WHITE PAPER

Fall Risk Assessment

2024

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Why did we develope this score?

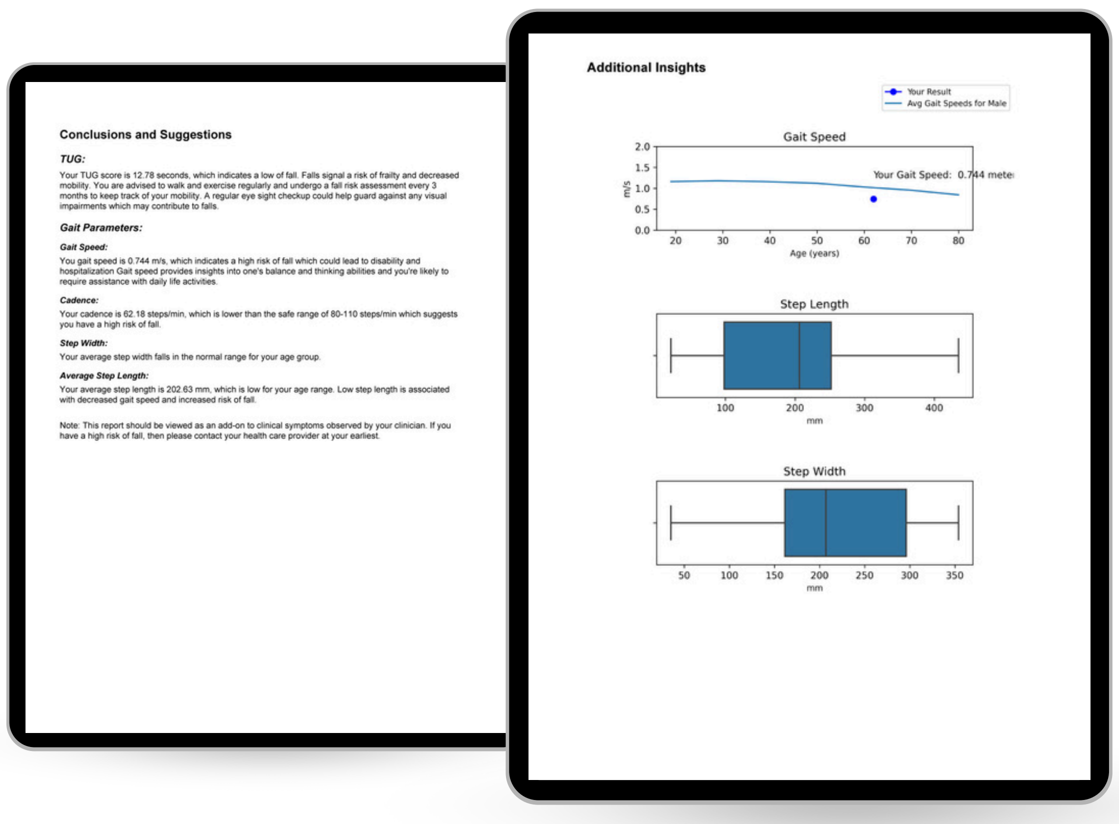
Falls among older adults continue to be a chronic and concerning problem, affecting healthcare outcomes and costs, despite extensive research into fall prevention in healthcare. Falls in the elderly can result in serious injuries, protracted hospital stays, higher healthcare costs, loss of patient autonomy, and even death. They still rank among the most common events in the community. Every 19 minutes, one person is injured due to falls in the US. (1) In China, falls are the primary cause of severe illnesses like fractures and bruises in around 12% of persons out of 5374. (2) Many factors can increase the risk of falls in older age, but being aged is one of the significant risks as muscular strength is decreased in older people. Other than that, hypertensive, diabetic, and those with a recent history of falls are more at risk of falling than normal-aged people. (3)

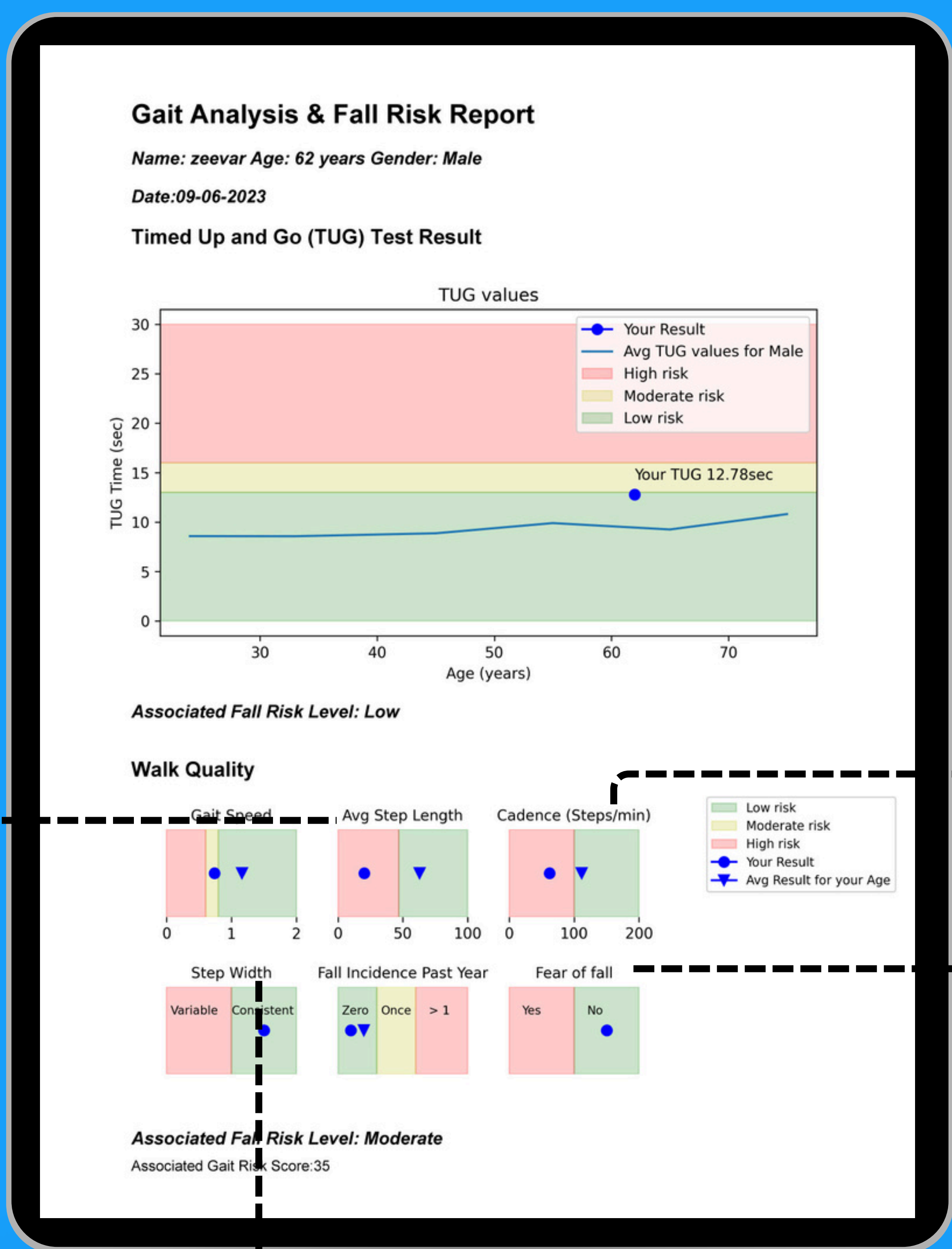
What is already in practice?

Prevention is better than cure; many healthcare systems revolve around this quote. (3) The Joint Commission International for Accreditation Standards for Institutions acknowledges and requires institutions to use fall risk assessment methods to prevent fall-related injuries in community-dwelling older adults. Implementing modern techniques in the prevention of falls can bring a significant decrease in hospital administration for the older population. (4)Several well-known tools are commonly used in healthcare settings, including the **Falls Efficacy Scale—International (FES-I), Activities-specific Balance Confidence Scale (ABC Scale), STRATIFY scale, Johns Hopkins Fall Risk Assessment Tool (JHFRAT), Tinetti Mobility Test (TMT), Morse Fall Scale (MFS).** While these tools serve their purpose, it's crucial to recognize that there is no one-size-fits-all tool due to the multidimensional nature of fall risks. High costs, lack of standardization, lack of objectivity and complexity are some identified problems in present solutions.

What is the value of it?

Early gait analysis through the Time Up and Go test can significantly decrease fall risk as it is a widely used tool for predicting falls. (5) The TUG (Timed Up and Go) test has proven to be a reliable method for predicting the likelihood of falls with high accuracy. (6) Modern technology integrated with reliable tests to predict falls is an effective solution for the modern world, as used by some mobile technologies, it can be a great and handy tool for supplying fall risk screening, leading to fewer falls in the future. (7) The gait is of great importance in predicting the bad outcomes in elder population. All the following gait parameters mentioned below are included in our fall risk report:





Cadence/No. of steps:

The Number of steps the participant takes is one of the significant parameters of gait that can significantly influence the risk of falls. (11)

Step Length and Gait Speed:

It is concluded that the lower and slower the step length and gait speeds, respectively, the higher the possibility of falling. (9)

Fear of Fall and Number of falls in past year:

The cycle of falling was explained in an article. It says that when a person falls, fear of losing develops, which leads to less physical activity and increased musculoskeletal issues, which in turn causes gait instability, resulting in a fall; in conclusion, fear of falls and recent history of falls are directly associated with increased risk of fall in elderly. (10)

Step Width (Consistent or Variable):

Step width is associated with those who had a fall in the past year. (8)

Why they should trust it?

Score formation:
Our score uses the following evidences mentioning the cutoff values presenting the values associated with risk of fall.

Step length	Gait speed	Cadence	Step width Variability is essential
Less than 47.2 cm (about 1.55 ft) is considered risk of fall: (12) 1.greater than 47.2 cm = Low risk of fall 2.less than 47.2 cm = High risk of fall	Less than 1 meter/second is considered risk of fall: (13) 1.0.8-1.0 m/s = Low risk of fall 2.0.6-0.8 m/s = moderate risk of fall 3.less than 0.6 m/s = high risk of fall	Less than 1 meter/second is considered risk of fall: (13) 1.0.8-1.0 m/s = Low risk of fall 2.0.6-0.8 m/s = moderate risk of fall 3.less than 0.6 m/s = high risk of fall	Variability is essential: (15) 1.Variability = high risk of fall 2.consistent = low risk of fall

4. How is it used to prevent falls?

- **Implementation guidelines**

This device uses the Microsoft Kinect sensor to generate a report predicting the risk of falls. It measures and analyzes factors such as Time Up and Go, gait speed, step length, step width variability, and cadence based on predefined cut-off values. The program also saves real-time recording frames in a folder for each participant, allowing the user to manually interpret and analyze the data as needed. (16) As fall risk rises with advancing age (17), the devices mainly focus on older adults aged at least 60 years.

5. How is it different from other scores in the industry?

Our fall risk score is differentiated from existing scores in the market through its unique integration of modern technology with the traditional Timed Up and Go (TUG) test, enhancing the precision and applicability of fall risk screening. Unlike conventional assessment tools, which rely on manual observation and subjective judgment, our score incorporates advanced analytics to quantify subtle variations in gait parameters that are critical for predicting falls. By utilizing real-time data capture and analysis, our approach provides a more detailed and objective assessment of fall risk factors such as step width variability, step length, and gait speed, which are often overlooked in less sophisticated scoring systems. This level of granularity not only improves the accuracy of fall risk prediction but also offers actionable insights for personalized intervention strategies.

Moreover, our fall risk score is pioneering in its consideration of the psychological aspects of mobility, specifically the fear of falling, which is directly incorporated into the risk calculation. This recognizes the complex interplay between mental and physical health in the elderly—a relationship that is frequently undervalued in other fall risk assessments. By combining both the physiological measurements of gait and cadence with the psychological element of fall anxiety, our score encapsulates a more comprehensive view of an individual's fall risk. Additionally, the use of our score in mobile technologies empowers users with convenient and consistent monitoring, a proactive step towards fall prevention not typically available in traditional models. This approach ensures that our score is not just a predictive tool but also a preventive solution, fostering independence and confidence among the elderly population.

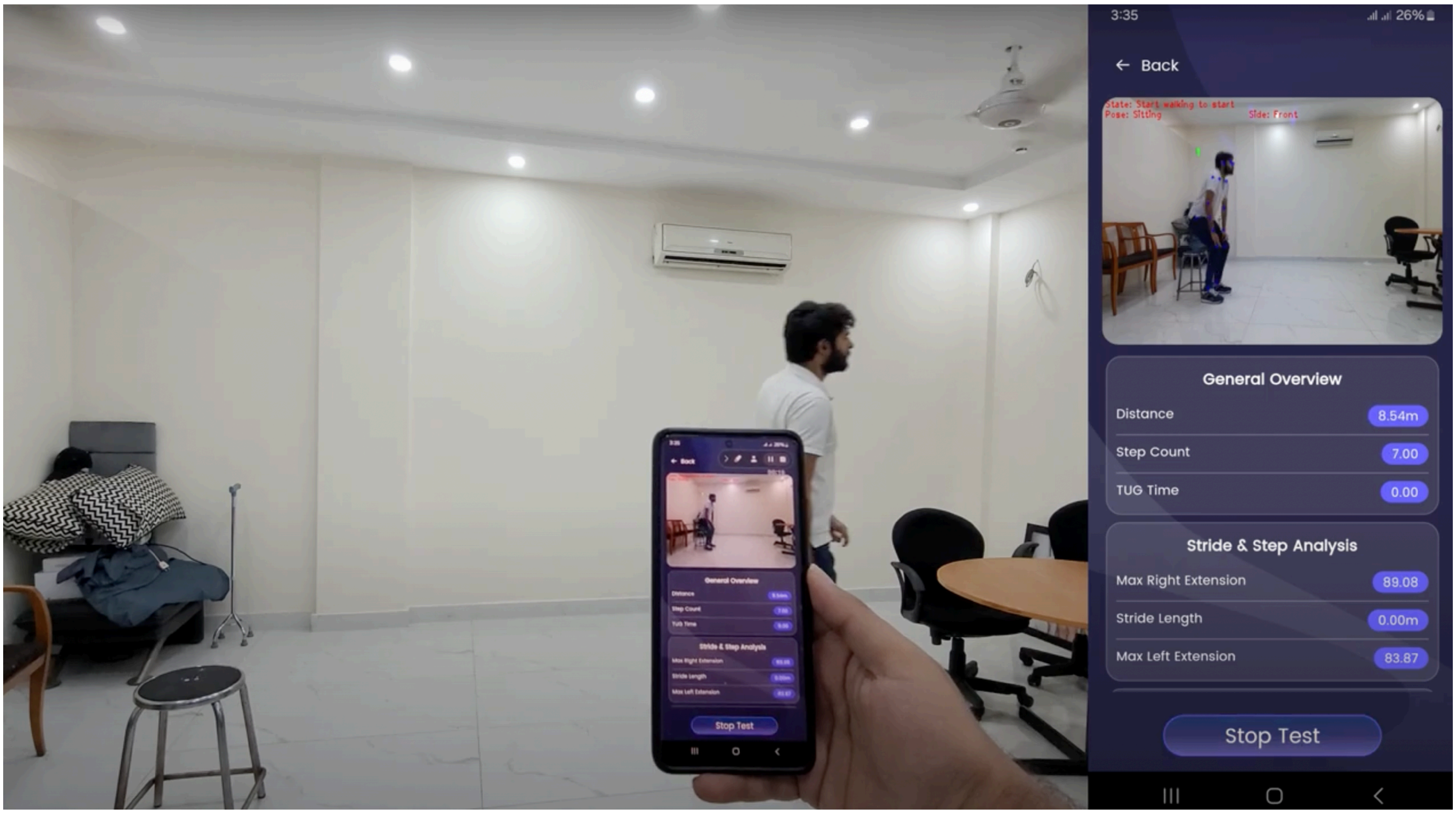
6. Our Technology

We offer a state-of-the-art Fall Risk Detection System that empowers health professionals with comprehensive insights into their patients' fall risk. By harnessing advanced technologies from the latest cutting-edge technologies, we ensure accurate gait analysis and report generation, making it accessible and understandable for participants of all technical backgrounds. The main components enabling the measurement, calculation and prediction of highly precision gait values:

1. Microsoft Azure Kinect depth camera: We use the high performing color and depth camera along with the open source yet official Microsoft maintained development kit to get a wide-angle colored view along with depth information for our processing. Microsoft Azure Kinect camera is the top-of-the-line off-the-shelf camera well known for providing the highest precision values. The Microsoft Azure Camera is packed with an RGB camera, a Depth sensor and an Infrared Sensor, all of the data is then fused in together to have get an accurate read on the environment along with the people of interest. “The Azure Kinect DK (Microsoft Inc., Redmond, WA, USA) includes a 12-megapixel color camera (4096 × 3072 px) and a 1-megapixel ToF depth sensor (1024 × 1024 px).” [4]

2. Nvidia TRT_Pose : 1.Trt-pose, also known TensorRT Pose, is a real-time pose estimation model that utilizes deep learning algorithms to estimate key points on a person's body accurate and efficient estimation of body key points, such as eyes, arms, and legs. The model is pre-trained and optimized with NVIDIA TensorRT, allowing it to run in real-time on devices like the Jetson Nano and hence works very efficiently on StepSense which leverages the high compute power of the Nvidia Jetson Xavier. It is widely used in various applications, including gait analysis, action recognition, and human behavior understanding. The Nvidia Trt_Pose is one of the most tested and highest performing pose estimation Deep learning solution since it has been trained on the largest human data and human activity database.

3. Various Gait Parameter predictors: we have trained various predictors and regressors using inhouse use case specific data as long as the standard IEEE opensource data sets to predict various complex gait parameters using the basic ones extracted using the depth information and the pose landmarks. These Predictors have undergone various training, validation and testing loops to ensure a high accuracy in the predicted values



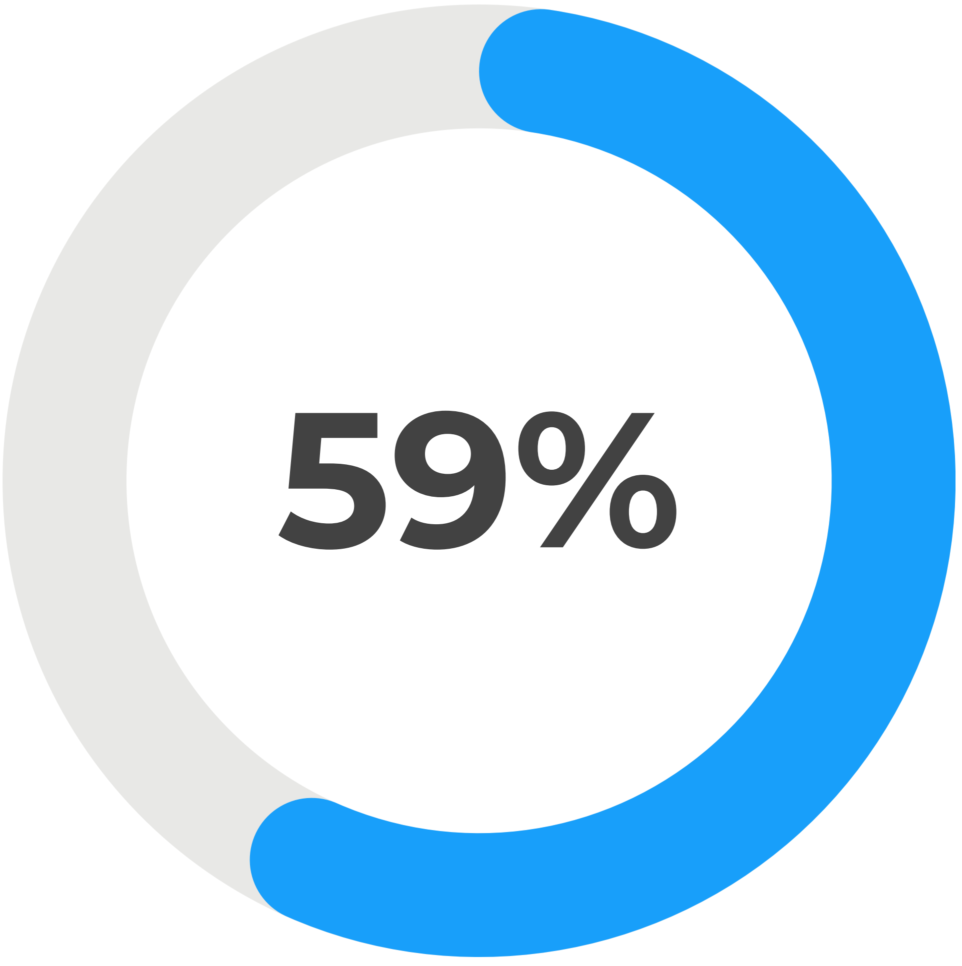
7. Supportive evidence about the Credibility of our solution:

A semi-structured analytical observational In-house study was conducted and involved 54 elderly participants. The inclusion criteria for the trial were individuals aged above 60 years, and both genders were considered eligible. Data collection took place over two months in 2023. Participants were contacted and provided with informed consent before being asked to walk at least three times in front of a camera. A designated 3-meter area was marked for their aid during the walking trials. The collected data encompassed various parameters, including participant names, age, gender, gait speed, cadence, step length, step width, fall incidence in the past year, fear of falling, Timed Up and Go (TUG) test results, and fall risk assessments based on TUG and walk quality reports generated by the device. Additionally, manually calculated parameters such as TUG, cognitive TUG, step count, gait speed, and step length were recorded. Data analysis was performed using IBM SPSS software for descriptive statistics.

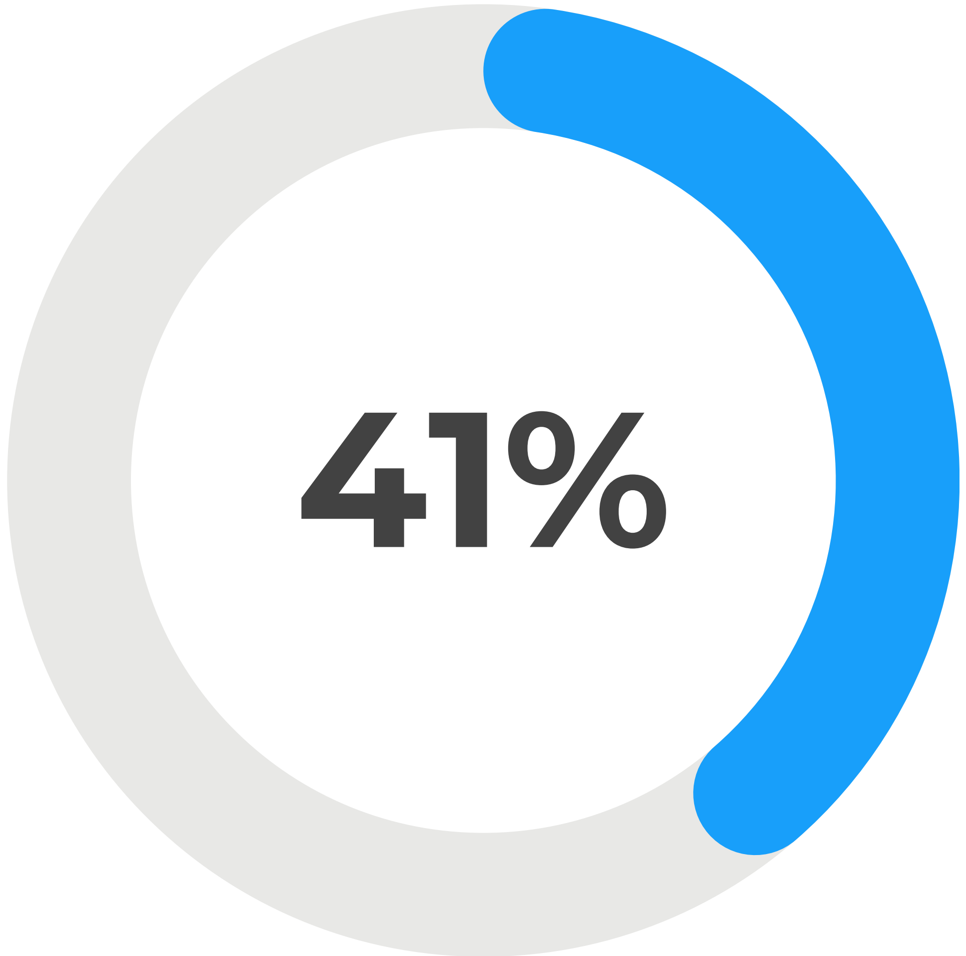
Manual parameter calculations were based on the following formulas:

Step length	Distance covered (in meters) / Steps taken
Gait speed	Distance covered (in meters) / Time taken to cover the distance
Step count	Total number of steps taken to cover the 3-meter distance
Cognitive TUG	Participants were instructed to count backward from 20 while walking.

Among the **54 participants**, the gender distribution included **32 (59%)** males and **22 (41%)** females. The age distribution of the participants was as follows:

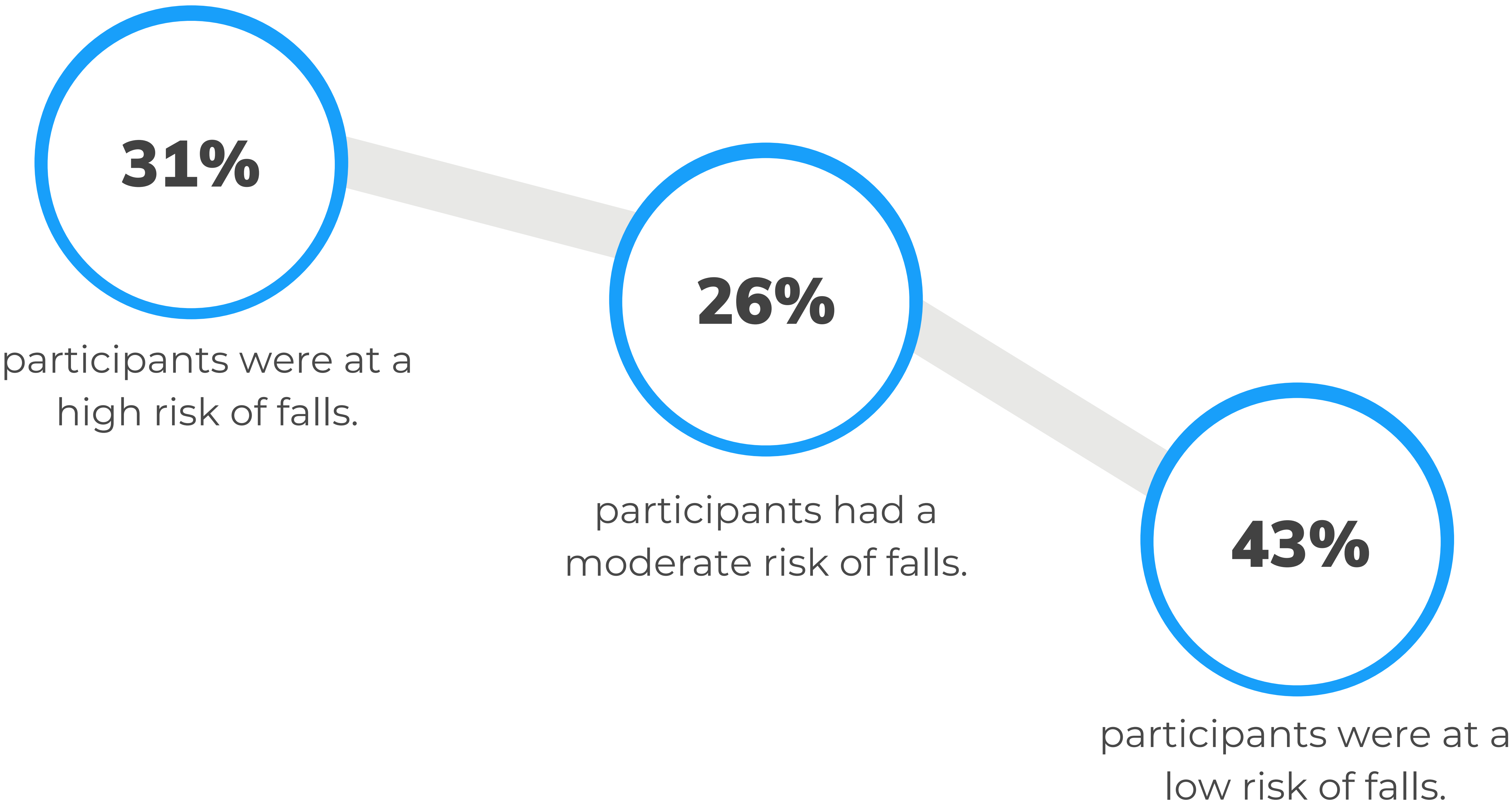


32 Males



22 Female

31 individuals were in the age range of 60 to 64 years, 10 were between 65 to 69 years, 10 were in the 70 to 74 years age group, and only 3 participants fell within the age range of 75 to 80 affectingly risk assessment based on the TUG test, the study found that:



When assessing fall risk based on walk quality reports, the results were as follows:

44% (participants had a high risk of falling.)

35% (participants had a moderate risk of falling.)

11% (participants had a low risk of falling.)

9% (participants were identified as having a very high risk of falling.)

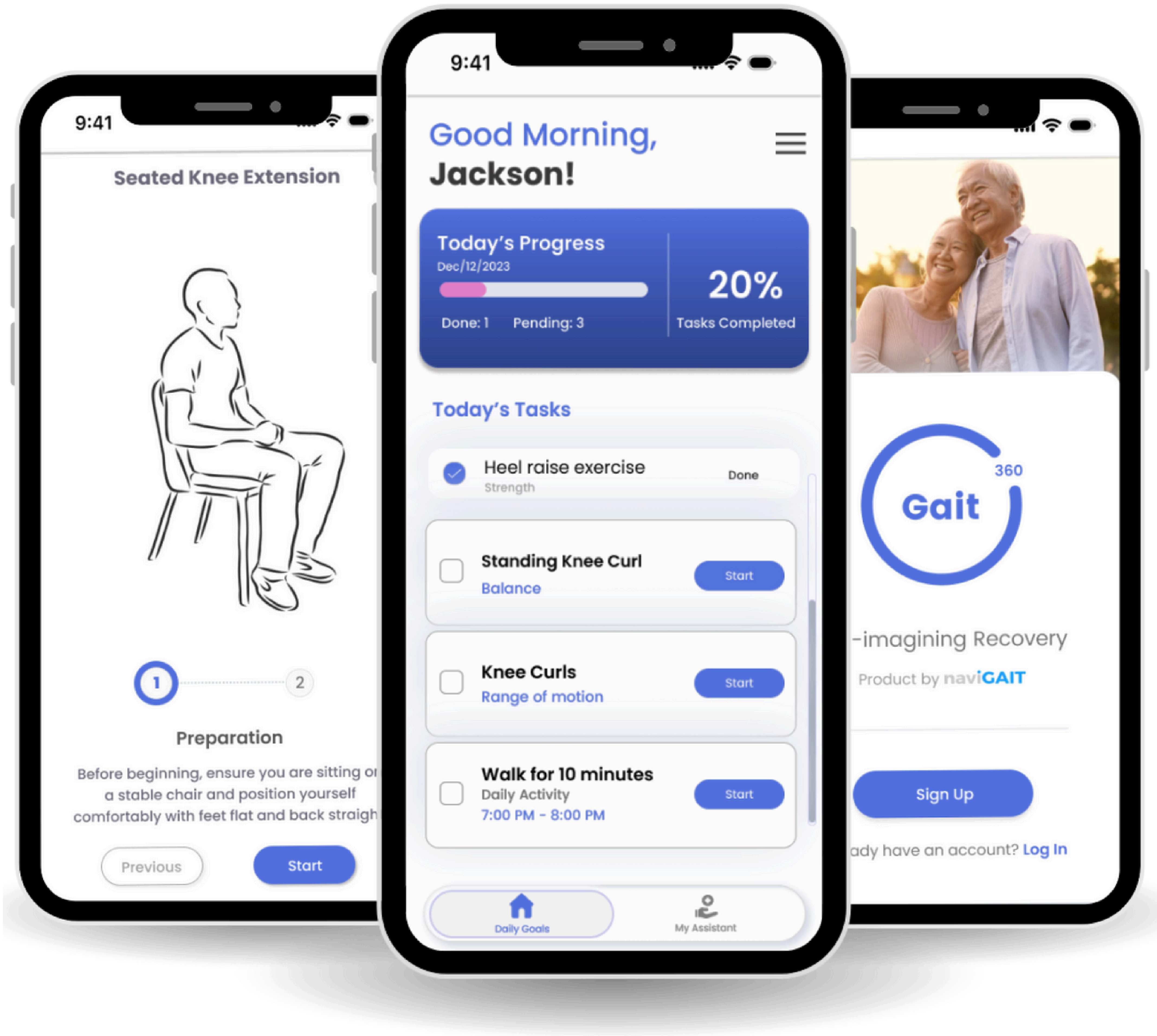
Analysis of error percentiles of TUG testing	70th percentile of error 90th percentile of error	+/- 0.64 seconds +/- 1.39 seconds
intra-rater reliability of Stepsense	12 out of 50 participants displayed a slightly different fall risk value, deviating by one unit above or below the mean value	

Based on the robust analysis conducted, the results obtained supply convincing evidence supporting the accuracy and reliability of the measurements in the study. The study's findings revealed a minimal difference in the TUG average between the manually measured and Stepsense-measured values, with an average error of only 0.177083333 seconds. This shows that Stepsense can accurately capture and measure the time it takes to complete the TUG test.

8. Limitations of our solutions:

- **Limited generalizability:** Our device only targets individuals aged 60 years or older, which limits its applicability to a broader age range of the population.
- **Fall risk contributing factors:** In an individual, other contributing factors to the risk of falling may include a history of ankle fracture or existing comorbidities that were not accounted for in our device.

9. Future developments:



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