Developing a Gait Data Analysis Dashboard to Streamline Data Processing for Researcher

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This thesis addresses the challenges in gait analysis by developing a user-friendly dashboard that facilitates the import, processing, visualization, and export of gait analysis data from raw data imports. Through a comprehensive literature review, the most commonly used running parameters in gait analysis were identified. Interviews with researchers provided insights into their preferences for these parameters and data visualization methods. The identified parameters were then extracted and analyzed using Python, with the results displayed on the dashboard. This tool allows researchers to efficiently access and export analyzed gait data, bypassing the need to handle raw data directly. The Technology Acceptance Model (TAM) was employed to evaluate the dashboard's perceived usefulness and ease of use. The results demonstrate the dashboard's potential to simplify the gait analysis process and improve data usability for researchers.

Additional Key Words and Phrases: gait analysis, dashboard

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1 INTRODUCTION

Human gait analysis plays a crucial role in clinical diagnostics, sports science, and rehabilitation [21]. Traditionally, it has relied on costly and complex lab-based systems. The advent of wearable technology, especially Inertial Measurement Units (IMUs), has improved gait analysis by enabling detailed motion capture for human in real-world settings [5]. However, the large amount of raw data processing after receiving data from wearable sensors brings some challenges to researchers, such as in terms of data noise handling and parameters analysis, etc. which often requires significant programming expertise. Many researchers lack the advanced programming skills needed to effectively handle IMU data [9]. Existing tools are either too complex or not tailored to the specific needs of gait analysis [11], leading to inefficiencies and limited use of wearable technology in real-world applications [13]. This gap underscores the need for a more accessible and comprehensive solution that can bridge the divide between raw data and meaningful analysis.

To address these challenges, this project aims to develop a user-friendly dashboard to streamline the gait analysis process. The proposed dashboard focuses on lowering the barrier to advanced gait analysis by providing an accessible interface, including commonly used running parameters and advanced analysis methods for comprehensive analysis. Additionally, the dashboard offers intuitive visualization tools, enabling researchers to easily interpret and present their findings.

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Conducting interviews was essential to identify the practical challenges researchers face, understand their preferences, and determine the necessary features for the dashboard. This ensures the tool is tailored to meet the specific needs of its users, ultimately contributing to advancements in human movement science.

The following research questions were formulated to guide the development of an effective gait analysis dashboard. These questions are crucial as they address the challenges and needs of researchers in the field of gait analysis:

Research Question 1 : In human gait analysis studies, what running parameters are most commonly used by researchers according to the literature review?

Research Question 2 : For analysing these running parameters, what are the researchers' preferences that can be identified through interviews?

Research Question 3 : How can the preferred running parameters and data visualization be effectively implemented, and how can these results be presented on the dashboard?

Research Question 4 : According to the Technology Acceptance Model (TAM), how well do user interface dashboards perform in terms of perceived usefulness and perceived ease of use?

2 RELATED WORK

2.1 Gait Analysis Techniques

Traditional gait analysis methods often rely on optical motion capture systems and force plates [20], which offer high accuracy but are limited to controlled environments. Recent advances have shifted towards the use of wearable sensors [17], such as IMUs [19], which allow for gait analysis in real-world settings. Studies have highlighted the importance of parameters such as stride length, cadence, and speed in assessing gait [1].

2.2 Data Processing and Visualization

Effective data processing and visualization are crucial for interpreting complex gait data. Tools and frameworks that facilitate the transformation of raw data into meaningful visual representations are essential. Research has demonstrated the effectiveness of various visualization techniques [22], including line charts, bar charts, and pie charts, in representing different aspects of gait data.

2.3 Usability and User Experience

The Technology Acceptance Model (TAM) was chosen to evaluate the usability of the dashboard due to its focus on perceived usefulness and perceived ease of use, which are critical factors in determining user acceptance of new technologies [10]. Unlike other models such as the System Usability Scale (SUS), which primarily assesses general usability, TAM provides a more detailed understanding of how these specific factors influence user behavior and acceptance. TAM is particularly suitable for evaluating specialized tools like the gait analysis dashboard, where both functionality and ease of use are paramount for researchers.

3 METHODS

3.1 Literature Review

A literature review was conducted to identify commonly used running parameters in gait analysis studies. The inclusion criteria [7] were:

- Relevance: Studies focused on human gait analysis.
- Quality: Peer-reviewed articles published in the last ten years.
- Detail: Comprehensive methodologies and use of advanced technologies in gait analysis.

Two foundational papers guided the search for relevant literature: Arellano-González et al. (2019) [3], which provided a comprehensive survey of biomechanical parameters, and Marit et al. (2023) [27], which explored the effects of running-induced fatigue on kinematics. These papers served as a starting point for a broader review, which revealed that parameters such as joint angles, stride length, cadence, speed, contact time, and flight time are widely used in gait analysis. The findings helped establish the essential metrics for developing the dashboard and informed the design of subsequent interviews.

3.2 Initial Interview

The initial interviews were crucial for understanding the specific preferences of researchers in the field of gait analysis. The objective was to identify challenges in data handling, parameter extraction, and visualization, and to ensure the dashboard would meet practical needs. The interviews aimed to collect qualitative data on their current practices, the tools they use, and the parameters they think most significant for their research. The interview categories were motivated by the need to address common issues faced by researchers, such as dealing with raw data and the desire for comprehensive yet intuitive visualization tools. The questions were categorized into several parts to gain a comprehensive understanding of the researchers' preferences.

- **Research Focus and Frequency of Gait Analysis**: Understanding the scope of their research and how regularly they perform gait analysis.
- **Challenges with Raw Gait Data**: Identifying common obstacles faced in handling and interpreting gait data.
- **Familiarity and Use of Gait Analysis Tools**: Gaining insights into the tools currently in use and their perceived strengths and weaknesses.
- **Preferred Format for Results Presentation**: Exploring the most effective format to present gait analysis results.
- **Relevance of Specific Gait Parameters**: Reviewing a predefined list of gait parameters to identify the most relevant ones for their research.
- **Visualization of Gait Analysis Results**: Understanding results are visualized is a good way.

The final list of running parameters and interview questions can be found in Appendix A.1, A.2.

To refine the interview questions and ensure their effectiveness, two mock interviews were conducted. The first mock interview lasted 40 minutes, indicating the need to streamline the questions. After revising the questions for conciseness, the second mock interview lasted 18 minutes, suggesting the improved format was appropriate. These refinements ensured that the actual interviews, conducted with three researchers from the University of Twente, were efficient and focused, providing valuable feedback on their preferences.

3.3 Initial Interview findings

The initial interviews provided critical insights into the needs and preferences of gait analysis researchers. This feedback highlighted several key challenges and areas for improvement in current gait analysis practices. The key findings from these interviews are summarized below:

- **Research Focus and Frequency of Gait Analysis**
  - Participants need to do gait analysis almost daily, highlighting the importance of an efficient and reliable analysis tool.
- **Challenges with Raw Gait Data**
  - The biggest challenges identified were dealing with raw data and extracting the desired parameters, which use too much time and effort for coding.
  - One participant mentioned the difficulty in synchronizing data from different files.
- **Familiarity and Use of Gait Analysis Tools**
  - One participant had experience using the online gait analysis tool Xsens MVN Link, which seamlessly exports motion capture data into major biomechanics and analysis software packages. This tool was found helpful for data extraction but limited in further data manipulation without specific scripts.
  - Another participant mentioned that their lab had internal resources and tools, accessible only to lab members.
- **Preferred Format for Results Presentation**
  - One participant preferred seeing all parameters on one scroll down page, which is easy to have a comprehensive overview.
  - Another participant suggested having a space to input commands and receive the most relevant results, or the ability to upload their own scripts for specific analyses.
- **Relevance of Specific Gait Parameters**
  - **More Importance**: Range (Acceleration), Duration (time), Contact Time (time), Flight Time (time), Speed (distance/time), Cadence (strike/time), Strike Length (distance)and Symmetry.
  - **less Importance**: Peak Angle (maximum joint angle during a gait cycle), Extension Angle, Angular Velocity.
  - **Newly Mentioned Parameters**: Gait phase percent, Impact acceleration and Joint contact force were highlighted as commonly used parameters that were not initially included in the list.
- **Visualization of Gait Analysis Results**

- All participants welcomed the idea of a dashboard to assist with fundamental gait data analysis, reducing the need to work directly with raw data.
- This feedback was crucial in designing the dashboard to meet the practical needs of the researchers.

Interviews with researchers revealed a consistent reliance on IMU data. All researchers emphasized the importance of IMU data in their gait analysis work.
One researcher highlighted the importance of analysing the percentage of gait swing and stance phases. To achieve this, a pie chart was included in the dashboard to visualize it within the detected sequences tab. Although one interviewee did not have specific preferences for data visualization, they emphasized the need to export results from raw data. Other researchers expressed a strong interest in a comprehensive platform that visualizes all results and allows for easy data selection. This feedback inspired the dashboard design, which includes an overview of raw data and detailed visualizations of each gait cycle, enabling researchers to select specific analysis results and export as needed.

3.4 Gait Sequences Detection

Gait sequences refer to the repetitive gait cycle of movements during walking [25], from one foot's initial contact with the ground to the next contact of the same foot [2]. To detect gait sequences, the following steps were implemented.
Filtering and Noise Reduction: The IMU data used for this project was sourced from Wearm.ai, a company in University of Twente. The data had a sampling rate of 60 Hz and was collected from a healthy adult participant.
Coordinate System: The coordinate conversion utilized the open-source library `gaitmap.utils.coordinate_conversion`, as referenced in the paper [14]. The sensor frame was aligned with the physical axes of the IMU sensor, expecting the x-axis to point forward, the y-axis to the left, and the z-axis upwards relative to the participant's body.
Normalization: The raw 3D acceleration data was normalized using the formula to convert it into 1D acceleration [26].

$$s_{1d} = \sqrt{acc_x^2 + acc_y^2 + acc_z^2}$$

Low-Pass Filtering: After normalization, a 4th order Butterworth low-pass filter with a cut-off frequency of 6 Hz was applied to the 1D acceleration data to remove noise, as referenced in [26].
Sliding Windows: The filtered data was then processed using a sliding window approach. Windows of 10 seconds in length, with a 50% overlap, were used to detect active signals, based on the methodology from [18].
Mean Subtraction and Activity Detection: To further refine the detection, the mean signal of the filtered data within each window was subtracted to remove offsets [26]. Active windows, which are segments of data showing significant gait activity. Only active windows were retained, as non-active windows contain no meaningful data for gait analysis [12].
Frequency Analysis: we utilized the open-source Gaitmap library, which is published under a MIT license.[14][25]. The process included the following steps: Dominant Frequency Determination, Frequency Domain Transformation, Harmonic Frequency Peaks Detection. Finally, successive windows without interruptions are linked into connected sequences of gaits.

3.5 Gait Segmentation

Gait segmentation involves dividing gait sequences into gait cycles [16]. Each gait cycle includes the stance and swing phases [2].
Gait cycle detection methods vary, including machine learning models, Dynamic Time Warping (DTW)[4], and straightforward methods like identifying the lowest point[2]. For this thesis, the straightforward method was selected due to its efficiency within the limited timeframe. While this approach has limitations in accuracy, it is sufficient for the current data from Wearm.ai.
Gait Cycle Detection: The detection of gait cycles began with identifying the initial contact (heel strike), which corresponds to the lowest position during the step. This was achieved using the `find_peaks` function from the Python library `scipy.signal`, with the `peak_prominence` parameter set to 21. The start and end indices of each detected gait cycle were stored in a pandas DataFrame [2].

3.6 Feature Extraction

After gait segmentation, we can extract the parameters we need from each gait cycle for analysis. The extracted parameters were based on researchers' preferences identified during interviews:
Stance and Swing Phase Detection: Within each gait cycle, the toe-off phase (pre-swing stage) was identified as the lowest point [2]. The `find_peaks` function was used to locate these local minima, excluding the start and end points [2]. The period before this point was classified as the stance phase, while the period after it was classified as the swing phase. Typically, the stance phase accounted for 60% of the gait cycle, while the swing phase accounted for 40%, consistent with normal gait patterns [15].
Cycle Duration: The duration of each gait cycle was calculated by subtracting the start index from the end index and dividing by the sampling rate.
Cycle Speed: The acceleration data along the x, y, and z axes was used to calculate the acceleration in the direction of movement.

$$a_d = \sqrt{acc_x^2 + acc_y^2}$$

By integrating this acceleration data [8], the velocity for each gait cycle was obtained, allowing for an analysis of speed changes over the study period.

$$v_d = \int_0^t a_d(t)\, dt$$

Cycle Length: The velocity data was further integrated to determine the position [8][24], and the step length was calculated as the difference between the initial and final positions of each gait cycle.

$$l_d = \int_0^t V_d(t)\, dt$$

Cycle Cadence: Cadence, or the number of cycles per second, was calculated to observe changes in cadence throughout the study.
Cycle Range: The peak and lowest points of each gait cycle were identified to determine the range.

Cycle Distance: The cycle distance [2] was computed by summing the lengths of each gait cycle using the `cumsum()` function.

$$l_{sum} = \sum_{i=0}^{n} l_d(n)$$

Symmetry: Assessing the balance between the left and right legs by comparing the extracted length values separately for each leg.

3.7 Usability Testing

The usability test involved 10 researchers from the University of Twente. Among them, seven participants were experienced researchers in the field of gait analysis, including PhD candidates and postdoctoral researcher. The remaining three participants were students familiar with gait data analysis. The study aimed to assess the dashboard using the Technology Acceptance Model (TAM), focusing on two main constructs: Perceived Usefulness and Perceived Ease of Use. The questionnaire consisted of 19 items, 18 of them are a 5-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5), at the end an open-ended question to gather additional suggestions and feedback from participants.The usability testing followed a structured procedure:

- Introduction to the Dashboard in person
- Interaction with the Dashboard
- Questionnaire Completion

The responses collected via Google Forms were analysed to determine the overall usability of the dashboard. Statistics were calculated to assess the dashboard's usefulness and ease of use.
Evaluating the usability of the dashboard during the summer was challenging due to researchers' busy schedules and conference commitments. Despite these challenges, valuable suggestions were gathered from both researchers and students, provided valuable insights into the strengths and areas for improvement of the dashboard, guiding further development and optimization.

4 PROTOTYPE

4.1 Lo-fi prototype

The Lo-Fi prototype was informed by the need to create an intuitive and user-friendly interface that addressed the common challenges identified during the interviews. Key features included a simple layout with essential functions to validate the overall design concept. It includes five main components, each aimed at have different aspects of data analysis and user interaction:
File Upload and information Display: This component allows users to upload CSV files and ensures the data is in the correct format and header, providing detail information for context.
Data Overview Tab: Provides an overview visualization of raw gait data with identified valid sequences, using a line graph to show valid detected gait sequences.
Detailed Gait Sequence Analysis: Uses a dropdown menu to select specific gait sequences, offering a focused view of selected gait sequences with stance and swing phases.
Gait Parameter Analysis: Employs radio buttons to select different gait parameters, displaying the results through various charts (line, bar, stacked bar) for analysis.
Analysis result Export: Summarizes analysis results in a table, allowing easy export to CSV format for further use. The Lo-Fi prototype can be found in Fig. 1.

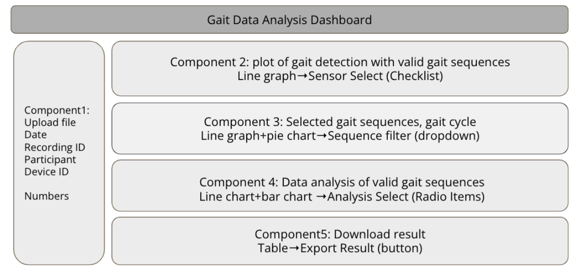


Fig. 1. Lo-fi prototype

4.2 Hi-fi prototype

This hi-fi prototype is designed to be intuitive and user-friendly, providing researchers with the tools they need to analyse gait data effectively without extensive technical expertise. All the components of the system were implemented in Python version 3.12 on a Windows operating system. The main libraries used were Plotly for generating graphs and tables, and Dash, with Dash Bootstrap Components, for creating an interactive dashboard.
Component 1: File Upload and information Display Facilitates easy data import and displays essential information. The interface checks for correct file formatting and provides feedback in case of errors. This information remains all sections of the prototype, ensuring users have context for the data they are analysing.

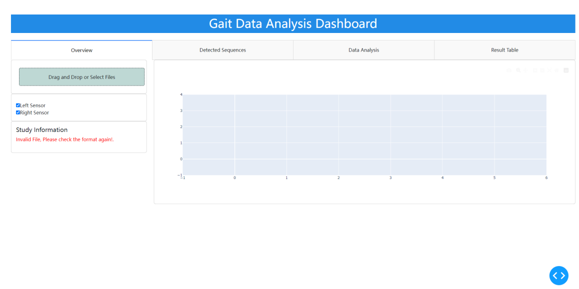


Fig. 2. Component 1: File Upload and error messag

Component 2: Overview Tab Provides an initial visualization of raw gait data, allowing users to toggle sensor data visibility. This tab is designed to offer a comprehensive initial impression of the dataset, with clear view of the identified gait sequences.

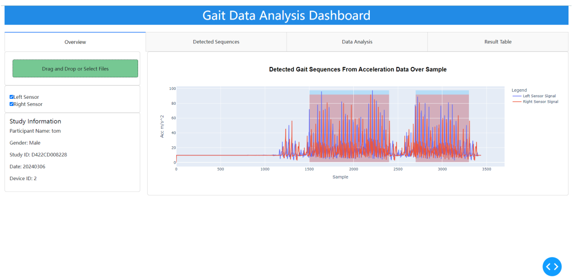


Fig. 3. Component 1 and 2: File information and overview Tab

Component 3: Detected Gait Sequence Analysis Tab Allows users to analyze specific gait sequences with detailed graphs and pie charts for stance and swing phases. This helps users quickly understand the distribution and characteristics of each phase.

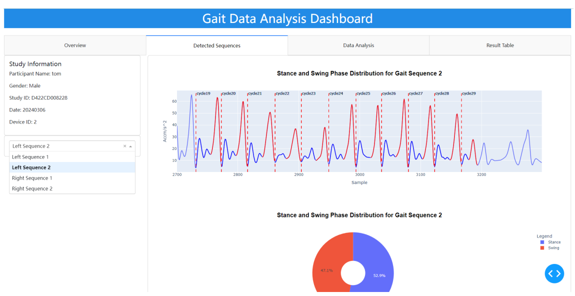
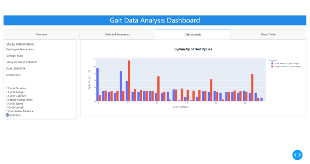
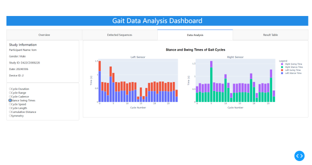


Fig. 4. Component 3: Detected sequences Tab

Component 4: Gait Analysis Tab Each parameter has unique characteristics, require different chart types for effective visualization. After researching best practices [23], the following decisions were made: Line charts were used to display parameters like length, range, cadence, and speed, as they effectively track changes over time. Bar charts were chosen for comparative symmetry, as they are well suited to visualize the distribution of data and comparisons between subgroups. Stacked bar charts were utilized to show stance and swing phases, clearly representing how different categories contribute to the total.



(a) Data analysis example1



(b) Data analysis example2

Fig. 5. Component 4:Data Analysis Tab

Component 5: Data Export Tab Enables easy export of analysed data for further use.

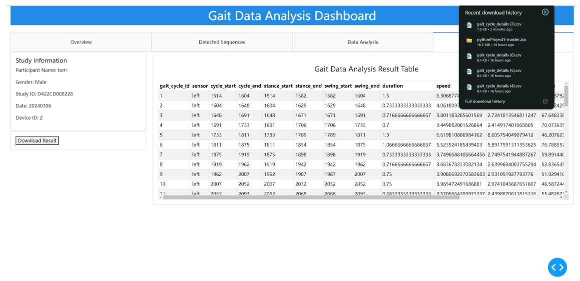


Fig. 6. Component 5: Result Table Tab

5 RESULT

5.1 Usability Test

The results were 0.809 for perceived usefulness and 0.860 for perceived ease of use, both of them are over 0.7. These values indicate good internal consistency within the questionnaire [6].
The mean score for perceived usefulness was **4.12** with a standard deviation of **0.844**. The mean score for perceived ease of use was **4.35** with a standard deviation of **0.808**. These high mean scores suggest and low standard deviations shows a agreement on the dashboard's usability and usefulness.

5.1.1 *Perceived Usefulness.*

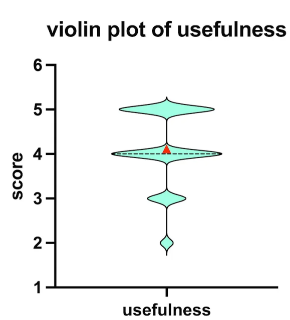


Fig. 7. Evaluation on perceived usefulness

The violin plot in Fig. 7 indicates that with most responses is 4. This positive feedback suggests that researchers find the dashboard useful for their work.

5.1.2 *Perceived Ease of Use.*

Fig. 8. Evaluation on Perceived Ease of Use

The violin plot in Fig. 8 reveals that the most responses is 5. This indicates that the dashboard is user-friendly and easy to understand.

5.1.3 Additional Feedback.

The addition feedback where gain from the open-end question which can help improve the dashboard in the future work:
Researcher 1:"Regarding information display, I wouldn't add the Participant information (name) for security and privacy reasons, but I would add the participant ID, or any other pseudo to protect the anonymity "
Researcher 2:"Add some description of what method used for the detection and analysis can be more meaningful" "The radio button are too close to the text, which is make me not easy to select" "The result table can be better if I can sort it by different column." "Dropdown not very clear, use checklist box can be better"
Research 3: "The second Tab is too slow when I select the sequences. And the updating symbol is not very clear "
Student 1: "Gait data analysis table should not just be a small window to slide through. Rather when scrolling through it one should scroll the entire page."
We will discuss the improvement in the next section.

6 DISCUSSION

The results from the usability test demonstrate that the dashboard is well-received by researchers, with high mean scores for both perceived usefulness (4.12) and perceived ease of use (4.35). These findings indicate that the dashboard effectively meets the needs of its users, providing a valuable tool for gait analysis.
The high mean scores and low standard deviations suggest that the dashboard's features are both beneficial and easy to navigate for researchers. The feedback gathered through open-ended questions further supports this, highlighting specific areas of strength and opportunities for improvement.
The interviews and usability testing provided critical insights into the practical needs and preferences of researchers in gait analysis. High perceived usefulness and ease of use scores validate the effectiveness of the dashboard. However, the feedback in section 5.1.3 also highlighted areas for improvement:

- **Information Display**: The need to ensure data privacy and security by using participant IDs instead of names.
- **Error Messages**: The current error messages are vague and should be more specific, such as show what is the error from and how to fix it, to help users understand and resolve issues.
- **Performance**: The second tab's performance needs optimization because it is slow when we select the gait sequences and affects the entire dashboard when updating.
- **Method Descriptions**: Adding descriptions of the methods used for detection and analysis can help users trust and understand the results.
- **Graph Details**: Improving the details of graphs, such as units and outlier removal, to enhance accuracy and clarity.
- **Interactive Tables**: Enabling the result table to be sortable by different columns for better data interaction.

The successful implementation of the dashboard's features, such as the comprehensive visualization tools and the ability to easily extract and analyze data, demonstrates its potential to significantly streamline the gait analysis process. This project achieved its goal of developing a user-friendly tool that addresses the common challenges faced by researchers in this field.

7 CONCLUSION

This project successfully developed a user-friendly dashboard to streamline gait analysis for researchers, focusing on commonly used running parameters identified through a literature review. Initial interviews with researchers informed the creation of a Lo-Fi prototype, validating the overall design concept. Feedback from these interviews and discussions with supervisors guided the refinement of the prototype into a Hi-Fi version, incorporating detailed functionalities and addressing researchers' preferences. Implemented using Python and Dash, the dashboard offers multiple tabs for data upload, overview, detailed sequence, and parameter visualization, employing various chart types for clear data representation. All the "More important parameters" in section 3.3 were successfully implemented.
The TAM usability evaluation with 10 researchers from the University of Twente demonstrated high perceived usefulness (mean score 4.12) and ease of use (mean score 4.35), validating the dashboard's effectiveness. Future work will focus on improving segmentation accuracy, integrating additional data types, enhancing the dashboard's reliability through better descriptions, and optimizing performance to handle larger datasets. These enhancements will make the dashboard more reliable, trustworthy, and capable of supporting more extensive gait analysis research.

8 FUTURE WORK

The development and evaluation of the gait analysis dashboard have laid a solid foundation for further enhancements and integrations. Future work will focus on the following key areas to improve the accuracy, functionality, and versatility of the dashboard

- The usability testing can be taken further by involving more researchers to participate.
- To improve the points from evaluation feedback, mentioned in section 6 improvements.
- The second Tab should be improved the layout, since if the dataset is too big, then the visualization could be not clear for

user. And also the performance of the algorithm processing the data.
- Explore more advanced models to improve gait segmentation accuracy.
- As one researcher mentioned from initial interview, synchronize different of the raw data should be addressed.

By addressing these areas, the dashboard can better support the research community, facilitating advanced gait analysis and contributing to the field of human movement science.

A INTERVIEW

This section provides all the necessary information about the research interviews

A.1 Running parameters

- **Gait Series Parameters : A set of data consisting of each gait cycle's data:**
  - Angle Joint Range: The range of motion measured in degrees that a joint travels through during a gait cycle.
  - Duration: The time taken for a particular segment of the gait cycle.
  - Step Length: The distance covered between the initial contact of one foot and the initial contact of the opposite foot.
  - Contact Time: The duration for which a foot remains in contact with the ground during a gait cycle.
  - Flight Time: The duration during which both feet are off the ground, typically occurring during running.
  - Speed: The rate of covering distance over time, typically measured in kilometres per hour (km/h).
  - Acceleration: The rate of change of velocity, indicating how quickly speed is increasing or decreasing.
  - Cadence: The number of steps taken per minute.
  - Pace: The time it takes to cover a specific distance, typically measured in seconds per kilometre.
  - Power: The rate at which work is done or energy is transferred, calculated as the product of torque and angular velocity.
- **Specific Parameters: Focus on analysis of one gait cycle**
  - Peak Angle: The maximum angle achieved by a joint during a gait cycle.
  - Extension Angle: The angle of the joint when it is fully extended during the gait cycle.
  - Peaking Time Point: The specific time point at which the peak angle or other peak values are achieved during the gait cycle.
  - Stance/Swing Switch Timing Point: The moment during the gait cycle when the foot transitions from stance (contact with the ground) to swing (moving forward).
  - Temporal Ratio: The ratio of the time spent in the swing phase to the time spent in the stance phase of the gait cycle.
  - Joint Stiffness: The resistance of a joint to movement, calculated as the change in torque divided by the change in joint angle.
- **Overall Estimation Parameters: Some of them are just a number**
  - Distance: The total distance covered during the exercise.
  - Metabolic Cost: The amount of energy expended per unit of body mass per unit distance, often measured in joules per kilogram per meter.
  - Recovery Time Estimation: The predicted time required for muscles and the body to recover after exercise.
  - Running Load: The cumulative impact of running, including distance, intensity, and frequency, on the body.
  - Symmetry: The degree of similarity between the movements of the left and right sides of the body, indicating balanced or unbalanced gait.

A.2 Interview Questions

- **General Questions:**
  - Can you briefly describe your research focus related to gait analysis?
  - What are the biggest challenges you face when working with raw gait data?
- **Tools and Features:**
  - Are there any gait analysis tools you are familiar with?
  - What are the main functions you usually use in those gait analysis tools?
  - Where do you think there is room for improvement in current gait analysis tools?
- **dashboard Specifics:**
  - How useful would a gait analysis tool be for you without the need for coding?
  - What format do you think would be more user-friendly to present gait analytics results on our dashboard?
- **Parameters and Usage:**
  - Could you review this list of running parameters and indicate which ones are most relevant to your research?
  - Are there any additional parameters not listed here that you frequently use or need?
  - Where and how do you use the results of gait analysis? What direction do you take after the analysis?

A.3 Prototype Evaluation Interview

- **Perceived Usefulness**
  - Component 1: File Upload and information Display
    - The information display (Participant, Date, Recording ID, Device ID) is useful to help me keep track of my data efficiently.
    - The error message is useful for me to notice the wrong file upload.
  - Component 2: Data Overview Tab
    - The Data Overview Tab provides a clear and comprehensive initial visualization of the raw gait data with detected gait sequences.
    - The ability to toggle sensor data visibility in the overview tab helps me focus on specific data streams.
  - Component 3: Detailed Gait Sequence Analysis
    - The dropdown menu for selecting specific gait sequences is useful to select particular segments of the data.

    * The detailed detected gait sequences graphs and pie charts for stance and swing phases provide valuable insights into the gait cycle.
  - Component 4: Gait Parameter Analysis
    * The radio buttons for selecting different gait parameters is useful for me to switch between various analyses.
    * The use of different chart types (line, bar, stacked bar) effectively represents the selected gait parameters.
  - Component 5: Data Export
    * The table summarizing analysis results is helpful for reviewing the analysed gait parameters.
    * The export feature facilitates the easy transfer of analysis results for further use, enhancing workflow efficiency.
- **Perceived Ease of Use**
  - General questions
    * The dashboard is user-friendly and easy to understand.
    * Learning to operate the dashboard did not require much effort.
    * The dashboard is easy to navigate.
  - Specific questions
    * The file upload process is straightforward and easy to use.
    * The checklist for toggling sensor data visibility is user-friendly.
    * The dropdown menu for selecting specific gait sequences is easy to use.
    * The radio buttons for selecting different gait parameters are intuitive and easy to use.
    * The export button makes it easy to download and use the analysis results.

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