Measuring Fall Risk Using the Internet-of-Things Chair

Alexander W. Lee[1][a], Melissa S. Lee[1][b], Chelsea Yeh[2][c] and Kyle Yeh[3][d]
[1]*Chino Premier Surgery Center, Chino, CA 91710, U.S.A.*
[2]*Yale University, New Haven, CT, 06520, U.S.A.*
[3]*Brown University, Providence, RI, 02912, U.S.A.*

Keywords: Lower Extremity Strength, Leg Strength, Falls, 30 Second Chair Stand Test, 5 Times Sit-to-Stand Test, Internet of Things, Automatic Chair, Wireless Chair, Clinical Study.

Abstract: Falls are one of the leading causes of injuries and deaths for U.S. adults ages 65 and older. People can fall because of imbalance and leg weakness. Fall risks are evaluated by standardized tests, including the 30-Second Chair Stand Test (30CST) and 5x Sit-to-Stand Test (5xSST). These tests are conducted by visual observation of the participant and manual counting, which can be inaccurate and tedious. This study clinically tested an Internet of Things Chair (IoT) on how well it performed on the 30CST and 5xSST. A clinical study was performed on 224 participants. The results of the IoT Chair were found to be similar to the traditional, visually observed method. The IoT Chair required less manual work and provided information that was not obtainable with the observer method. The IoT Chair was able to calculate the weight exerted on the individual chair legs, rate of weight change, lag time between each sit-stand cycle, the amount of time spent standing during each cycle, and the amount of time each sit-stand cycle required. This additional information can allow for a better understanding of a person's leg strength and improves the prediction for falls, which can save lives and lower healthcare costs.

1 INTRODUCTION

Falls in adults over 65 years old are the leading cause of injury-related deaths in the United States (CDC, 2020). The rate of age-adjusted deaths due to falls has increased by 41% from 2012 to 2022 (CDC, 2024). In a 2016 National Study of Long-Term Care Providers conducted by the National Center for Health Statistics, they found that 22% of adults living in an assisted-living facility or residential care communities had fallen in the prior 90 days. Of the individuals who fell, 19% had to go to the hospital, and 15% had sustained injuries (Harris-Kojetin & Sengupta, 2018).

Impairments in vision (Jin et al., 2024), hearing (Riska et al., 2021), muscle strength (Rodrigues et al., 2023), reflexes (Marigold et al., 2005), cognition (Chantanachai et al., 2021), balance (Papalia et al., 2020), side effects of medications (Hartikainen et al., 2007), and environmental hazards can all cause falls (Campani et al., 2020), (National Institute on Aging, 2022). Preventing these falls is critical in keeping older adults healthy and active. The 30-Second Chair Stand Test (30CST) (Jones et al., 1999) (Chan-Mei Ho-Henriksson et al., 2024), and 5-Time Sit-to-Stand Test (5xSST) (Muñoz-Bermejo et al., 2021), (Albalwi & Alharbi, 2023) are well-established tests that objectively evaluate lower extremity strength, balance, and fall risks. In the 30CST, patients are evaluated on how many times they can change from sitting to standing in 30 seconds, with the observer visually counting. Their arms are crossed across the chest and cannot be used during the test. If the person performs less than what is established for their age group and gender, then they are at higher risk for falls (CDC, 2017). The 5xSST is performed in the same manner as the 30CST with the participant's arms crossed at the chest and cannot be used during the test. For the 5xSST, the longer the person takes to

[a] https://orcid.org/0000-0001-7809-8181
[b] https://orcid.org/0000-0002-3975-821X
[c] https://orcid.org/0000-0002-0502-8235
[d] https://orcid.org/0000-0002-2979-7143

Lee, A. W., Lee, M. S., Yeh, C. and Yeh, K.
Measuring Fall Risk Using the Internet-of-Things Chair.
DOI: 10.5220/0013404500003944

In *Proceedings of the 10th International Conference on Internet of Things, Big Data and Security (IoTBDS 2025)*, pages 353-360
ISBN: 978-989-758-750-4; ISSN: 2184-4976

complete the test, the higher their fall risk (*5 Times Sit to Stand Test (FTSST)*, n.d.). There are no standardized cut-off ranges published by the Center for Disease Control (CDC) for the 5xSST. Buatois et al. studied 1,618 community-dwelling people over the age of 65 and found that if they took longer than 15 seconds to complete their 5xSST, their risk of falls would double. This study is cited in many tests as the cut-off number (Buatois et al., 2010).

Experimental studies have evaluated the use of electronics applied to the sit-to-stand test. For instance, a study by Collado-Mateo et al. used an automatic chronometer developed by Chronopic to evaluate the patient during the 30CST trial (Collado-Mateo et al., 2019). The participant had to wear a vest with metallic tape. That metallic tape would have to come into contact with the Chronopic device attached to the chair seat. The Chronopic device could detect the time the tape was in contact, thereby establishing the amount of time the patient was sitting or standing. If the person was not sitting correctly and the metallic tape on the vest did not come into contact with the Chronopic device, the change to the sitting position would not be recorded.

Yeh et. al. (Yeh, C. et al., 2022) developed an Internet of Things (IoT) Chair designed to evaluate patient movement from the chair. A pressure pad placed on the chair could detect the movement of patients changing from a sitting position on the chair to a standing position by detecting pressure and motion changes. This data would then be transmitted to a cellular phone app. A significant limitation of that study was that the chair was not tested for accuracy. Another problem was that the pressure pad on the chair could shift with use, decreasing the accuracy of the measurements. The shifting pad could also cause patients to slip out of the chair and injure themselves. The chair only detected whether or not the person was sitting on the chair. No sensors were detecting the amount of pressure placed on the chair.

Lee et al. (Lee et al., 2024) improved upon Yeh et al.'s chair and developed a novel Internet-of-Things (IoT) Chair utilizing built-in sensors to evaluate fall risks in adults. This type of sensor technology has been previously applied to other medical devices (Lee et al., 2023), (Lee & Yeh, 2022), (Yeh, C. et al., 2022), (Yeh, C. et al., 2022), (Yeh. K. et al., 2021) including the measurement of human body movement (Yeh H.J. et al., 2020), and to computer networking (Yeh. H.-J. et al., 2019).

Lee et al. designed the entire system as a single unit so that no sensors were attached to the patients and no sensors needed to be set up external to the chair. The participant also did not need to sit in a particular position in order for the chair to measure the amount of force exerted on the chair. There were built-in sensors in the chair which transmitted the data to a cloud-based server. The chair was designed to perform the Fullerton Functional Tests, which included the 30CST and the 5xSST. The technical aspects of the devices used and their integration into the chair are detailed in the paper by Lee et al.

This paper examined how well Lee et al.'s IoT Chair (Lee et al., 2024) performed in test participants with both the 30CST and the 5xSST. We chose to test the chair on the 30CST and 5xSST because studies have shown that they are highly reliable across different adult populations (Figueiredo et al., 2021), (Gill et al., 2012), (Goldberg et al., 2012). Prior to conducting the clinical trials, we received IRB approval #23-130 from Azusa Pacific University. A total of 224 people participated in the study. Testing was conducted over a period of 12 months, from November 2023 through October 2024.

2 MATERIALS AND METHOD

The use of strain-gauge force sensors for the measurement of dynamic human weight distribution is novel and presents significant advantages over other sensing technologies. Strain gauges are commonly used to measure static human weight distribution and are the sensing element in many commercial and most electronic consumer scales. Because of their widespread use, economies of scale in their design and manufacturing have been achieved, leading to broad availability and low cost. Designing with these components leads to decreased end-user costs that offset high equipment costs that beset the healthcare industry.

The use of weight sensors that are mounted on the chair provides significant improvements over previous automatic chair-stand measurement apparatus. Many of the previous devices, such as accelerometers or contact sensors, require the attachment of sensors on the body of the subject (Cobo et al., 2020), (Hellmers et al., 2019), (Millor et al., 2013). This can lead to significant complications during the trial process, increasing preparation time for each patient and reducing participation. Additionally, other previous devices using distance sensors (Takeshima et al., 2019), (Cobo et al., 2020), (José Gonçalves et al., 2015) require a more complicated setup, which limits their portability.

Two designs were created for the placement of the strain gauge weight sensors. Four weight sensors were integrated into the four corners of common chairs. For human body scale applications, the four sensors are typically wired into a single Whetstone bridge that provides a single reading, which is the sum of the four weights. In this application, the four sensors were wired into four separate bridges to provide four separate channels – right front, right back, left front, and left back.

For the initial design, the four strain gauges were mounted on the frame of the chair directly under the four corners of the seat of the chair. This design had issues in securing the seat on the chair while providing accurate measurements. A second design solved the issue by mounting the sensors under the four legs of the chair. Since the diameters of typical chair legs are smaller than the sensors, the chair is first mounted on a rigid board, and the sensors are secured to the bottom of the board directly under the legs (Figure 1).

Figure 1: This picture shows the chair that was designed for this clinical study.

The completed apparatus directly measures dynamic weight distribution on the four separate chair legs as the subject performs each trial. This is not available with other sensing methodologies. Distance sensors and accelerometers will be able to provide velocity data but not measure the weight distribution.

Another improvement over previous work is the use of a novel network infrastructure that uses cloud computing. This system architecture provides user-friendly control and data flow, storage, and retrieval during data collection and processing. The benefit of this architecture is that the data collection is highly scalable and portable; because existing and popular network protocols are used, migrating or duplicating the system to different or multiple servers is extremely simple – often with the simple copying of the relevant scripts with little or no setup or provisioning. This design greatly simplifies the deployment of new systems.

Commands to the system (inputting the patient number or id, tuning the data collection parameters such as the collection period or sample rate, and starting the data collection after the patient is ready) are done on a web interface that runs on any browser (Figure 2). The browser runs standard HTML (hypertext markup language) and JavaScript. The commands issued from the browser to the chair (red arrows) and the responses and messages from the chair to the browser (orange arrows) utilize MQTT (message queuing telemetry transport), which is the de facto standard for IoT devices. This allows the user interface to run on virtually any device – personal computers, laptops, cell phones, etc.

After data from a trial has been collected, it is sent to the cloud-based server via a standard HTML POST request (blue arrow). The server runs standard PHP (hypertext processor) to receive, store, and provide access to the patient trial data. PHP is supported on virtually all servers without customization, which provides excellent system portability. The stored data on the server can be accessed from the browser interface (green arrow) if the proper permission is granted. This is important for the confidentiality of the patient data. The stored data can be graphed, and various statistics, such as the times of sit-to-stand transitions, can be computed.

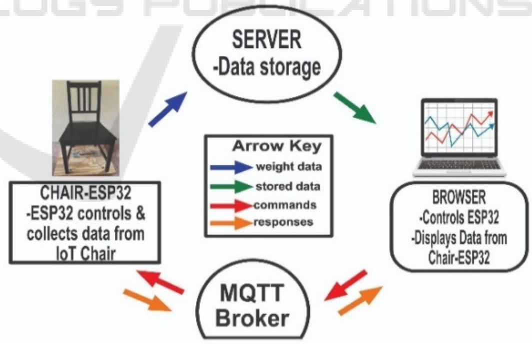

Figure 2: This diagram displays the data and command flow for the IoT Chair.

We recruited male and female adults ages 18 years and older. Any participants in a wheelchair or regularly used assistive devices, including canes and walkers, were excluded from this study. If they had good leg strength and only occasionally needed the use of canes or walkers, they were included in this study. If the participant appeared fatigued, struggling, or imbalanced, the test was immediately stopped to prevent a fall. If needed, a walker was also placed in front of the chair for the participants to hold onto if they felt fatigued or might fall. Once the participant required the assistance of the walker, the trial was immediately ended. The participants could also voluntarily end the study if they felt tired or unable to continue by verbally informing us or by raising either their right or left hand.

A questionnaire was given to all participants, who recorded their age, use of the assistive walking devices, history of falls, and any musculoskeletal pain. Vital signs, including height, weight, body mass index (BMI), blood pressure, and heart rate, were measured in all participants.

Participants were given instructions on the 30CST and the 5xSST. The participant needed to have their feet flat on the floor, sit in the middle of the chair, and have their hands on the opposite shoulder with their arms against the chest. When instructed to “Go,” the participant needed to go from sitting to a full standing position and then sit back down again. Data collection was initiated by clicking a “Start” button on the custom-designed, secure IoT Chair browser (website) hosted by the web server. The IoT Chair programming automatically recorded the number of sit-stand-sit cycles in 30 seconds. For the 30CST test, the participants needed to repeat this cycle as many times as they could in 30 seconds. During the 30CST, the time required to do the first five sit-stand-sit cycles was used to record the 5xSST. In essence, the 30 CSST and 5xSST tests were done simultaneously for efficiency and participant convenience. Besides automatic recording by the IoT Chair programming, we manually recorded how long it took to do the first five sit-stand cycles (5xSST) and the number of sit-stand cycles completed in 30 seconds (30CST).

3 RESULTS

There were 224 participants in this clinical study. Fifty-six participants occasionally used assistive walking devices such as walkers and canes. Seventy-three participants had fallen within the past year. Two hundred and eight participants described either some joint or back pain.

The IoT Chair programming default setting (on the browser) allowed 30 seconds to complete the 30CST and 5SST tests. Thirty seconds was chosen because that is the time needed for the 30CST. The slowest 5xSST completion time cut-off is 10.8 seconds (for people 70 years and above). That means anyone taking longer than 10.8 seconds is considered to have failed the 5xSST. Thirty seconds would be more than sufficient time to test the 5xSST. Test Figure 3 shows the results of a typical 30CST and 5xSST trial. An important note was that the IoT Chair could automatically record, with a precision of 12.5 milliseconds, how long it took for the person to do 5x sit-stand cycles. In contrast, the human observer recordings only measured the 5xSST to the seconds.

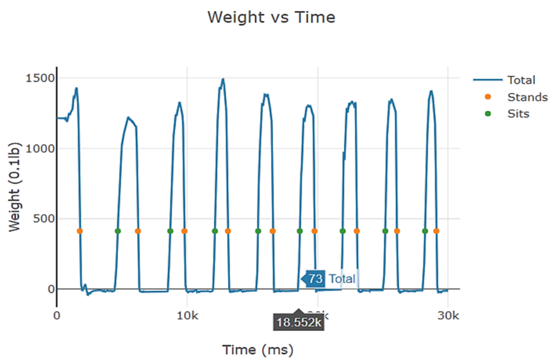

Figure 3: A typical example of a completed IoT Chair clinical trial, with the orange dot recording a "stand" and the green dot recording a "sit". The blue graph showed the patient's total weight sitting (140 lb) and at full standing (0 lb). The total time elapsed is 30 seconds (i.e. 30,000 ms), and 8 sit-stand cycles were completed for the 30 CST. The cursor is on the fifth completed sit-stand cycle, displaying the amount of time (18.55 seconds) needed to complete the 5xSST test.

In the 30CST trials, the mean in observer-recorded sit-stand cycles was 7.72 cycles (median 7.0, SD 3.74, 95% CI 0.53) compared to the mean IoT Chair-recorded sit-stand cycles was 6.93 cycles (median 7.0, SD 3.76, 95% CI 0.56). This data is displayed in a box plot analysis in Figure 4, showing that the two different methods have overlapping 50% quartiles.

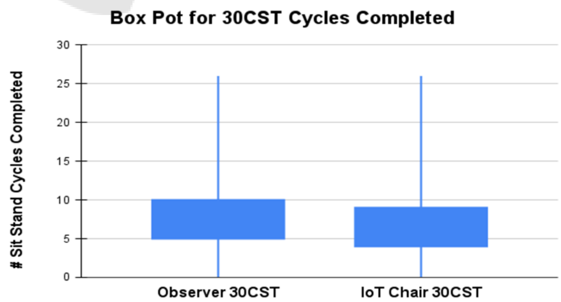

Figure 4: The 30CST Observer (visually) recorded method and IoT Chair (automatic) recorded method have an overlapping 50% quartile range.

For the 5xSST, the mean time to complete the test recorded by the observer was 19.83 seconds (median 18.03, SD 8.83, 95% CI 18.03) compared to the IoT

Chair mean time of 21.33 seconds (median 20.95, SD 6.41, 95% CI 0.98). This data is displayed on a box plot diagram in Figure 5, showing that the two different measuring methods are not statistically different.

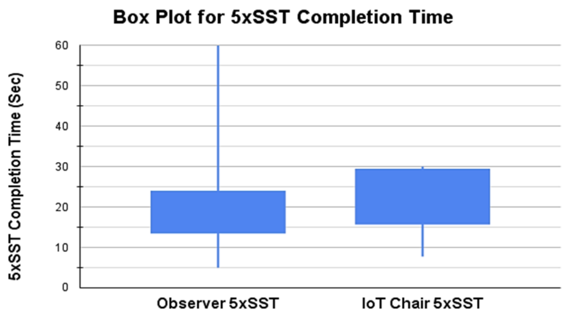

Figure 5: The Observer (visually) recorded method and IoT Chair (automatic) recorded method for the 5xSST have medians within the comparison 50% quartile box plot, meaning the difference between these two methods is not statistically significant. It is important to note that the IoT Chair was programmed to not record after 30 seconds, affecting the difference in the IoT Chair vs Observer box plot range.

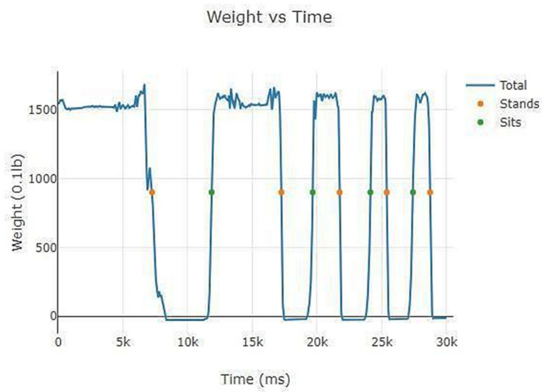

Figure 6: In this trial, the graph clearly depicted the initially slower first sit-stand cycle compared to the other sit-stand-sit cycles, with a pause in the standing phase.

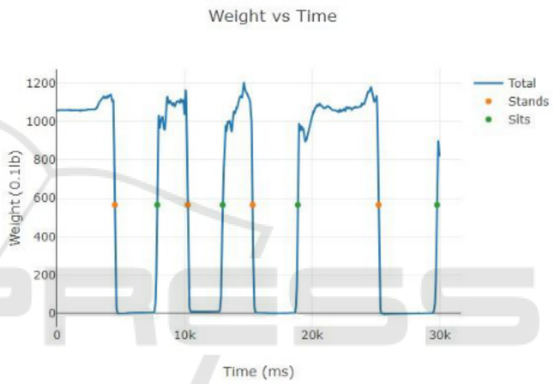

Figure 7: This graph shows a prolonged sit-stand cycle near the end, at about 20 seconds.

4 DISCUSSION

By using the Box Plot analysis, the 50% quartiles for the observer method and the IoT Chair overlapped on both the 30CST and 5xSST, meaning that the IoT chair results were not statistically different compared to the observer method. That means both methods had similar results, and the IoT Chair results were just as reliable as the standard observer method for the 30CST and 5xSST.

Being able to analyze each sit-stand cycle and its characteristics is very useful. For instance, the IoT Chair browser displays the sit-stand cycles as a graph, showing time on the X-axis and weight on the Y-axis. Thus, the IoT Chair programming can calculate how long each sit-stand cycle takes. Patients who are slower with the first or last sit-stand cycle may indicate leg weakness. Initially, these participants may need to build momentum going from sitting to standing. They may initially sit longer or stand longer. Figure 6 shows an example of a person with difficulty in the first sit-stand cycle, with a pause in the standing phase. At the end of the trial, if the participants are slower in a sit-stand cycle, this may also indicate increasing fatigue (Figure 7). Increasing fatigue would be a risk for falls. Again, this nuanced data would not be recorded via the human observer method.

Since the chair measures the weight placed on each chair leg, we can make inferences about a participant's balance issues. For instance, in Figure 8, the person consistently placed higher pressure on the left front and left back chair leg. This difference in chair leg pressure may indicate that the person has a right-sided weakness and favors his left leg. Some possibilities for favoring one side may be due to a history of stroke, vestibular, or balance issues. This type of information is not available with the traditional observer counting method. A physician or physical therapist can use this additional information to diagnose leg weakness or imbalance better and improve patient treatments and outcomes.

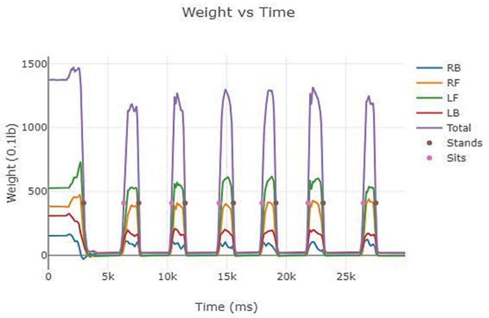

Figure 8: The different color lines indicate the weight exerted on each chair leg. As the legend describes RB (blue line)= weight on right back IoT Chair leg, RF (orange line)= weight on right front leg, LF (green line)= weight on left front leg, LB (red line)= weight on left back leg, Total (purple line)= weight on all four legs.

As seen in Figure 9, the IoT Chair also calculated and displayed the rate of change in weight or weight velocity of each sit-stand and stand-sit curve. The weight velocity measures the weight change placed on the chair over time, which can be a proxy for how fast the person goes from sitting to standing and from standing to sitting. These values can help predict if a person is at a greater risk of falling. For instance, participants with a faster change in weight exerted on the chair indicate they can sit or stand quickly due to greater lower extremity strength. A slower change in weight exerted on the chair indicates a slower speed in sitting or standing, suggesting that the person may be weaker or have more instability and, thus, are at a greater risk for falls. Figure 9 shows an overall decreasing rate of weight change amplitude over subsequent sit-stand cycles starting at about the halfway point (15 seconds) of the 30CST. This decreasing rate of weight change can indicate that the patient has increasing leg muscle weakness and may be at higher risk of falls compared to a person with a consistent rate of weight change amplitudes throughout the trial.

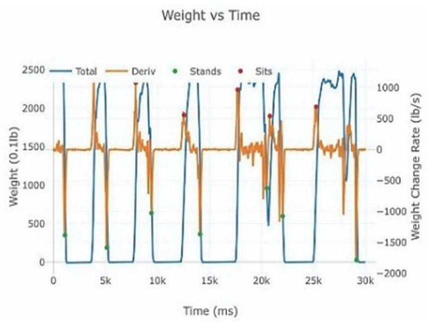

Figure 9: This graph shows a 30-CST trial with the rate of weight change (orange line) or weight change rate.

The graphs in the IoT Chair sit-to-stand trials (Figure 10) even have an interesting pattern reminiscent of an electrocardiogram (EKG) of the heart. In reading an EKG, the physician looks at the rhythm, rate, and type of electrical pattern peaks and troughs to determine different heart conditions (Hockstad, n.d.). The IoT Chair data can be viewed similarly. Each person has a different rhythm, rate, and pattern of sitting and standing. Future studies can see if the IoT Chair graph patterns can be used to help determine the patient's leg strength and fall risks.

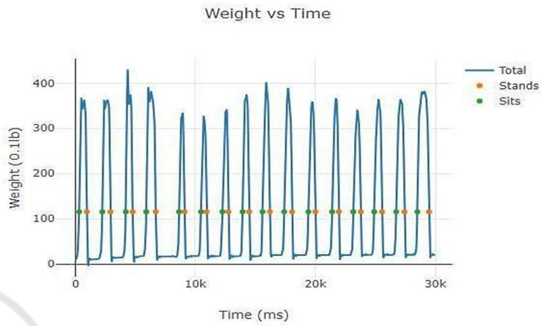

Figure 10: This figure shows the pattern of a participant performing 15 total sit-stand cycles (sit-stand-sit again) and shows a particular, repetitive pattern.

More clinical tests can be done on the IoT Chair to gather data that can be applied to a broader patient population, including patients with certain comorbid conditions such as pain, obesity, heart disease, and lung disease. Machine learning has been widely used in various applications (Yeh & Khan, 2022) and can be applied to the IoT Chair data. Machine learning can help determine normal or abnormal rates of weight changes placed on the chair and how much uneven pressure on the four different chair legs can indicate leg weakness. Algorithms can also be developed to determine how much standing or sitting time is normal or abnormal.

5 CONCLUSION

Clinical testing for the 30CST and the 5xSST on the IoT Chair developed by Lee et al. showed that the chair not only provided automatic data collection and freed up the work of the observer, but the chair was easy to use for both observer and participant, just like a manual chair. Furthermore, the measurements were accurate and reliable, as shown by the box plot analysis. The chair also produced additional data that was unavailable using the manual observer method. The IoT Chair displayed the completion time for each sit-stand cycle, the amount of time spent sitting and standing, the amount of weight placed on each chair leg, and the rate of weight change placed on the chair. This additional data, along with the traditional measurements of time and the number of sit-stand cycles, can more precisely help doctors give earlier and better predictions of fall risks and leg weakness in patients. In turn, preventing falls would improve quality of life, increase life expectancy in older Americans, and save on the enormous annual healthcare costs.

REFERENCES

Albalwi, A. A., & Ahmad Abdullah Alharbi. (2023). Optimal procedure and characteristics in using five times sit to stand test among older adults: A systematic review. *Medicine*, *102*(26), e34160–e34160. https://doi.org/10.1097/md.0000000000034160

Buatois, S., Perret-Guillaume, C., Gueguen, R., Miget, P., Vançon, G., Perrin, P., & Benetos, A. (2010). A Simple Clinical Scale to Stratify Risk of Recurrent Falls in Community-Dwelling Adults Aged 65 Years and Older. *Physical Therapy*, *90*(4), 550–560. https://doi.org/10.2522/ptj.20090158

Campani, D., Caristia, S., Amariglio, A., Piscone, S., Ferrara, L. I., Barisone, M., Bortoluzzi, S., Faggiano, F., Dal Molin, A., Silvia Zanetti, E., Caldara, C., Bellora, A., Grantini, L., Lombardi, A., Carimali, C., Miotto, M., Pregnolato, A., & Obbia, P. (2020). Home and environmental hazards modification for fall prevention among the elderly. *Public Health Nursing*, *38*(3), 493–501. https://doi.org/10.1111/phn.12852

CDC. (2017). *ASSESSMENT Patient Date Time 30-Second Chair Stand*. https://www.cdc.gov/steadi/pdf/STEADI-Assessment-30Sec-508.pdf

CDC. (2020, October 8). *Deaths from Older Adult Falls*. Www.cdc.gov. https://www.cdc.gov/falls/data/fall-deaths.html

CDC. (2024). *Older adult falls data*. Older Adult Fall Prevention. https://www.cdc.gov/falls/data-research/index.html

Chan-Mei Ho-Henriksson, Thorstensson, C. A., & Nordeman, L. (2024). Self-assessment using 30-second chair stand test for patients with knee osteoarthritis – an intra- and inter-rater reliability study. *European Journal of Physiotherapy*, 1–7. https://doi.org/10.1080/21679169.2024.2337419

Chantanachai, T., Sturnieks, D. L., Lord, S. R., Payne, N., Webster, L., & Taylor, M. E. (2021). Risk factors for falls in older people with cognitive impairment living in the community: Systematic review and meta-analysis. *Ageing Research Reviews*, *71*. https://doi.org/10.1016/j.arr.2021.101452

Cobo, A., Villalba-Mora, E., Hayn, D., Ferre, X., Pérez-Rodríguez, R., Sánchez-Sánchez, A., Bernabé-Espiga, R., Sánchez-Sánchez, J.-L., López-Diez-Picazo, A., Moral, C., & Rodriguez-Mañas, L. (2020). Portable Ultrasound-Based Device for Detecting Older Adults' Sit-to-Stand Transitions in Unsupervised 30-Second Chair–Stand Tests. *Sensors*, *20*(7), 1975. https://doi.org/10.3390/s20071975

Cobo, A., Villalba-Mora, E., Pérez-Rodríguez, R., Ferre, X., Escalante, W., Moral, C., & Rodriguez-Mañas, L. (2020). Automatic and Real-Time Computation of the 30-Seconds Chair-Stand Test without Professional Supervision for Community-Dwelling Older Adults. *Sensors*, *20*(20), 5813. https://doi.org/10.3390/s20205813

Collado-Mateo, D., Madeira, P., Dominguez-Muñoz, F. J., Villafaina, S., Tomas-Carus, P., & Parraca, J. A. (2019). The Automatic Assessment of Strength and Mobility in Older Adults: A Test-Retest Reliability Study. *Medicina*, *55*(6), 270. https://doi.org/10.3390/medicina55060270

Figueiredo, P. H. S., Veloso, L. R. de S., Lima, M. M. O., Vieira, C. F. D., Alves, F. L., Lacerda, A. C. R., Lima, V. P., Rodrigues, V. G. B., Maciel, E. H. B., & Costa, H. S. (2021). The reliability and validity of the 30-seconds sit-to-stand test and its capacity for assessment of the functional status of hemodialysis patients. *Journal of Bodywork and Movement Therapies*, *27*, 157–164. https://doi.org/10.1016/j.jbmt.2021.02.020

5 Times Sit to Stand Test (FTSST). (n.d.). APTA. https://www.apta.org/patient-care/evidence-based-practice-resources/test-measures/5-times-sit-to-stand-test-ftsst-

Gill, S. D., de Morton, N. A., & Mc Burney, H. (2012). An investigation of the validity of six measures of physical function in people awaiting joint replacement surgery of the hip or knee. *Clinical Rehabilitation*, *26*(10), 945–951. https://doi.org/10.1177/0269215511434993

Goldberg, A., Chavis, M., Watkins, J., & Wilson, T. (2012). The five-times-sit-to-stand test: validity, reliability and detectable change in older females. *Aging Clinical and Experimental Research*, *24*(4), 339–344. https://doi.org/10.1007/bf03325265

Harris-Kojetin, L., & Sengupta, M. (2018). Falls Among Assisted Living Residents: Results From the 2016 National Study of Long-Term Care Providers. *Innovation in Aging*, *2*(suppl_1), 766–766. https://doi.org/10.1093/geroni/igy023.2833

Hartikainen, S., Lonnroos, E., & Louhivuori, K. (2007). Medication as a Risk Factor for Falls: Critical Systematic Review. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, *62*(10), 1172–1181. https://doi.org/10.1093/gerona/62.10.1172

Hellmers, S., Fudickar, S., Lau, S., Elgert, L., Diekmann, R., Bauer, J., & Hein, A. (2019). Measurement of the Chair Rise Performance of Older People Based on Force Plates and IMUs. *Sensors*, *19*(6), 1370. https://doi.org/10.3390/s19061370

Hockstad, E. (n.d.). *ECG Review 2020 2020 American Heart Association Virtual Cardiac Symposium*. https://www.heart.org/-/media/files/affiliates/mwa/kansas-city/kc-cardiac-and-stroke-symposium/2020-event-documents/cardiac-presentations/2-ecg-hockstad.pdf?la=en

Jin, H., Zhou, Y., Stagg, B. C., & Ehrlich, J. R. (2024). Association between vision impairment and increased prevalence of falls in older US adults. *Journal of the American Geriatrics Society*, *72*(5), 1373–1383. https://doi.org/10.1111/jgs.18879

Jones, C. J., Rikli, R. E., & Beam, W. C. (1999). A 30-s Chair-Stand Test as a Measure of Lower Body Strength in Community-Residing Older Adults. *Research Quarterly for Exercise and Sport*, *70*(2), 113–119. https://doi.org/10.1080/02701367.1999.10608028

José Gonçalves, Batista, J., & Novo, A. (2015). Fully-Automated "Timed Up and Go" and "30-Second Chair Stand" Tests Assessment: A Low Cost Approach Based on Arduino and LabVIEW. *Lecture Notes in Electrical Engineering*, 669–678. https://doi.org/10.1007/978-3-319-10380-8_64

Lee, A. W., & Yeh, H.-J. J. (2022). Real-Time Monitoring of Urine Output with Internet-of-Things Connected Foley Catheters. *2021 International Conference on Computational Science and Computational Intelligence (CSCI)*, 1808–1811. https://doi.org/10.1109/csci58124.2022.00322

Lee, A., Lee, M., & Yeh, H.-J. J. (2023). An IoT-Based Automatic and Continuous Urine Measurement System. *BioMedInformatics*, *3*(2), 446–454. https://doi.org/10.3390/biomedinformatics3020030

Lee, A. W., Lee, M. S., Yeh, D. P., & Yeh, H.-J. J. (2024). Sensor-Integrated Chairs for Lower Body Strength and Endurance Assessment. *Sensors*, *24*(3), 788. https://doi.org/10.3390/s24030788

Marigold, D. S., Eng, J. J., Dawson, A. S., Inglis, J. T., Harris, J. E., & GylfadÃ³ttir, S. (2005). Exercise Leads to Faster Postural Reflexes, Improved Balance and Mobility, and Fewer Falls in Older Persons with Chronic Stroke. *Journal of the American Geriatrics Society*, *53*(3), 416–423. https://doi.org/10.1111/j.1532-5415.2005.53158.x

Millor, N., Lecumberri, P., Gómez, M., Martínez-Ramírez, A., & Izquierdo, M. (2013). An evaluation of the 30-s chair stand test in older adults: frailty detection based on kinematic parameters from a single inertial unit. *Journal of NeuroEngineering and Rehabilitation*, *10*(1), 86. https://doi.org/10.1186/1743-0003-10-86

Muñoz-Bermejo, L., Adsuar, J. C., Mendoza-Muñoz, M., Barrios-Fernández, S., Garcia-Gordillo, M. A., Pérez-Gómez, J., & Carlos-Vivas, J. (2021). Test-Retest Reliability of Five Times Sit to Stand Test (FTSST) in Adults: A Systematic Review and Meta-Analysis. *Biology*, *10*(6). https://doi.org/10.3390/biology10060510

National Institute on Aging. (2022). *Falls and Fractures in Older adults: Causes and Prevention*. National Institute on Aging. https://www.nia.nih.gov/health/falls-and-fractures-older-adults-causes-and-prevention

Riska, K. M., Peskoe, S. B., Kuchibhatla, M., Gordee, A., Pavon, J. M., Kim, S. E., West, J. S., & Smith, S. L. (2021). Impact of Hearing Aid Use on Falls and Falls-Related Injury. *Ear & Hearing*, *43*(2). https://doi.org/10.1097/aud.0000000000001111

Papalia, G. F., Papalia, R., Diaz Balzani, L. A., Torre, G., Zampogna, B., Vasta, S., Fossati, C., Alifano, A. M., & Denaro, V. (2020). The Effects of Physical Exercise on Balance and Prevention of Falls in Older People: A Systematic Review and Meta-Analysis. *Journal of Clinical Medicine*, *9*(8), 1–19. https://doi.org/10.3390/jcm9082595

Riska, K. M., Peskoe, S. B., Kuchibhatla, M., Gordee, A., Pavon, J. M., Kim, S. E., West, J. S., & Smith, S. L. (2021). Impact of Hearing Aid Use on Falls and Falls-Related Injury. *Ear & Hearing*, *43*(2). https://doi.org/10.1097/aud.0000000000001111

Rodrigues, F., Monteiro, A. M., Forte, P., & Morouço, P. (2023). Effects of Muscle Strength, Agility, and Fear of Falling on Risk of Falling in Older Adults. *International Journal of Environmental Research and Public Health*, *20*(6), 4945. https://doi.org/10.3390/ijerph20064945

Takeshima, N., Kohama, T., Kusunoki, M., Fujita, E., Okada, S., Kato, Y., Kofuku, K., Islam, M. M., & Brechue, W. F. (2019). Development of Simple, Objective Chair-Standing Assessment of Physical Function in Older Individuals Using a Kinecttm Sensor. *The Journal of Frailty & Aging*, 1–6. https://doi.org/10.14283/jfa.2019.23

Yeh, C., Lee, A., Dy, H., & Li, K. (2022). *Internet-of-Things Management of Medical Chairs and Wheelchairs*. 183–188. https://doi.org/10.5220/0011059600003194

Yeh, C., Lee, A. W., Lee, M. S., & Li, K. C. (2022). Internet-of-Things Monitoring of Physical Restraint Patients. *2021 International Conference on Computational Science and Computational Intelligence (CSCI)*, 1803–1807. https://doi.org/10.1109/csci58124.2022.00321

Yeh, C., Lee, A., Dy, H., & Li, K. (2022). *Internet-of-Things Management of Medical Chairs and Wheelchairs*. 183–188. https://doi.org/10.5220/0011059600003194

Yeh, C., & Khan, F. H. (2022). *Citizen Science Mobile Apps with Machine Learning for Recyclable Objects*. 1539–1542. https://doi.org/10.1109/csci58124.2022.00273

Yeh, K., Yeh, C., & Li, K. (2021). Internet-of-Things Management of Hospital Beds for Bed-Rest Patients. *Transactions on Computational Science and Computational Intelligence*, 439–448. https://doi.org/10.1007/978-3-030-71051-4_33

Yeh, J. H.-J., Bartholio, C., Shackleton, E., Costello, L., Perera, M., Yeh, K., & Yeh, C. (2020). *Environmentally Embedded Internet-of-Things for Secondary and Higher Education*. 543–547. https://doi.org/10.1109/icict50521.2020.00092

Yeh, H.-J. J., Stambaugh, M., Zahnd, A., & Yeh, K. (2019). IoT Sensing and Control Network for Pico-Hydroelectric in the Nepal Himalayas. *2021 International Conference on Computational Science and Computational Intelligence (CSCI)*, 1184–1189. https://doi.org/10.1109/csci49370.2019.00223