A Falls Risk Screening Tool Based on Millimetre-Wave Radar

Elif Dogu[1][a], Jose A. Paredes[1,2][b], Akram Alomainy[1][c], Janelle M. Jones[3][d] and Khalid Z. Rajab[1][e]

[1] *School of Electronic Engineering and Computer Science, Queen Mary University of London, London E1 4NS, U.K.*

[2] *School of Arts, Humanities and Social Sciences, University of Roehampton, London SW15 5PU, U.K.*

[3] *School of Biological and Behavioural Sciences, Queen Mary University of London, London E1 4NS, U.K.*

Keywords: FMCW, mm-Wave Radar, Health Informatics, Medical Decision Support, Fall Risk Assessment, Timed Up and Go, Gait, Mobility.

Abstract: Falls among the older adults pose a global health concern, necessitating innovative approaches for timely and effective falls risk screening. Aiming to develop a real-time falls risk screening tool, this study explores the integration of millimeter-wave (mmWave) radar technology with the Timed Up and Go (TUG) test, which is a widely used screening tool that combines parameters measuring a person's dynamic balance and functional mobility. Radar technology has emerged as a promising tool for non-intrusive, continuous monitoring of movements – including gait patterns and mobility – in real-life scenarios. By leveraging Frequency Modulated Continuous Wave (FMCW) radar, the study assesses its performance against video recordings in TUG completion time measurement. The completion time, conventionally measured manually with a timer in clinical settings, was derived from radar measurements using two different methods based on distance, and micro-Doppler (i.e. velocity). Results indicate radar's superior accuracy in distance-based measures with 3.48% error and a correlation of 0.9996, surpassing manual timing (4.26% error, 0.9960 correlation) and demonstrating viability for falls risk screening protocols. The velocity-based determination performed slightly poorer (6.49% error, 0.9936 correlation), which is attributable to the very high sensitivity of the radar in detecting small motions, such as shuffling in a chair, that are not a part of the TUG sequence. This study contributes to healthcare technology innovation, emphasising radar's transformative role beyond falls risk assessment. The precision of radar-based measurements opens avenues for enhanced diagnostics, monitoring, and personalised care.

1 INTRODUCTION

A fall is defined as an event which results in a person coming to rest inadvertently on the ground or floor or other lower level (WHO, 2021). Every year, millions of older adults, and their families face the life-altering consequences of falls. The World Health Organization (WHO) reports that falls represent the second leading cause of unintentional injury deaths worldwide (WHO, 2021). These incidents not only have immediate critical impacts such as injury, pain, disability, and increased mortality (NICE, 2013), but they also cast a long shadow of psychological distress leading to fear of falling (Lavedán et al., 2018), reduced daily activity and reduced self-confidence in mobility.

The American Geriatrics Society and the British Geriatrics Society recommend that all adults over the age of 65 should be screened for falls risk at least once a year (Moncada, 2011). However, effective fall risk screening is still underutilised and not routinely integrated into clinical practice (Sun and Sosnoff, 2018). There might be several reasons such as constraints of clinical time and environment.

From a broader perspective, another limitation of current falls risk screening tools is that they only provide a snapshot of the patient's condition at their best, under clinical conditions. The tests are carried out during the working hours of clinicians, when patients are less likely to be affected by factors like hunger, thirst, or fatigue. Meaningful insights into how the

[a] https://orcid.org/0000-0003-4883-3450
[b] https://orcid.org/0000-0002-0412-0179
[c] https://orcid.org/0000-0002-5802-9194
[d] https://orcid.org/0000-0002-0910-2404
[e] https://orcid.org/0000-0003-1337-2965

Dogu, E., Paredes, J., Alomainy, A., Jones, J. and Rajab, K.
A Falls Risk Screening Tool Based on Millimetre-Wave Radar.
DOI: 10.5220/0012618900003699

In *Proceedings of the 10th International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2024)*, pages 161-168
ISBN: 978-989-758-700-9; ISSN: 2184-4984

patient's gait pattern may vary at different times of the day, such as when they wake up in the morning or when they get up at night, remain understudied.In light of the weak association between natural gait speed and in-laboratory gait speed (Takayanagi et al., 2019), integrating technology with established practices can offer a promising avenue for real-time and continuous monitoring beyond clinical confines, in the diverse and dynamic scenarios of everyday life.

In the present research, a millimetre-wave (mmWave) radar was chosen to integrate with the TUG test, to develop a falls risk screening tool, as a digital health technology tool (DHTT) (Taylor et al., 2020).

Radar technology is a promising solution for ambient sensing, as it is minimally intrusive: it does not rely on wearables, nor does it capture camera images or video. It can provide real-time remote monitoring of individuals in a home, allowing for the continuous evaluation of gait (Gambi et al., 2020; Alanazi et al., 2022), mobility patterns, and overall wellbeing (Cardillo et al., 2022). FMCW (Frequency Modulated Continuous Wave) radar captures subtle movements with high precision, making it an effective tool for classifying daily-life activities such as walking, sitting, standing and sleeping (Rajab et al., 2021; Yu et al., 2022). Radars also have the capability to operate through various materials and work in challenging environmental conditions such as adverse weather and low visibility. In homes, the radars provide effective continuous monitoring which enables early detection of deviations from normal mobility patterns.

In this work, we observe the feasibility of integrating radar technology with the TUG test and assess its performance compared to video camera recordings. For this purpose, the paper is organised as follows: in section 2, previous studies implementing new technologies to the TUG test are summarised. Section 3 provides information on the procedures followed while designing the experiments. Section 4 presents the results of the experiments and their analyses. Discussions of the outcomes are provided in Section 5 and the paper is concluded in Section 6.

2 RELATED WORK

The TUG test is widely used in current clinical practice to detect gait and balance impairment. To conduct a TUG test, patients wear their regular shoes, and may use a walking aid if necessary. The setup involves a standard stable chair and a three-meter line in front of it. The patient is instructed as: "When I say 'Go', I want you to stand up from the chair, walk to the line on the floor at a normal pace, turn around, walk back to the chair at a normal pace and sit down again." The timing starts on the word 'Go' and ends when the patient sits back down. The TUG completion time is measured by the clinician manually, using a timer. If a patient's TUG test takes more than 15s, they are identified as being at risk of falling. Therefore, by definition, the TUG test involves 4 parameters: sit-to-stand time, 3m walking time (where the gait speed can be inferred), a 180° turn time, and stand-to-sit time. The TUG test is usually preferred for its simplicity. It has shown to be predictive in lower functioning adults (Beck Jepsen et al., 2022).

The TUG test recently attracted significant attention from researchers. New technologies have been developed to instrument the TUG test in several ways, including wearable sensors, cameras, and ambient sensors.

Greene, Doheny, O'Halloran and Kenny used the TUG test with shank-mounted inertial sensors and developed a regression-based method for the assessment of frailty. The experiments were conducted with 399 community-dwelling older adults (Greene et al., 2014). Using inertial sensor data obtained during the TUG test, the participants were classified as frail or non-frail with mean accuracy of 75.20% (stratified by gender). Spina et al. investigated the parameter of 180-degree turns derived from an instrumented TUG test in stroke patients (Spina et al., 2022). They placed a single inertial measurement unit (IMU) sensor on the lower back of patients. 48 chronic stroke patients and 23 healthy controls were included in the experiment. They reported turning speeds as accurate measures of mobility, capable of discriminating stroke patients with normal and impaired mobility. Fudickar, Hellmers, Lau, Diekmann, Bauer, and Hein introduced an unsupervised screening system for older adults and evaluated its validity for the TUG and Five Times Sit-to-Stand test (Fudickar et al., 2020). The system involved both wearable and ambient movement sensors. The sensor data sets of 91 participants aged 73 to 89 years was compared to conventional measurement with stopwatches. With ambient sensor data, significant correlations of 0.89 and 0.73 were detected for TUG and sit-to-stand, respectively. With wearable sensors, they were reported as 0.78 and 0.87.

Choi, Parker, Knarr, Gwon and Youn proposed a model that predicts the TUG test using three-dimensional acceleration data collected from wearable sensors during normal walking (Choi et al., 2021). They recruited 37 older adults with an average age of 69.6 and used seven IMU-based wearable sensors for the experiments. They obtained better prediction accuracy with two foot sensors. However, they recommended the use of a single IMU sensor at the pelvis for greater comfort. Diao et al. developed an environment-adaptive TUG test with wearable inertial sensors attached to the two shanks (Diao et al., 2021). They conducted the experiment with 103 older adults, reporting an average accuracy 9.52% higher than the conventional TUG in classification of high-risk and low-risk groups for falls. Dierick, Stoffel, Schütz, and Buisseret proposed placing a single wearable IMU sensor on the lower back during the TUG test to enhance the predictive accuracy (Dierick et al., 2022). They recruited 73 nursing home residents for the experiments. They reported 74% accuracy, with a specificity of 95.9% and a sensitivity of 29.2% using the sensor, while the conventional TUG was 64% accurate. Kataoka et al. observed lower-limb kinematics of patients with Locomotive Syndrome (LS), using a TUG test with wearable gait sensors (Kataoka et al., 2023). They recruited 140 patients with an average age of 72.6 in Japan for the experiments. Their sensors consisted of tri-axial acceleration and gyro sensors that were placed on seven lower-limb body segments. Their results showed that the subjects with LS have longer TUG completion time than the subjects with non-LS.

Wearable devices in assessing gait and mobility with the TUG test have yielded promising results. The main concern in these studies was the comfort associated with wearing the sensors. Configurations involving wires or tapes on the body, while suitable for clinical or research environments, may pose challenges in everyday life due to their intrusive nature. Moreover, their practicality is constrained by the factor of limited battery life.

Savoie, Cameron, Kaye, and Scheme proposed the automation of the TUG test using a single conventional video camera (Savoie et al., 2020). They recorded 30 healthy participants with both Microsoft Kinect V2 and a standard video camera while performing two versions of the TUG test with 3-meter and 1.5-meter walking distances. They developed a video-based vTUG system leveraging advanced computer vision techniques. vTUG system yielded the same error as the standard Kinect-based system for all six key transitions points, and average errors of less than 0.15 seconds from a multi-observer hand-labelled ground truth. Li et al. developed a video-based activity classification method to infer the TUG parameters of Parkinson's disease patients (Li et al., 2018). 24 patients were recruited, and their TUG test videos were recorded in semi-controlled environments having different backgrounds. They reported more than 90% on average for the classification of frames.

Cameras, coupled with computer vision technology, have shown good performance with, however their use for continuous monitoring can be limited due to privacy concerns.

Frenken, Brell, Gövercin, Wegel, and Hein used a light barrier, four force sensors, and a laser range scanner built into a single apparatus and proposed the ambient TUG (aTUG) test for gait and balance analysis (Frenken et al., 2013). The experiment was conducted with five older patients in a residential care facility, demonstrating that aTUG could reliably and precisely measure total duration of TUG and durations of the single components with a mean error of only 0.05 seconds and mean standard deviation of 0.59 s. Ayena, Chioukh, Otis, and Deslandes combined the performance of ultra-wideband radar and instrumented insole for an unobtrusive TUG test (Ayena et al., 2021). They conducted 14 tests with a single participant and the results reported the feasibility of the TUG test using a sensor combination. Soubra Mourad-Chehade, and Chkeir proposed the automation of TUG test using Doppler radar system (Soubra et al., 2023). The radar was set into the backrest of the chair used for TUG test. They recruited 26 healthy participants, aged between 22 and 60. The participants performed 3 slow, 3 normal, 3 fast TUG tests as experiments. An infrared camera system was used as the ground truth. The Doppler radar system achieved 4.8% error on the TUG completion time.

Ambient sensors have the potential to deal with the limitations of wearable sensors and cameras. However, the generalisability of previous findings may be constrained by small sample sizes. There is a need for the radar to be validated for TUG test, and other falls screening tools to disseminate their use in various settings.

When all the risk factors are detected, the third step of designing the targeted intervention and control measures begins. This step may include exercise and education programs, modifications in home environment, revision of medications and other actions to eliminate the risk factors one by one from patients' lives.

3 SYSTEM OVERVIEW AND SETUP

Our standard TUG test setup includes a chair with a 3m line as the walking lane, as depicted in Fig. 1.

During the experiments, the radar device is placed at two different locations to observe the variations. In both positions, the height of the radar was 0.5m. In

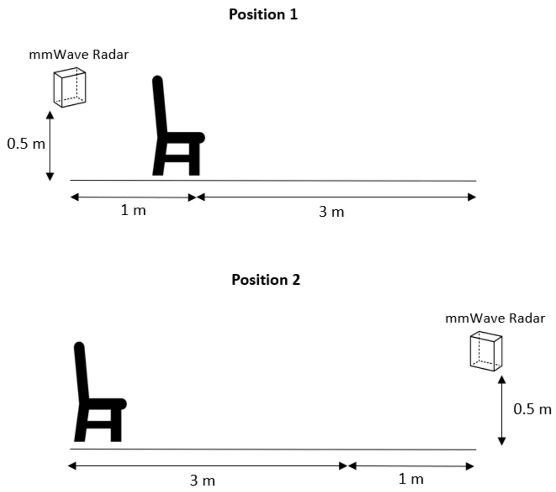

Figure 1: Two positions of the radar for the TUG test.

position 1, the radar was placed 1m behind the chair and in position 2, 4m in front of the chair.

3.1 Radar Data Acquisition

A millimeter-wave (mmWave) radar system emits high-frequency chirp-like signals within the GHz range. Certain configurations incorporate multiple receive (RX) and transmit (TX) antennas, constituting Multiple-Input Multiple-Output (MIMO) radars. These systems present the capability to extract comprehensive information about range, angle (azimuth, elevation) and radial velocity.

The Doppler frequency, which is the difference between emitted and received signals, is measured by the radar as f_{IF} – a.k.a. intermediate frequency –, and the distance r to the object can be expressed as:

$$r = \frac{\mathrm{c}T}{2B} f_{\mathrm{IF}}, \tag{1}$$

where c represents the speed of light, T signifies the emission period, and B denotes the signal bandwidth. For a more comprehensive exposition, please consult (Richards, 2014).

The emission of several signals in a row, what is known as a frame, enables the precise measurement of radial velocities. By emitting a sequence of signals equally spaced in time by T_c, a resultant phase shift $\Delta\varphi$ appears. Then, radial velocity can be computed by:

$$v = \frac{\lambda}{4\pi T_c} \Delta\varphi, \tag{2}$$

where λ is the wavelength of the original emitted signal.

In this work, a Fast Fourier Transform (FFT) is applied over each emitting-receiving antenna pair, in order to obtain the distance r from equation (1). And a Capon beamforming algorithm is used to determine the velocity from equation (2).

The radar utilised in this work was manufactured by NodeNs Medical Ltd (NodeNs Medical Ltd., 2023) and is based on the Texas Instruments IWR6843 chipset. It operates within the unlicensed 60 GHz band. For detailed specifications, its configuration is outlined in Table 1.

Table 1: Radar configuration.

Start Frequency (GHz)	60.6
Slope (MHz/µs)	54.725
Samples per chirp	96
Chirps per frame	288
Frame duration (ms)	50
Sampling Rate (Msps)	2.950
Bandwidth (MHz)	2249
Range Resolution (m)	0.084
Velocity resolution (m/s)	0.17
Number of Rx antennas	4
Number of Tx antennas	3

4 EXPERIMENTS AND RESULTS

4.1 Data Collection Protocols

Two participants are recruited to repeat the TUG test at three different speeds (normal, fast, slow) for two different positions of the sensor (Positions 1 and 2), which resulted in 12 experiments in total (see Table 2). The TUG test procedure explained in the section 2 is applied. The TUG completion time is obtained manually using a timer, as this is the clinical standard (Time-Manual column of Table 2). The experiments were recorded on camera to obtain the ground truth, which was defined as the TUG completion time gathered from the video (Time-Video column of Table 2). The ground truth was calculated by determining the total number of frames captured during the movement, and the video frame rate was set at 30 frames per second (fps). To assess the radar implementation to the TUG test, the completion time is also inferred from the radar signals with two different methods, using velocity (micro-Doppler signatures) and distance measures.

4.2 Distance-Based Proposal Analysis

The distance graph presents data on the temporal variation of the distance between the subject and the

Table 2: Experiments. 'Time-Video*' shows the ground truth of the TUG completion time gathered from video recordings, 'Time-Manual' shows the version measured manually as in clinical practice, 'Time-Doppler' shows the results of velocity-based analysis and 'Time-Distance' shows the results of distance-based analysis.

Experiment	Participant	Position	TUG Test	Time-Video* (s)	Time-Manual (s)	Time-Doppler (s)	Time-Distance (s)
1	1	2	Normal	11.6	11	11.88	11.83
2	1	2	Fast	8.6	8	9.68	9.08
3	1	2	Slow	17.5	18	18.48	17.88
4	2	2	Normal	10.4	11	10.56	10.73
5	2	2	Fast	6.6	7	6.60	6.88
6	2	2	Slow	14.5	15	14.96	14.85
7	1	1	Normal	9.6	9	11.88	9.90
8	1	1	Fast	7.5	7	8.36	7.98
9	1	1	Slow	22.3	22	23.32	22.00
10	2	1	Normal	10.4	10	11.00	10.73
11	2	1	Fast	7.9	8	8.36	8.53
12	2	1	Slow	21.3	21	21.56	21.18

radar. For example, Figure 2 provides the distance graphs of the experiments 4,5 and 6. These are normal, fast and slow versions of the TUG test with the radar placed at the front. During these tests, the distance initially decreases as the subject walks towards the sensor, and then increases when the subject returns to the chair. The variations of the tests can be observed from the kurtosis of their curves. While the fast TUG test has a more pointed structure, the slow TUG test has the widest curve.

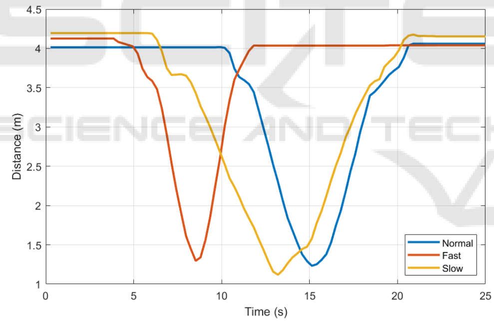

Figure 2: Distance graphs of experiments 4 (normal), 5 (fast) and 6 (slow).

When the radar position changes, it is expected that the curve gets mirrored for the distance measure. Figure 3 depicts the distance graphs of experiments 6 and 12, which are slow TUG tests from different positions. The slow version of the tests are selected here as examples, for a better distinction of boundaries. In both distance plots, instead of a perfectly smooth curve, small curve variations are observed at the beginning and end. These represent the movements of getting up and sitting down at the beginning and end of the TUG test. This is attributable to the inclination of the body leaning forward when rising from the chair, and conversely, a backward lean when seated. These movements change the distance to the sensor, but more slowly than the walking movement. Hence, different slopes are observed at the beginning and end of the curve.

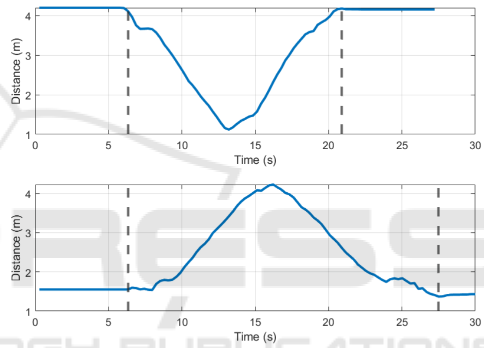

Figure 3: Distance graphs of experiments 6 (top) and 12 (bottom), corresponding to positions 2 (radar in front) and 1 (radar behind) respectively.

The TUG completion time is inferred from the distance parameter by determining start and end points of the curve, as depicted with dashed lines in Figure 3. The results for all experiments are provided in the Time-Distance column of Table 2.

4.3 Velocity-Based Proposal Analysis

The micro-Doppler effect captures the subtle movements and rotations of body segments, providing distinct signatures for different activities. Figure 4 depicts the micro-Doppler signatures of the experiments 6 and 12, with the axes of velocity (m/s) vs time. It is observed that the TUG test results in a characteristic S-shaped micro-Doppler curve, which is due to the subject walking away from the radar (positive velocities), turning (approximately zero velocity) and then walking back to the radar (negative velocities). The S-shape can be reversed based on the position of the sensor. The action of sitting and standing also result in

Doppler responses. Similarly to the distance graphs, the test boundaries can be easily detected. We note that the micro-Doppler signatures are more prominent when the radar is in front of the chair than when it is behind (experiment 6 compared to experiment 12), which is likely due to the chair obstructing the radar signal. This can be mitigated against by increasing the height of the radar. Nevertheless, test boundary timings can still clearly be detected.

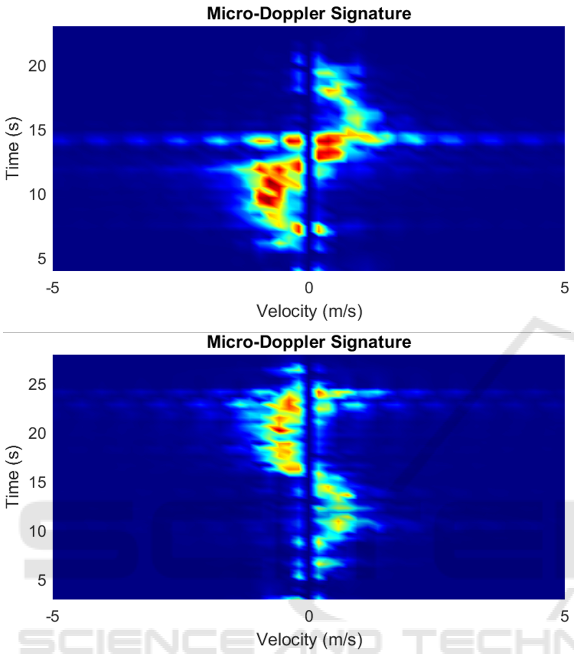

Figure 4: Micro-Doppler signatures of experiments 6 and 12.

Using the micro-Doppler signature, the time between the start and end of the movement is calculated. The results for all experiments are provided in Time-Doppler column of Table 2.

4.4 Performance Evaluation

The TUG completion time gathered from the video recording is selected as the ground truth, as the video provides the most accurate timings through frame-by-frame analysis to identify precise activity time segments. The TUG completion times measured manually and inferred from radar data with two different methods are compared to the ground truth. For the evaluation, root mean square error (RMSE), mean absolute error (MAE), mean absolute percent error (MAPE) and correlation coefficient are calculated. Table 3 provides the performance evaluation measures.

Current clinical practice uses manual timing of the TUG test. It is important to recognise that manual timing does not guarantee 100% accuracy, and so we use camera recordings to measure our ground truth. Nonetheless, consultations with healthcare professionals have indicated a permissible margin of error of 10% in timing, and clinicians have expressed a preference for manual timing due to its simplicity and cost-effectiveness.

Table 3: Performance evaluation measures.

Pe.Measure	Manual	Micro-Doppler	Distance
RMSE	0.4743	0.9156	0.3695
MAE	0.4500	0.7033	0.3479
MAPE	4.26%	6.49%	3.48%
Correlation	0.9960	0.9936	0.9996

Based on the outcomes, the TUG completion time deduced from the distance measurement of radar signals demonstrated superior performance compared to manual timing. The TUG completion time inferred from the micro-Doppler signature exhibited slightly poorer performance. Nevertheless, it is noteworthy that all measures yielded an error of less than 10%.

5 DISCUSSIONS

There might be several underlying reasons for the difference in performance of the two radar measures. To observe the influence of the sensor's position on the results, the differences from the ground truth (the errors) are calculated for manual, micro-Doppler and distance timings. The mean of the errors are compared for two different positions of the radar. There was no significant difference between the mean errors from the two positions for any of the methods. Therefore, the superior performance of distance-based analysis over velocity-based analysis is not contingent on the sensor's position. From closer inspection of the results in Table 2 it is evident that the velocity-based (Time-Doppler) measurements consistently overestimate the duration of the TUG sequence. This can be explained by the sensitivity of the radar in detecting small movements, such as moving around in a chair, which might occur just before the motion of standing up. The inclusion of these additional movements therefore increases the detected sequence duration.

While the TUG completion times inferred from the micro-Doppler signature exhibit less accuracy than the ones from the distance measure, the performance of both methods remains acceptable to healthcare professionals. The distance measure yielded an even better performance than the manual timing. The outcomes of the first experiments are promising for the implementation of radar as a falls risk screening tool. Furthermore, the sensitivity of the micro-Doppler measurements will be combined, in a future study, with the distance measurements for automatic boundary detection, to more precisely determine the TUG sequence activity boundaries and duration.

Despite the promising outcomes, certain limitations should be acknowledged that provide insights into the boundaries of our study and contribute to a nuanced understanding of the findings. The participants of this study are not older adults and they have no known gait or balance problems. The inherent differences in walking patterns between young individuals and older adults with gait and balance problems may introduce variations not explicitly addressed in this study.

The experiments were performed in a cluttered environment – an office space with multiple desks and moving occupants – which shows the robustness of the technique to environmental noise and movements. Nevertheless, the TUG test's actions were controlled, which would not reflect the complexities of natural movements during daily activities. Additionally, the sample size in our study was limited to only two participants, which may constrain the broader applicability of our results. A larger and more diverse participant pool could provide a better understanding of the effectiveness and reliability of the radar-based timing of TUG test across various demographic groups and conditions.

6 CONCLUSIONS

This study was designed to observe the innovative application of radar technology in conjunction with the TUG test as a means of falls risk screening. To develop a real-time falls risk screening tool, we explored the ways to automate the process of capturing the TUG completion time through non-intrusive ambient sensing.

The TUG completion time inferred from the distance measurements of radar has achieved a level of accuracy surpassing that of manual timing. Although micro-Doppler timings were less accurate than distance, due to the radar's high sensitivity in detecting small movements, both techniques had sufficient performance to satisfy the requirements set by healthcare professionals. This suggests a viable and effective incorporation of radar technology into falls risk screening protocols.

The results of this study not only underscore the feasibility of integrating radar technology into falls risk screening but also highlights the importance of continuous innovation in healthcare technology. The superior performance of radar-based measurements hints at the transformative role this technology can play in healthcare. The implementation of radar as a falls risk screening tool represents just one facet of its potential application. The ability to capture movements and timings with precision, without interfering with privacy, opens avenues for enhanced diagnostics, monitoring, and personalised care.

A noteworthy finding emerged from this study by examining the impact of environmental clutter on measurement outcomes. The over-estimation of TUG sequence duration by the velocity-based (micro-Doppler) technique, due to the high sensitivity of the radar, highlights a potential area for refinement. Future research endeavours could expand its assessment of radar placement, or encompass use of multiple radars to measure gait and posture. Another possibility is to expand the participant pool to include individuals with varying levels of mobility and balance challenges. Finally, future research could also explore a more generalised model of subjects' activities than the TUG test, so that a radar-based falls risk assessment may more adaptively fit continuous measurement during day-to-day living.

ACKNOWLEDGEMENTS

This work was supported by the UK Engineering and Physical Sciences Research Council (EPSRC) grant EP/W03199X/1, "Smart sensors for a wearable-free and contactless virtual ward at home".

REFERENCES

Alanazi, M., Alhazmi, A., Alsattam, O., Gnau, K., Brown, M., Thiel, S., Jackson, K., and Chodavarapu, V. (2022). Towards a low-cost solution for gait analysis using millimeter wave sensor and machine learning. *Sensors*, 22(5470).

Ayena, J., Chioukh, L., Otis, M., and Deslandes, D. (2021). Risk of Falling in a Timed Up and Go Test Using an UWB Radar and an Instrumented Insole. *Sensors*, 21(3).

Beck Jepsen, D., Robinson, K., Ogliari, G., Montero-Odasso, M., Kamkar, N., Ryg, J., Freiberger, E., and Masud, T. (2022). Predicting falls in older adults: an umbrella review of instruments assessing gait, balance, and functional mobility. *BMC Geriatrics*, 22(1):615.

Cardillo, E., Li, C., and Caddemi, A. (2022). Millimeter-wave radar cane: A blind people aid with moving human recognition capabilities. *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, 6(2):204–211.

Choi, J., Parker, S. M., Knarr, B. A., Gwon, Y., and Youn, J.-H. (2021). Wearable Sensor-Based Prediction Model of Timed up and Go Test in Older Adults. *Sensors*, 21(20):6831. Number: 20 Publisher: Multidisciplinary Digital Publishing Institute.

Diao, Y., Lou, N., Liang, S., Zhang, Y., Ning, Y., Li, G., and Zhao, G. (2021). A Novel Environment-Adaptive Timed Up and Go Test System for Fall Risk Assessment With Wearable Inertial Sensors. *IEEE Sensors Journal*, 21(16):18287–18297.

Dierick, F., Stoffel, P., Schütz, G., and Buisseret, F. (2022). High Specificity of Single Inertial Sensor-Supplemented Timed Up and Go Test for Assessing Fall Risk in Elderly Nursing Home Residents. *Sensors*, 22(6).

Frenken, T., Brell, M., Gövercin, M., Wegel, S., and Hein, A. (2013). aTUG: technical apparatus for gait and balance analysis within component-based Timed Up & Go using mutual ambient sensors. *Journal of Ambient Intelligence and Humanized Computing*, 4(6):759–778.

Fudickar, S., Hellmers, S., Lau, S., Diekmann, R., Bauer, J., and Hein, A. (2020). Measurement System for Unsupervised Standardized Assessment of Timed "Up & Go" and Five Times Sit to Stand Test in the Community-A Validity Study. *Sensors*, 20(10).

Gambi, E., Ciattaglia, G., Santis, A. D., and Senigagliesi, L. (2020). Millimeter wave radar data of people walking. *Data in Brief*, 31(105996).

Greene, B., Doheny, E., O'Halloran, A., and Kenny, R. (2014). Frailty status can be accurately assessed using inertial sensors and the TUG test. *Age and Ageing*, 43(3):406–411.

Kataoka, Y., Saito, Y., Takeda, R., Ishida, T., Tadano, S., Suzuki, T., Nakamura, K., Nakata, A., Osuka, S., Yamada, S., Samukawa, M., and Tohyama, H. (2023). Evaluation of Lower-Limb Kinematics during Timed Up and Go (TUG) Test in Subjects with Locomotive Syndrome (LS) Using Wearable Gait Sensors (H-Gait System). *Sensors*, 23(2).

Lavedán, A., Viladrosa, M., Jürschik, P., Botigué, T., Nuín, C., Masot, O., and Lavedán, R. (2018). Fear of falling in community-dwelling older adults: A cause of falls, a consequence, or both? *PLoS one*, 13(3):e0194967.

Li, T., Chen, J., Hu, C., Ma, Y., Wu, Z., Wan, W., Huang, Y., Jia, F., Gong, C., Wan, S., and Li, L. (2018). Automatic Timed Up-and-Go Sub-Task Segmentation for Parkinson's Disease Patients Using Video-Based Activity Classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 26(11):2189–2199.

Moncada, L. V. V. (2011). Management of Falls in Older Persons: A Prescription for Prevention. *American Family Physician*, 84(11):1267–1276.

NICE (2013). National Institute for Health and Care Excellence. Falls in older people: assessing risk and prevention. Clinical guideline [CG161]. Technical report, NICE.

NodeNs Medical Ltd. (2023). Millimetre Wave Radar. https://nodens.eu.

Rajab, K. Z., Wu, B., Alizadeh, P., and Alomainy, A. (2021). Multi-target tracking and activity classification with millimeter-wave radar. *Applied Physics Letters*, 119(3):034101.

Richards, M. A. (2014). *Fundamentals of Radar Signal Processing*. McGraw-Hill Education, New York, 2nd edition edition.

Savoie, P., Cameron, J. A. D., Kaye, M. E., and Scheme, E. J. (2020). Automation of the Timed-Up-and-Go Test Using a Conventional Video Camera. *IEEE Journal of Biomedical and Health Informatics*, 24(4):1196–1205. Conference Name: IEEE Journal of Biomedical and Health Informatics.

Soubra, R., Mourad-Chehade, F., and Chkeir, A. (2023). Automation of the Timed Up and Go Test Using a Doppler Radar System for Gait and Balance Analysis in Elderly People. *Journal of Healthcare Engineering*, 2023:e2016262. Publisher: Hindawi.

Spina, S., Facciorusso, S., D'ascanio, M. C., Morone, G., Baricich, A., Fiore, P., and Sandamato, A. (2022). Sensor based assessment of turning during instrumented Timed Up and Go Test for quantifying mobility in chronic stroke patients. *European Journal of Physical and Rehabilitation Medicine*, 59(1):6–13.

Sun, R. and Sosnoff, J. J. (2018). Novel sensing technology in fall risk assessment in older adults: a systematic review. *BMC Geriatrics*, 18(1):14.

Takayanagi, N., Sudo, M., Yamashiro, Y., Lee, S., Kobayashi, Y., Niki, Y., and Shimada, H. (2019). Relationship between Daily and In-laboratory Gait Speed among Healthy Community-dwelling Older Adults. *Scientific Reports*, 9(1):3496. Number: 1 Publisher: Nature Publishing Group.

Taylor, K. I., Staunton, H., Lipsmeier, F., Nobbs, D., and Lindemann, M. (2020). Outcome measures based on digital health technology sensor data: data- and patient-centric approaches. *npj Digital Medicine*, 3(1):1–8. Number: 1 Publisher: Nature Publishing Group.

WHO (2021). World Health Organization fact sheet on falls providing key facts and information on scope of the problem, who is at risk, prevention, who response. Falls, https://www.who.int/news-room/fact-sheets/detail/falls.

Yu, Z., Taha, A., Taylor, W., Zahid, A., Rajab, K., Heidari, H., Imran, M. A., and Abbasi, Q. H. (2022). A Radar-Based Human Activity Recognition Using a Novel 3-D Point Cloud Classifier. *IEEE Sensors Journal*, 22(19):18218–18227.