on extracting detailed gait features, including step length, stride length, cadence, etc. This contributes to a more nuanced understanding of gait dynamics, especially relevant in the context of elderly individuals with gait disorders.

**Proof-of-Concept Survey:** While Paper 2 does not incorporate a proof-of-concept survey, our research adds a crucial real-world dimension by surveying individuals with various gait disorders. This inclusion ensures that our study is grounded in the practical challenges and scenarios encountered by individuals with diverse gait conditions.

**Paper 3: Developing a Mixed Sensor Smart Chair System for Real-Time Posture Classification (Haeseok, J.; Woojin, P., 2021)]**

[3] **Holistic Body Dynamics:** Our proposed smart bench module aims to enhance comprehensiveness beyond sitting posture, addressing the gap identified in Paper 3. We intend to evaluate body dynamics beyond posture, considering parameters such as the force exerted by the hands during standing up or the strength applied when sitting up. This expansion ensures a more holistic understanding of human posture dynamics in real-time scenarios.

**Diverse Machine Learning Algorithms:** Unlike Paper 3, which relies on a single machine learning algorithm (k-Nearest Neighbour), our research plans to incorporate multiple machine-learning algorithms. This approach allows for a robust performance comparison, offering a nuanced exploration of the strengths and limitations inherent in different techniques.

**Paper 4: Designing a Testing Device for Athletes Assessing Trunk Control in Seated Environments (Rosso, V. et al., 2017)**

[4] **Inclusive Participant Pool:** Addressing the limitation of small sample size in Paper 4, our research aims to include individuals with diverse impairment levels. This expansion enhances the generalizability of our findings and contributes to a more comprehensive understanding of the interplay between force production, balance control, and impairment.

**Rigorous Statistical Analyses:** Unlike Paper 4, which mentions the absence of statistical analyses due to small sample size, our study commits to incorporating rigorous statistical analyses. This ensures meaningful and statistically significant conclusions, addressing a critical gap in the existing literature.

**Paper 5: Gait Phase Estimation of Unsupervised Outdoors Walking Using IMUs and a Linear Regression (Ahmed, S., et al., 2022)**

[5] **Unsupervised Outdoor Experiments:** The methodology introduced in Paper 5 facilitates unsupervised outdoor experiments, capturing natural gait variations. Our research builds on this uniqueness by emphasizing the study of gait disorders in real-world outdoor conditions, enhancing the ecological validity of our proposed methodology.

**Real-Time Gait Phase Estimation and Wearable Assistive Device Control:** Paper 5 explores real-time gait phase estimation and controlling wearable assistive devices, showcasing potential applications beyond traditional lab settings. Our research extends this advantage, emphasizing Lidar sensors and machine learning for real-time gait analysis in outdoor environments.

## 3.3 Justification of Scientific Value and Novelty

**Paper 1 - Development and Validation of 2D-LiDAR-Based Gait Analysis (Yoon, S et al., 2021)**

[1] **Clinical Relevance:** Our research justifies its scientific value by shifting the focus from protocol development to clinical relevance. While Paper 1 establishes the accuracy of 2D LiDAR in tracking gait parameters, our study aims to correlate these gait parameters with clinical disorders, providing meaningful insights for healthcare interventions.

**Three-Dimensional Point Cloud Models:** Our proposed solution introduces novelty by planning to showcase the 2D LiDAR's capability to generate three-dimensional point cloud models. This novel approach contributes to overcoming the limitations associated with the exclusive capture of depth data in a two-dimensional plane, advancing the field of LiDAR-based gait analysis.

**Paper 2 - Gait-Based Person Identification using 3D LiDAR & LSTM Networks (Yamada, H. et al., 2020)**

[2] **Clinical Relevance:** Like Paper 1, our research justifies its scientific value by introducing clinical relevance. While Paper 2 focuses on person identification, our study places specific emphasis on gait features and the early detection of gait disorders in the elderly, aligning with clinical objectives.

**Inclusive Demographic Focus:** Our proposed solution introduces novelty by ensuring inclusivity in demographic representation. Unlike Paper 2, which lacks clarity regarding demographics, our study plans to encompass individuals with various gait disorders and a control group, contributing to a more comprehensive understanding of gait dynamics across diverse populations.

**Paper 3: Developing a Mixed Sensor Smart Chair System for Real-Time Posture Classification (Haeseok, J.; Woojin, P., 2021)**

[3] **Expanded Body Dynamics Understanding:** Our research justifies its scientific value by expanding beyond Paper 3's exclusive focus on sitting posture. By evaluating body dynamics comprehensively, and considering parameters beyond posture, our study contributes to a more nuanced and holistic understanding of human posture dynamics in real-time scenarios.

**Incorporation of Diverse Machine Learning Algorithms:** The introduction of multiple machine-learning algorithms in our research adds novelty. While Paper 3 relies on a single algorithm, our approach ensures a more comprehensive analysis, enhancing the scientific value of our study.

**Paper 4: Designing a Testing Device for Athletes Assessing Trunk Control in Seated Environments (Rosso, V. et al., 2017)**

[4] **Insights into Muscular Strength Disorders:** Our research justifies its scientific value by building on Paper 4's insights into force production and balance control. By expanding the participant pool and incorporating statistical analyses, our study enhances understanding regarding the interplay between muscular strength and associated disorders.

**Understanding through Comparative Tests:** The commitment to conducting additional tests comparing different levels of impairment adds scientific value. This approach provides a nuanced understanding of how trunk range of motion (ROM) and angular velocity function as indices of trunk control across various impairment levels, addressing a gap identified in Paper 4.

**Paper 5: Gait Phase Estimation of Unsupervised Outdoors Walking Using IMUs and a Linear Regression (Ahmed, S., et al., 2022)**

[5] **Advancements in Gait Phase Estimation Techniques:** Paper 5 makes significant contributions to gait phase estimation using IMUs in outdoor scenarios. Our research justifies its scientific value by advancing gait phase estimation techniques, highlighting the relevance of IMUs for outdoor gait analysis without the need for fixed thresholds or specialized insoles.

**Unsupervised Outdoor Experiments:** The introduction of unsupervised outdoor experiments in Paper 5 represents a novel approach, providing a unique perspective on gait dynamics. Our research justifies its novelty by adopting a similar approach, emphasizing Lidar sensors and machine learning for studying gait disorders in uncontrolled outdoor environments, contributing to the scientific understanding of natural gait patterns.

## 3.4 Filling Gaps & Offering Improvements

**Paper 1 - Development and Validation of 2D-LiDAR-Based Gait Analysis (Yoon, S et al., 2021)**

[1] **Demographic Inclusivity:** Our research addresses a gap left by Paper 1, which exclusively enrols young and healthy participants. By focusing on individuals with various gait disorders, our study fills a crucial gap in the existing literature, ensuring that gait analysis solutions apply to a broader demographic.

**Clinical Correlation:** Our proposed solution aims to fill the gap identified in Paper 1, where the implications of gait parameters for clinical outcomes were not definitively established. By striving to establish a definitive correlation between gait parameters and clinical disorders, our research contributes to improved clinical understanding.

**Paper 2 - Gait-Based Person Identification using 3D LiDAR & LSTM Networks (Yamada, H. et al., 2020)**

[2] **Gait Feature Emphasis:** Our research fills a gap left by Paper 2, which focuses on overall person identification through gait recognition. By placing specific emphasis on extracting detailed gait features, our study provides a more nuanced understanding of gait dynamics, addressing a critical aspect of gait analysis in the context of elderly individuals with gait disorders.

**Paper 3: Developing a Mixed Sensor Smart Chair System for Real-Time Posture Classification (Haeseok, J.; Woojin, P., 2021)**

[3] **Dynamic Posture Assessment:** Our research introduces a dynamic posture assessment component that adapts to users' movements. Unlike Paper 3, which primarily focuses on static posture classification, our approach fills the gap by considering real-time adjustments and capturing the dynamics of changing postures, especially relevant in scenarios where users may shift positions frequently.

**Integration of Environmental Context:** Addressing the limitation in Paper 3, our proposed smart bench module incorporates environmental context awareness. By considering factors like lighting conditions and user surroundings, our system aims to enhance posture classification accuracy. This addition fills the gap in the literature by acknowledging the impact of the environment on posture dynamics.

**Paper 4: Designing a Testing Device for Athletes Assessing Trunk Control in Seated Environments (Rosso, V. et al., 2017)**

[4] **Multidimensional Assessment:** In contrast to Paper 4's focus on specific aspects of trunk control, our research proposes a multidimensional assessment. We aim to fill the gap by considering not only the range of motion but also factors like stability, coordination, and response time.

**Utilization of Sensor Fusion Techniques:** Addressing the limitations in Paper 4 related to sensor data analysis, our study incorporates advanced sensor fusion techniques. By combining data from multiple sensors, including accelerometers and gyroscopes, our approach aims to offer a more accurate and holistic representation of trunk control.

**Paper 5: Gait Phase Estimation of Unsupervised Outdoors Walking Using IMUs and a Linear Regression (Ahmed, S., et al., 2022)**

[5] **Advancement Beyond Linear Regression:** Paper 5's use of a linear regression model for gait phase estimation is acknowledged. Our research intends to advance beyond this model, exploring more sophisticated techniques for real-time predictions, especially in diverse outdoor conditions.

**Comprehensive Exploration of Gait Patterns:** While Paper 5 focuses on outdoor gait events (Heel Strike and Toe Off), our research commits to a more comprehensive investigation of diverse gait patterns in outdoor scenarios. Moving beyond basic gait events, we aim to explore and analyze various aspects of gait, ensuring a thorough understanding of gait dynamics in real-world settings.

# Chapter 4

# Efficiency & Limitations Evaluation

## 4.1 Cost-Effectiveness and Resource Utilization

The research overall aims to maintain cost-effectiveness, efficient resource utilization, and time-saving benefits even beyond the proof-of-concept stage. The use of simulated sensors not only streamlines the initial data collection process but also offers a cost-effective alternative to deploying physical sensors in diverse outdoor settings. This cost-effectiveness ensures that the implementation of gait analysis solutions remains economically viable, making it accessible for broader applications in real-world scenarios. The affordability of LiDAR was further explored in the LiDAR Availability research (see Appendix A).

Optimized resource utilization continues to be a focal point throughout the research. Simulating sensor data minimizes the demand for physical resources, reducing the associated costs and environmental impact. This approach aligns with sustainability goals, making the research not only efficient but also environmentally responsible. As the research progresses to real-world implementations, the emphasis on resource efficiency will contribute to the scalability and adaptability of the proposed solution.

## 4.2 Time Savings

Timesaving remains a crucial aspect of the research's efficiency in real-world environments. Simulated data allows for swift prototyping, testing, and algorithm development, enabling a quicker turnaround in the implementation of gait analysis solutions. This time-saving element is particularly valuable in real-world settings where prompt insights are essential for addressing dynamic situations, such as healthcare interventions or infrastructure planning. These factors collectively contribute to the scalability, accessibility, and sustainability of gait analysis solutions, positioning the research as a valuable and efficient asset for diverse real-world environments.

## 4.3 Acknowledgment of Limitations

The development and evaluation of the proposed solution faced several limitations and challenges. The exclusion of the simulation of LiDAR sensors for 3D point cloud data was a notable limitation due to its computational intensity and time-consuming nature. This decision impacts the completeness of the solution, particularly in scenarios where 3D point cloud data is integral to accurate gait analysis. Additionally, the deliberate omission of machine learning algorithms in the proof-of-concept phase limits the depth of data analysis. While the initial focus was on collecting and simulating sensor data, the absence of machine-learning applications highlights the need for a subsequent phase dedicated to algorithmic enhancements.

## 4.4 Impact on Generalizability and Applicability

These limitations may affect the generalizability and applicability of the solution in real-world scenarios. The absence of 3D point cloud data limits the solution's effectiveness in environments where precise spatial information is crucial. The exclusion of machine learning algorithms hinders the solution's ability to provide sophisticated gait pattern analyses.

Both limitations underscore the need for further improvement to enhance the generalizability of the solution across diverse scenarios. Moreover, the current state of the solution, being a proof of concept, emphasizes the necessity of additional resources for expanding datasets, implementing machine learning algorithms, and validating the solution in real-life settings.

## 4.5 Areas for Further Improvement

To address these limitations, future improvements should focus on incorporating the simulation of LIDAR sensors for comprehensive 3D point cloud data. This enhancement would significantly contribute to the accuracy and completeness of gait analysis. Additionally, the next phase should involve the integration of machine learning algorithms for more sophisticated data processing and pattern recognition. This will require a concerted effort to acquire more extensive and accurate datasets. Seeking additional resources, both in terms of funding and technical support from the university, becomes pivotal for the successful implementation of these improvements. The transition from proof of concept to real-life application hinges on these enhancements to ensure the solution's robustness and applicability in diverse environments.

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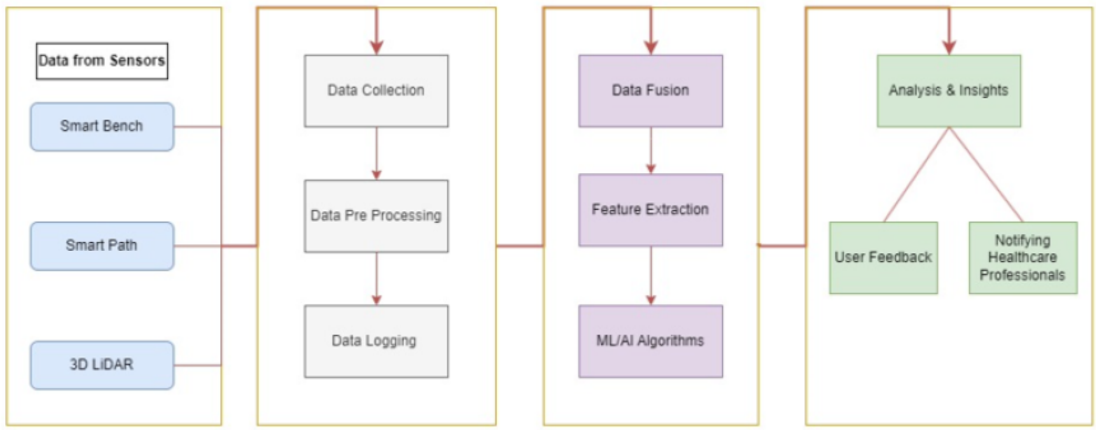
# Appendix A: Table - LiDAR Availability

| Model Name | Type | Working | Features | Important Specifications | Cost |
|---|---|---|---|---|---|
| N301 | 2D | An optical structure with receiving and transmitting levels side by side.<br>A polar coordinate system is defined, using its centre point as the pole, clockwise as positive, and the outlet direction as zero degrees.<br>The operation involves a laser diode emitting ultrashort laser pulses onto a target object. The diffusely reflected pulses are detected by an optical sensor.<br>Accurate distance measurement to the object is achieved by calculating the time between laser emission and receipt of the returning beam. | TOF principle, with a 360 ° scanning and range of up to 30m. The ranging accuracy is ±3cm,<br>IP67 protection and anti-sunlight glare | Measurement Technique: TOF<br>Wavelength: 905nm<br>Measurement Range: 30m<br>Ranging Accuracy: ±3cm<br>Horizontal: 20Hz:0.36°<br>10Hz:0.18°<br>Data Content: Distance /Angle<br>Data Points Generated: Max 20,000 points per second.<br>Rotation Speed: 10Hz / 20 Hz<br>FOV – Horizontal: 360°<br>IP: IP67<br>Communication: Ethernet<br>Voltage: 10V~36VDC<br>Weight: 420g<br>Dimensions: 80*79.1mm | US$691.00 – US$746.00 |
| WxxxC Anti-Collision | 2D | The LiDAR sensor with internal rotation utilizes the Time of Flight (TOF) distance measurement method, enabling a comprehensive 270-degree two-dimensional scanning capability. The sensor scans the entire 270-degree circle area. By calculating distances in polar coordinates, the sensor determines the presence of obstacles within the set area. Connected to a PC through a USB interface, the LiDAR can configure detection areas (up to 15) by shifting through switching value signals. Additionally, three independent Regions of Interest (ROI) can be freely set within each area. | The farthest working distance reaches xxx*0.1m (eg: W050C, 050*0.1 = 5m), within which the user can set freely according to the environment.<br>IP67 protection and anti-sunlight glare. | Output: Switching value and point cloud rate<br>Scanning Angle: 270°<br>Measurement Range: 5m, 10m<br>Angular Resolution: 1°<br>Monitoring area: Correlation / Independent<br>Rotation Speed: 10Hz<br>Interface: NPN, PNP<br>IP: IP67<br>Weight: 397g<br>Dimensions (D*H): 80*77.3mm | US$753.00 – US$829.00 |

| | | | | | |
|---|---|---|---|---|---|
| **M10** | **2D** | The M10 LiDAR adopts the TOF principle to be capable of 2-D scanning detection of the surrounding 360 ° environment. M10 uses a wireless power supply and optical communication, measuring frequency for 10khz. The accuracy is to reach ± 3cm with the maximum range from 10 meters. It is mainly used in precise positioning and obstacle avoidance applications. | 360° FOV, long measurement range<br>The minimum angular resolution reaches 0.36°, ensuring measurement data is accurate and stable.<br>Configuring an Ethernet interface for high-speed data transmission | Measurement Technique: TOF<br>Wavelength: 905nm<br>Laser Classification: Class 1 Eye-safe/ IEC 60825-1:2007 & 2014<br>Measurement Range: 5m @ 70% (10m @ 10%)<br>Ranging Accuracy: ±3cm<br>Horizontal: 0.36°<br>Data Content: Distance /Angle<br>Rotation Speed: 10Hz<br>FOV – Horizontal: 360°<br>IP: IP67<br>Communication Interface: UART (Baud rate 460800)<br>Operation Voltage: 5V<br>Weight: 200g<br>Dimensions (D*H): Φ80*40mm | US$413.00 |
| **HS Series** | **3D** | HS series high-speed scanning LiDAR sensor has excellent detection accuracy and anti-interference performance, Its measurement range is up to 100 m, and distance accuracy is ±2cm. 200Hz high scan frequency can easily sense high-speed movement objects in time, and accurately capture vehicle contour information. Widely used in over-dimensional vehicle detection, V2X vehicle-road collaboration, high-accuracy surveying and mapping, etc. | The LiDAR sensor has a range of 100m with 10% reflectivity.<br>Operating with a wavelength of 905nm, it employs the Time of Flight (ToF) measurement technique The precision of this sensor is ±2cm, ensuring reliable and detailed distance measurements | **Point Rate:**<br>HS1: 106,000 points/s<br>HS4: 426,000 points/s<br>HS8: 426,000 points/s<br><br>**FOV (Field of View):**<br>HS1: 120°(H), N/A (V)<br>HS4: 120°(H),-4° ~0° (V)<br>HS8: 120°(H), -6.66° ~2.66° (V)<br><br>Rotation Rate: 80Hz, 120Hz & 160Hz<br><br>Channel: 1, 4 & 8<br><br>Power Consumption:<br>CH128: 14W<br>CH32: 10W<br>CH16: 9W | |
| **CX16** | **3D** | The C16 mechanical high-accuracy lidar scanner adopts the Time-of-Flight method. The 3D laser scanner starts timing (t1) when the laser pulses are sent out. When the laser encounters the target object and the light returns to the | High point density, capable of generating approximately 320,000 3D point cloud coordinates per second. | Channels: 16<br>Measurement Technique: TOF<br>Wavelength: 905nm<br>Measurement Range: 150m<br>Ranging Accuracy: ±3cm<br>Angle resolution: | US$2,187.00 |

# Appendix B: Proposed IoT Based - Framework




The Proposed IoT-Based Framework introduces two modules designed to revolutionize health monitoring and gait analysis. The Smart Bench Gait Monitoring System, forming the initial phase, employs NFC technology for user identification and integrates various sensors to capture comprehensive data during bench interaction. The Surface Sensor Map, Sensor Mat, and capacitive touch sensors record sit-to-stand exercises, landing dynamics, and user support transitions. Simultaneously, the Smart Path, the second module, utilizes sensor tiles and advanced 3D LiDAR technology for in-depth gait analysis. The framework encompasses data collection, pre-processing, and logging, followed by data fusion techniques to create a unified data stream. Feature extraction methods specific to each sensor type pave the way for the application of Machine Learning (ML) and Artificial Intelligence (AI) algorithms. These algorithms serve diverse objectives, including gait analysis, health assessment, anomaly detection, user feedback, and the coordination of a multi-agent system. The framework culminates in analytics and insights, incorporating data visualization, user profiling, predictive analytics, and real-time monitoring for a holistic understanding of user behavior and health status.

# Appendix C: Datasets

The datasets used in this research are available on GitHub. You can access and download them from the following links:

1. **Gait Dynamics Dataset**
2. **Handrail Reliance Dataset**
3. **Smart Path Merged Dataset**
4. **Attendance with Frequent Visitor Dataset**
5. **Landing Coordinates Forces Dataset**
6. **Landing Coordinates Forces with Weight Dataset**
7. **NFC and Pressure Sensor Dataset**
8. **NFC NFC Users Dataset**
9. **Pressure Sensor Multi-Person Dataset**
10. **Sit-Stand Exercise Dataset**
11. **Smart Bench Combined Cleaned Dataset**
12. **User Statistics Dataset**

# Appendix D: Existing Research Papers

This research builds upon existing literature in the field. You can access the relevant research papers from: Research Papers. Accessing the relevant research papers from the provided link will offer a comprehensive understanding of the background, methodologies, and findings of prior studies in the field. By building upon existing research, this study aims to contribute to the body of knowledge and advance understanding in the domain.

# Appendix E: Python Code for Research

The Python code utilized in this research project is available for reference at: Python Code. This code provides insight into the methodology, data processing, analysis, and visualization techniques employed in the study. Researchers and practitioners interested in replicating or extending the findings of this research can access and explore the Python code to gain a deeper understanding of the computational aspects of the study.