

# Validity and reliability of an android device for the assessment of fall risk in older adult inmates

Enrique J. Vera-Remartínez<sup>1</sup> | Rocío Lázaro-Monge<sup>1</sup> | Sofía V. Casado-Hoces<sup>2</sup> |  
Elena Garcés-Pina<sup>3</sup> | María Pilar Molés-Julio<sup>4</sup> 

<sup>1</sup>Penitentiary Center of Castelló I, Castelló, Spain

<sup>2</sup>Penitentiary Center of Madrid III, Madrid, Spain

<sup>3</sup>Penitentiary Center of Zuera, Zaragoza, Spain

<sup>4</sup>Predemartmental Unit of Nursing, Universitat Jaume I, Castelló, Spain

## Correspondence

María Pilar Molés-Julio, Predemartmental Unit of Nursing, Universitat Jaume I, Avda. de Vicent Sos Baynat s/n, 12071 Castelló, España.

Email: [mjulio@uji.es](mailto:mjulio@uji.es)

## Abstract

**Aim:** To validate the Android device, FallSkip, as a tool to assess the fallers in older adult inmates.

**Design:** A cross-sectional descriptive and analytical study.

**Methods:** For the validation of the FallSkip, the diagnostic criterion used was the risk of having suffered a fall during the last year.

**Results:** The results for the FallSkip tool were as follows: sensitivity 60.7%; specificity 83.0%; positive predictive value 65.4%; negative predictive value 80.0%; accuracy 75.3%. In total, 32.1% of participants were found to be at high risk of falls, 23.5% were at mild risk and 7.4% were found to have no risk.

**Conclusion:** The FallSkip device is shown to be a very suitable tool for fall risk assessment. The sample studied presented a statistically significant percentage of fall risk, which made it necessary to carry out interventions through physical activities to improve balance and stability.

## KEYWORDS

falls, older person, prisons, validation study

## 1 | INTRODUCTION

Falls in the elderly are a major public health issue due because of all the consequences that can result from them. Over 30% of individuals aged over 65 fall at least once each year, with rates increasing to 35% and 50% for those over 75 and 80 years of age, respectively (Petronila Gómez et al., 2017).

Falls generate concern in those affected which can exacerbate fragility, leading to a loss of physical, cognitive and functional capacity that can result in reduced quality of life (Hernandez-Martínez & Ramirez-Campillo, 2017).

There are increasing numbers of older adults within the prison population. These individuals have special characteristics that make them more vulnerable as compared to the general population. It

appears that the onset of ageing-related health conditions occurs earlier in the prison population as compared to other groups (Greene et al., 2018). This situation can thus lead to geriatric emergencies that must be resolved. Many of these involve functional deterioration as a consequence of recent falls, as described by Humphreys et al. (2018). This same study reported that emergency services were required in 43% of falls occurring in prison, vs. 24% that did not require emergency assistance.

## 2 | BACKGROUND

The Spanish population is ageing, as the nation has a decreasing birth rate and an increasing share of the population is aged over 65.

This is an open access article under the terms of the [Creative Commons Attribution-NonCommercial-NoDerivs](https://creativecommons.org/licenses/by-nc-nd/4.0/) License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

© 2022 The Authors. *Nursing Open* published by John Wiley & Sons Ltd.

By 2050, 36.7% of Spanish inhabitants will be older people, making it one of the oldest populations in the world (Mejías Arriaza et al., 2019).

Falls are an indicator of frailty. Multiple factors are involved in the occurrence of falls, including chronic diseases, age, cognitive impairment, visual disturbances, the use of medication and extrinsic environmental factors such as poor lighting, rugs and uneven floors (Petronila Gómez et al., 2017). It is essential that fall risk assessment tools are reliable and comfortable to use for both the patient and the professional (Herrera Ligeró et al., 2021). At the same time, they must be simple for a rapid evaluation of the fallers. This will allow professionals to establish the appropriate interventions at the right time, since falls have psychological, social, physical and economic consequences that affect quality of life of the older person (Bloch, 2021).

The number of older inmates in prisons is increasing. The profile of these people corresponds to that of people who look 10 to 12 years older than their natural years. It implies a faster ageing than that of people at liberty. This is due to a possible history of consumption of toxic substances, the stress produced by the stay in prison or the presence of psychiatric pathologies.

Older persons who enter prison, they do not promote initiatives, nor do they tend to participate in general activities. They are people who go unnoticed and are not usually associated with conflicts or fights (Sánchez Prieto & de Quirós y Lomas, 2016).

These are people who usually have a high number of chronic diseases such as hypertension, diabetes, metabolic syndrome and, to a lesser extent, other infectious diseases such as hepatitis C or HIV (Vera-Remartínez, 2016).

The experience of ageing in prison conditions is an acceleration of the physical and cognitive deterioration of these people.

There are instruments in clinical practice that can be used to assess the fallers, including the Timed Up and Go (TUG) test (Richardson, 1991) and the Short Physical Performance Battery (SPPB) (Guralnik et al., 1994).

Technology is evolving, and the tools that we have at our disposal can assist for health professionals, as these tools allow for a quicker and more accurate assessment of patients (Brown et al., 2013).

Several applications are already available on the market to assess the fallers and can include inertial sensors, videos, pressure platforms and laser sensors (Sun & Sosnoff, 2018). Of these, inertial sensors are the most practical and widely used tool. Usually, a sensor is placed on the lumbar area to measure and record the movement of the centre of mass, as occurs in the case of the FallSkip tool.

The FallSkip Android device for fall risk assessment (Serra Añó et al., 2020). Such mobile applications should be validated prior to their use in the health sector (Tavares et al., 2020).

#### Research question:

*P (Problem or population):* Prison population over 65 years of age.

*I (Intervention):* Fall risk assessment.

*C (Comparison):* With other conventional tests that assess fall risk such as the TUG and SPPB.

*O (Outcome):* The FallSkip tool provides a better assessment of fall risk (in terms of test accuracy) than the TUG and SPPB.

Does the FallSkip tool provide a better assessment of fall risk than the TUG and SPPB tests in the prison population over 65 years of age?

The aim of this study is to validate the FallSkip as a tool for the assessment of falls risk in older inmates and to compare it with other common tests used to assess falls risk in the same sample, such as the Timed up and go (TUG) and Short Physical Performance Battery (SPPB).

## 3 | THE STUDY

### 3.1 | Design

Observational, analytical, cross-sectional, multicentre study to evaluate the diagnostic validity of the FallSkip application.

### 3.2 | Scope

This study was conducted between December 2020 and March 2021 in a prison population over 65 years of age residing in four Spanish prisons (Madrid III Penitentiary Center; Zuera Penitentiary Center; Picassent Penitentiary Center; and Castelló I Penitentiary Center). All inmates aged 65 years or older were invited to participate.

### 3.3 | Study participants

#### Inclusion criteria

- Age 65 years or older.
- Willingness to give written informed consent.
- Not presenting with any of the exclusion criteria.

#### Exclusion criteria

- Unable to give consent.
- Significant ambulation issues: wheelchair use.
- Cognitive impairment score of three or greater on the Pfeiffer test.
- Being under the influence of alcohol, drugs or psychotropic medication.

### 3.4 | Sample size calculation

There are no references on the sensitivity of FallSkip in the scientific literature.

Regarding other tests, such as get up and walk, some studies report a sensitivity of 0.65 (50/77) and a specificity of 0.52 (88/163) (Martínez Carrasco, 2015).

To calculate the sample size, we used the EPIDAT v4.2 software.

Depending on the accuracy for diagnostic tests and for an expected sensitivity of 65% and specificity around 75%, with a confidence level of 95%, we find that for accuracy between 13–14%, the sample ranges between 82–95 subjects.

With tighter precisions, we need a larger sample size, so we decide to lose being able to obtain an adequate and feasible sample. Since it is a population older than 65 years and, in this environment, it is difficult to obtain large samples.

### 3.5 | Method

Once selected, all participants signed an informed consent form to participate. Once consent was given, they were interviewed, who collected sociodemographic data (age, sex of the participants). Anthropometric variables (weight, height, body mass index). Hearing or visual limitations, and having fallen during the last year.

The aim of this study was to assess the risk of falls in inmates aged 65 years or older. We considered as a diagnostic test having suffered a fall during the last year, obtaining this information from the interview with the subject and from the clinical history. We define a fall as: “that involuntary event that causes the body to lose its balance and hit the ground or another firm surface that stops it”.

The Pfeifer test to assess cognitive status and the Charlson test for comorbidity of the subjects were also evaluated.

Once interviewed, they went on to perform a battery of balance and stability tests. The tests were always carried out in the same order and with enough time in case any person got tired.

The tests were carried out by four different observers who were adequately informed about how to perform them and used the same tools (which were sent by courier to each centre). This was due to limited access to the different centres because of the preventive measures against the COVID-19 pandemic during the fieldwork period.

The tests were carried out successively, starting with the classic Timed Up and Go (TUG) test. In this test, the time taken for a patient to get up from a chair after a verbal order from the evaluator, walk to a mark located 3 m away and return to the starting position by sitting down again was measured. Timing stopped when the patient's bottom met the seat. Scores of less than 10 s were considered normal, while those between 11 and 13 s were considered to be indicative of mild disability, and scores greater than 13 s were considered to reflect a high risk of falls (Richardson, 1991).

The Short Physical Performance Battery (SPPB), which is a slightly more complete test, was then applied. This test consists of 3 individual tests to assess balance, gait speed and chair stands. In the balance test, participants attempted to maintain 3 positions for 10 s each: feet together, a semi-tandem stance and a tandem stance. These subtests followed a hierarchical sequence. In the gait speed test, participants walked at their usual pace for 4 m. This test was performed twice, and the shortest time was recorded. Finally, in the

chair stand test, the participants rose and sat down in a chair 5 times as quickly as possible, and the total time taken was recorded. Each test was scored from 0 (worst performance) to 4 (best performance). For the balance test, scoring occurred according to a hierarchical combination of performance in the 3 subtests, while for the other 2 tests a score of 0 was assigned to those who did not attempt or complete the task and scores of 1 to 4 were given based on the time taken, as reflected in the SPPB test. In addition, a total score was calculated for the entire battery, comprising the sum of the scores of the three tests. This ranged from 0 to 12 points (Guralnik et al., 1994).

Thirdly, the FallSkip test was performed. This test consists of the application of an Android-based device to the lumbar area to record the accelerations generated by the movement of the patient throughout the test. Using the measured accelerations, the system performs segmentation of the test phases and parametrization to allow the biomechanical variables associated with fall risk to be calculated. Measurements were taken during 4 consecutive phases: standing, walking, sitting-rising and walking again in the opposite direction until the initial position was reached (Medina Ripoll et al., 2017). At the end of the exercise, the device automatically provided a percentage, allowing the classification of fall risk as being very low (80%–100%), low (60%–80%), moderate (40%–60%), high (20%–40%) or very high (<20%).

Where the percentages refer to the degree of normality of each of the variables as compared to the database. The database belongs to the manufacturer of the device.

- Balance: Categorized as very low, low, moderate, high, high or very high. This is measured by analysing the displacements of the centre of mass during the standing phase.
- Gait: Categorized as very low, low, moderate, high, high or very high. This is assessed by analysing the displacement of the centre of mass and the execution time of the gait phase.
- Muscle strength in lower limbs: Categorized as very low, low, moderate, high, high or very high. This is measured by analysing the power used to perform the movement.
- Assessment of the reaction time to a sound stimulus in the transition between the first and second phase of the test.

We completed the study by assessing the comorbidities of the patients using a validated questionnaire to determine the Charlson Comorbidity Index (Charlson et al., 1987).

#### 3.5.1 | Analysis

A descriptive analysis of the sample was carried out. For the quantitative variables, the Kolmogorov–Smirnov test for normality was applied. Those variables that followed a normal distribution were expressed as their means with the corresponding 95% confidence intervals. Those that were not normally distributed were expressed as the median (50th percentile) with the corresponding interquartile

range (distance between the 25th and 75th percentiles). Qualitative or categorical variables were expressed as absolute and relative frequencies.

For any diagnostic test, validity and reliability must be assessed.

VALIDITY is the degree to which a test measures what it is intended to measure. This is determined by assessing the sensitivity and specificity of the test, which are aspects which do not depend on prevalence.

Sensitivity refers to the test's ability to detect ill patients. It can be defined as the proportion of ill patients who test positive in relation to the total number of patients with the disease. When the obtained data are classified (as per Table 1), sensitivity can be calculated using the following formula:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

Specificity refers to the test's ability to detect healthy individuals. It can be defined as the proportion of healthy patients who test negative in relation to all healthy patients. In accordance with Table 1,

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Reliability refers to the consistency with which the test which will predict the presence or absence of the disease. That is, what is the probability that a positive result will indicate the presence of the disease? Conversely, given a negative test result, what is the probability that this will indicate the absence of disease? Reliability is determined based on positive predictive values (PPV) and negative predictive values (NPV). These are related to the prevalence of the disease.

The positive predictive value is the probability of suffering from a disease when a positive value is obtained in the test. This can be determined using the proportion of patients who test positive and those who are ultimately ill. As per Table 1,

$$\text{PPV} = \frac{TP}{TP + FP}$$

The negative predictive value is the probability that an individual with a negative test result is truly healthy. This can be determined in accordance with as follows,

$$\text{NPV} = \frac{TN}{FN + TN}$$

Predictive values are very useful for making clinical decisions and communicating diagnostic information to patients. However, one limitation is that they depend to a great extent on the frequency of the disease in question in the population under study. When the prevalence of the disease is low, a negative result will make it possible to rule out the disease with greater confidence, and thus the negative predictive value is greater. On the contrary, a positive result will not allow confirmation of the diagnosis, resulting in a low positive predictive value.

To avoid the influence generated by the prevalence of the disease, indices known as likelihood ratios or odd ratios are used. These measure how much more likely a specific positive or negative result is according to the presence or absence of disease.

The positive likelihood ratio is the probability of a positive result in ill individuals divided by the probability of a positive result in healthy individuals. It is therefore the quotient between the fraction of true positives (sensitivity) and the fraction of false positives (1-specificity).

$$\text{Likelihood ratio (+)} = \frac{\text{Sensitivity}}{(1 - \text{Specificity})}$$

The negative likelihood ratio is the probability of a negative result in the presence of disease divided by the probability of a negative result in the absence of disease. It is therefore calculated as the quotient between the fraction of false negatives (1-sensitivity) and the fraction of true negatives (specificity).

$$\text{Likelihood ratio (-)} = \frac{(1 - \text{Sensitivity})}{\text{Specificity}}$$

Finally, other indicators include:

The percentage of false positives, which is the probability that the test will be positive (T+) among patients who do not have the characteristic (E-).

The percentage of false negatives, which is the probability that the test will be negative (T-) among patients with the characteristic (E+).

$$\text{PFP} = P(T+ | E-) \text{ and } \text{PFN} = P(T- | E+).$$

Test accuracy, which is the probability that the test will classify correctly:

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FN + TN)}$$

Test results	Gold standard	
	Falls	No falls
Positive (high risk of falls)	TP True Positives	FP False Positives
Negative (no or low risk of falls)	FN False Negatives	TN True Negatives

TABLE 1 Relationship between the occurrence of falls in the past year and the results of fall risk assessment measures

### 3.6 | Ethics

This preliminary study is part of a larger intervention project aimed at reducing the risk of falls in people over 65 years of age, for which authorization was requested from the General Sub-Directorate of Institutional Relations and Territorial Coordination based on Instruction 12/2019. Data confidentiality was guaranteed according to Organic Law 3/2018, of December 5, on the Protection of Personal Data and Guarantee of Digital Rights as well as General Data Protection Regulation (EU) 2016/679 (GDPR).

The project was approved by the Deontological Commission of Jaume I University (registration number CD/46/2020).

The participants were informed prior to the study and signed an authorized consent form which was saved in their electronic medical records.

## 4 | RESULTS

All inmates over 65 years of age from four prisons were invited to participate. Only one person refused to participate, and four were excluded due to mobility issues (use of wheelchairs). The sample thus consisted of 81 inmates.

Sociodemographic and anthropometric data, information on the prevalence of limitations (occurrence of falls in the past year and

visual/hearing alterations), and comorbidity indices are indicated in [Appendix A](#).

The three consecutive tests were performed on the entire sample. The results of the Timed Up and Go (TUG) test show how according to the test, one in six subjects was at high risk of falls ([Table 2](#)).

The results for the Short Physical Performance Battery (SPPB), which consists of a set of several tests (as described in the [Section 3.5](#)), showed that one in seven subjects presented with limitations in movement ranging between moderate and severe, with a consequent risk of falls ([Table 2](#)).

Finally, the test with the Android-based FallSkip device identified a greater number of persons as being at fallers than the earlier tests.

Nearly one in three subjects presented with a high risk of falls, with a slightly higher figure obtained for those at moderate risk ([Table 2](#)).

The fall prevalence in the study sample was 34.6% (95 CI: 24.2–44.9).

After analysing the validity of all the tests, we found the FallSkip test had higher validity as compared to the SPPB and TUG, as can be seen from the described indices ([Table 3](#)). The value obtained for sensitivity, that is, the ability to detect individuals at fallers without error, was 60.7% (95% CI 42.2–67.4), as compared to 21.4% (95% CI 10.2–39.5) for the SPPB and 17.9% (95% CI 7.9–35.6) for the TUG test. This is probably one of the most important indices, as it allows us to determine the likelihood of falls in those people who are most at risk.

Even higher values were found for specificity (around 83–89% depending on the test), indicating the ability to detect those individuals not at risk of falls without error.

Reliability is about ensuring that the test will predict the presence or absence of fall risk in terms of probability. The FallSkip test presented higher positive predictive value percentages than the other tests at 65.4% (95% CI 46.2–80.6), as compared to 50.0% (95% CI: 25.4–74.6) for the SPPB and 38.5% (95% CI: 17.7–64.5) for the TUG test.

We must also highlight the rates with which the tests misclassified patients. Regarding the classification of individuals as being at

**TABLE 2** Classification of fall risk according to different test

	TUG	SPPB	FALLSKIP
Normal	49 (60.5%)	19 (23.5%)	14 (17.3%)
Slight	19 (23.5%)	50 (61.7%)	26 (32.1%)
Moderate		7 (8.6%)	26 (32.1%)
High	13 (16.0%)	5 (6.2%)	15 (18.5%)

Note: TUG test does not have a moderate category.

Abbreviations: TUG, Test Timed Up and Go; SPPB, Short Physical Performance Battery.

**TABLE 3** Diagnostic tests to assess fall risk

	FallSkip (95% CI)		SPPB (95% CI)		TUG (95% CI)	
Sensitivity	60.7	(42.2–76.4)	21.4	(10.2–39.5)	17.9	(7.9–35.6)
Specificity	83.0	(70.8–90.8)	88.7	(77.4–94.7)	84.9	(72.9–92.1)
Positive predictive value	65.4	(46.2–80.6)	50.0	(25.4–74.6)	38.5	(17.7–64.5)
Negative predictive value	80.0	(67.6–88.4)	68.1	(56.4–77.9)	66.2	(54.3–76.3)
% False positives	17.0	(9.2–29.2)	11.3	(5.3–22.6)	15.1	(7.9–27.1)
% False negatives	39.3	(23.6–57.6)	78.6	(60.5–89.8)	82.1	(64.4–92.1)
Test accuracy	75.3	(64.9–83.4)	65.4	(54.6–74.9)	61.7	(50.8–71.6)
Likelihood ratio (+)	3.58	(1.84–6.96)	1.89	(0.67–5.33)	1.18	(0.43–3.28)
Likelihood ratio (-)	0.47	(0.29–0.76)	0.89	(0.67–1.17)	0.97	(0.73–1.29)
Pre-test probability (Prevalence)	34.6	(24.2–44.9)	34.6	(24.2–44.9)	34.6	(24.2–44.9)

Abbreviations: SPPB, Short Physical Performance Battery; TUG, Timed Up and Go.

fallers when they were not (false positives), for the FallSkip test this occurred in 17% of cases (95% CI: 9.2–29.2), while for the SPPB this occurred in 11.3% of the sample (95% CI: 5.3–22.6) and for the TUG test in 15.1% (95% CI: 7.9–21.7) of cases.

Furthermore, there is the possibility of misclassifying people at fallers as if they are not (false positives). For the FallSkip test, this occurred in 39.3% (95% CI: 23.6–57.6) of cases, while for SPPB this occurred 78.6% (95% CI: 60.5–89.8) of the time, and for the TUG test this occurred in 82.1% (95% CI: 64.4–92.1) of cases.

As can be deduced from the above, proper classification is very important. If we consider the accuracy of the tests, that is, the capacity of each test to correctly classify those individuals at higher fallers, the FallSkip app showed an accuracy of 75.3% (95% CI: 64.9–83.4). That is, for every four people at risk of falls, the test detected three who were truly at risk. The SPPB did so in 65.4% of cases (95% CI: 54.6–74.9) and the TUG test in 61.7% of cases (95% CI: 50.8–71.6).

## 5 | DISCUSSION

On validation of the measurement tool, an accuracy of 75% was established. FallSkip showed superior accuracy as compared to the SPPB and the TUG test, which presented accuracy values of 65.4% and 61.7%, respectively, in line with the results of other studies (Gómez Arias, 2021; Park, 2018). Gómez Arias used inertial sensors in a group of 25 young people and 12 older persons, achieving a test accuracy of 76.6% in the 3-m extended test with twisting before sitting, the results are similar to those obtained by us.

In Park's review (2018), 5 studies on the TUG test (including a total of 427 older persons) were analysed, obtaining a pooled sensitivity of 76% (95% CI: 68–83) and a specificity of 49% (95% CI: 43–54). These findings contrast with those of this study, where the TUG test was found to have very low sensitivity (17.9%, 95% CI: 7.9–35.6) and much higher specificity (84.9%, 95% CI: 72.9–92.1). We must bear in mind that assessments carried out on TUG test may be influenced by the subjectivity of the evaluators. Furthermore, the studies analysed by Park did not report the optimal cut-off points for the time spent completing the test. Depending on the established cut-off point, sensitivity and specificity can vary greatly.

One test that is currently considered to be a reference or gold standard for assessing the risk of falls is the Physiological Profile Assessment (PPA). This approach involves 5 independent tests and presents an intraclass correlation (ICC) that varies between 55% and 85% depending on the test, with predictive precision between 70% and 75% (Lord et al., 1994, 2003).

Other systematic review studies on fall risk assessment devices conclude that they provide objective and more accurate data. A review of a wide range of inertial sensors concluded that these devices provide accurate, cheap and easy to implement assessment. There is also a great deal of variability depending on where the sensors are

placed and the type of task performed. The accuracy of the various tests analysed ranged from 47.9% to 88.0%. Our work achieved an accuracy of 75.0%, a figure within the range analysed in this review. (Sun & Sosnoff, 2018).

In other work, (Montesinos et al., 2018) a meta-analysis is carried out which shows that there is great heterogeneity among the studies, fundamentally in terms of the location of the inertial sensors, the task being evaluated or the different characteristics of the test. They concluded that the results showed that with a gait test, the most effective feature for assessing the risk of falling was the speed with the sensor placed on the shins. In contrast, during the standing test, linear acceleration measured at the lower back was the most effective combination of feature placement. Similarly, during the sitting and/or standing tests, linear acceleration measured at the lower back appeared to be the most effective combination of feature placement.

FallSkip is more effective than the TUG test for assessing the risk of falls as it involves a greater number of parameters, including the balance and reaction time of the older persons. Some findings in the literature indicate that a greater number of parameters are necessary to assess the fallers, and The Timed Up and Go test has limited ability to predict falls in community-dwelling elderly and should not be used in isolation to identify individuals at high risk of falls in this setting (Barry et al., 2014).

The results obtained using FallSkip are similar to those of the PPA in terms of predictive precision and are considerably better than those obtained for the TUG test and the SPPB. The FallSkip does not present a higher workload for the professional and is more comfortable for both the professional and the patient as compared to other methods, according to other studies (Folch et al., 2019).

After the FallSkip test was completed, a fall risk prevalence of 34.6% was found for this study sample of individuals aged over 65. This instrument has also been used in another study where 58.33% were found to be at high risk of falling. (Guillén Fernández, 2021). Similarly, other studies have reported prevalence values of 28% and 37% in older institutionalized Spanish populations (Carballo-Rodríguez et al., 2018; Rodríguez-Molinero et al., 2015).

Among the main limitations, we have to consider that falls can be due to multiple factors that can influence. However, our intention is that from the probability of falling of a subject, we try to evaluate how the test used is or is not able to detect that probability of falling.

Another limitation is the lack of retrospective studies. Consequently, future research should consider retrospectively investigating fall risk assessment.

No interobserver reliability study was performed either. Although an attempt was made to minimize possible interference by adequately training the people who were to perform the tests, we did not carry out an inter-observer reliability study.

In conclusion, the FallSkip device has been shown to be a very suitable tool for assessing fall risk in the prison population. Advantages include its ease of implementation as the device performs measurements automatically, avoiding subjectivity between observers. It is a valid and reliable test for the detection of fall risk.

## ACKNOWLEDGEMENT

The authors thank all participants for their collaboration.

## CONFLICT OF INTEREST

The authors have no conflicts of interest to report.

## DATA AVAILABILITY STATEMENT

The data of this study cannot be publicly share due to ethical consideration and protection of the participants confidentiality.

## ETHICAL APPROVAL

A model informed consent form was drawn up and presented together with the appropriate information in accordance with the Declaration of Helsinki (Asociación Médica Mundial [AMM], 2008).

## ORCID

María Pilar Molés-Julio  <https://orcid.org/0000-0002-8954-480X>

## REFERENCES

- Barry, E., Galvin, R., Keogh, C., Horgan, F., & Fahey, T. (2014). Is the timed up and go test a useful predictor of risk of falls in community dwelling older adults: A systematic review and meta-analysis. *BMC Geriatrics*, 14, 14. <https://doi.org/10.1186/1471-2318-14-14>
- Bloch, F. (2021). Caídas en la persona anciana. *EMC - Tratado de Medicina*, 25(2), 1–6.
- Brown, W., Yen, P. Y., Rojas, M., & Schnall, R. (2013). Assessment of the health IT usability evaluation model (health-ITUEM) for evaluating mobile health (mHealth) technology. *Journal of Biomedical Informatics*, 46(6), 1080–1087. <https://doi.org/10.1016/j.jbi.2013.08.001>
- Carballo-Rodríguez, A., Gómez-Salgado, J., Casado-Verdejo, I., Ordás, B., Fernández, D., Carballo-Rodríguez, A., Gómez-Salgado, J., Casado-Verdejo, I., Ordás, B., & Fernández, D. (2018). Estudio de prevalencia y perfil de caídas en ancianos institucionalizados. *Gerokomos*, 29(3), 110–116.
- Charlson, M., Pompei, P., Ales, K., & Mackenzie, C. (1987). A new method of classifying prognostic comorbidity in longitudinal studies: Development and validation. *Journal of Chronic Diseases*, 40(5), 373–383.
- Folch, B., Donato, C., Ruivo, M., Ruiz, A., Tapia, A., Palop, V., Pitarch Corresa, S., Pedrero, J., Garrido Jaen, J. D., & Andrade Celdrán, J. (2019). Innovación sanitaria en la gestión del riesgo de caídas de personas mayores en Atención Primaria. *Revista de Biomecánica*, 66, 1–6. <https://riunet.upv.es/handle/10251/128736>
- Gómez Arias, B. (2021). *Desarrollo e implementación de una estrategia para la evaluación automática del riesgo de caídas en personas usando sensores inerciales*. Universidad de Concepción.
- Greene, M., Ahalt, C., Stijacic-Cenzer, I., Metzger, L., & Williams, B. (2018). Older adults in jail: High rates and early onset of geriatric conditions. *Health & Justice*, 6(1), 3. <https://doi.org/10.1186/S40352-018-0062-9>
- Guillén Fernández, M. (2021). *Estudio piloto comparativo entre los resultados obtenidos en posturografía dinámica y el Fallskip en paciente con hipofunción vestibular*. Universidad católica de valencia san vicente mártir.
- Guralnik, J. M., Simonsick, E. M., Ferrucci, L., Glynn, R. J., Berkman, L. F., Blazer, D. G., Scherr, P. A., & Wallace, R. B. (1994). A short physical performance battery assessing lower extremity function: Association with self-reported disability and prediction of mortality and nursing home admission. *Journal of Gerontology*, 49(2), M85–M94. <https://doi.org/10.1093/geronj/49.2.M85>
- Hernandez-Martínez, J., & Ramirez-Campillo, R. (2017). Efectos del entrenamiento vibratorio sobre el riesgo de caída en adultos mayores institucionalizados: una revisión breve. *Revista Ciencias de La Actividad Física*, 18(2), 1–7. <https://doi.org/10.29035/rcaf.18.2.10>
- Herrera Ligeró, C., Ruíz García, A., Garrido Jaén, J. D., Bermejo Bosch, I., Andrade Celdrán, X., & Porcar Seder, R. (2021). FallSkip: aportaciones al ámbito clínico. *Revista de Biomecánica*, 68, 40–47.
- Humphreys, J., Ahalt, C., Stijacic-Cenzer, I., Widera, E., & Williams, B. (2018). Six-month emergency department use among older adults following jail incarceration. *Journal of Urban Health*, 95(4), 523–533. <https://doi.org/10.1007/s11524-017-0208-4>
- Lord, S., Menz, H., & Tiedemann, A. (2003). A physiological profile approach to falls risk assessment and prevention. *Physical Therapy*, 83(3), 237–252. <https://doi.org/10.1093/PTJ/83.3.237>
- Lord, S. R., Ward, J. A., Williams, P., & Anstey, K. J. (1994). Physiological factors associated with falls in older community-dwelling women. *Journal of the American Geriatrics Society*, 42(10), 1110–1117. <https://doi.org/10.1111/j.1532-5415.1994.tb06218.x>
- Martínez Carrasco, Á. (2015). *Análisis del riesgo de caídas en ancianos institucionalizados mediante escalas de marcha y equilibrio*. Universidad de Murcia.
- Medina Ripoll, E., Pedrero Sánchez, J. F., Garrido Jaen, J. D., Lopez Pascual, J., Bermejo Bosch, I., Pitarch Corresa, S., Sinovas Alonso, I., Chirivella Moreno, C., Montero Vilela, J., & Andrade Celdrán, J. (2017). FallSkip: Valoración del riesgo de caídas en personas mayores. *Revista de Biomecánica*, 64, 1–6. <https://riunet.upv.es:443/handle/10251/104205>
- Mejías Arriaza, E. J., Martínez Martínez, L., & Fernández Silva, L. (2019). Análisis comparativo relacionando las caídas y el uso de dispositivos de ayuda en dos cortes de tiempo. *Higiene de Enfermería*, 102, 49–52.
- Montesinos, L., Castaldo, R., & Pecchia, L. (2018). Wearable inertial sensors for fall risk assessment and prediction in older adults: A systematic review and meta-analysis. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 26(3), 573–582. <https://doi.org/10.1109/TNSRE.2017.2771383>
- Park, S. (2018). Tools for assessing fall risk in the elderly: A systematic review and meta-analysis. *Aging Clinical and Experimental Research*, 30(1), 1–16. <https://doi.org/10.1007/s40520-017-0749-0>
- Petronila Gómez, L., Aragón Chicharro, S., & Calvo Morcuende, B. (2017). Caídas en ancianos institucionalizados: valoración del riesgo, factores relacionados y descripción. *Gerokomos*, 28(1), 2–8.
- Richardson, S. (1991). The timed “up & go”: A test of basic functional mobility for frail elderly persons. *Journal of the American Geriatrics Society*, 39(2), 142–148.
- Rodríguez-Moliner, A., Narvaiza, L., Gálvez-Barrón, C., de la Cruz, J. J., Ruiz, J., Gonzalo, N., Valldosera, E., & Yuste, A. (2015). Caídas en la población anciana española: incidencia, consecuencias y factores de riesgo. *Revista Española de Geriatria y Gerontología*, 50(6), 274–280.
- Sánchez Prieto, L., & de Quirós y Lomas, L. (2016). Las personas mayores en los centros penitenciarios: carencias en los recursos especializados y necesidad de programas educativos. *Revista de Educación Social*, 22, 1–21.
- Serra Añó, P., Pedrero Sánchez, J., Inglés, M., Aguilar Rodríguez, M., Vargas Villanueva, I., & López Pascual, J. (2020). Assessment of functional activities in individuals with Parkinson's disease using a simple and reliable smartphone-based procedure. *International Journal of Environmental Research and Public Health*, 17(11), 1–13.

- Sun, R., & Sosnoff, J. J. (2018). Novel sensing technology in fall risk assessment in older adults: A systematic review. *BMC Geriatrics*, 18(1), 14. <https://doi.org/10.1186/S12877-018-0706-6>
- Tavares, B., Pires, I., Marques, G., Garcia, N., Zdravevski, E., Lameski, P., Trajkovic, V., & Jevremovic, A. (2020). Mobile applications for training plan using android devices: A systematic review and a taxonomy proposal. *Information*, 11(7), 343.
- Vera-Remartínez, E. J. (2016). Nuevos tiempos para la Sanidad Penitenciaria: los condicionantes de la edad y del síndrome metabólico. *Rev Esp Sanid Penit*, 18, 73–75.

**How to cite this article:** Vera-Remartínez, E. J., Lázaro-Monge, R., Casado-Hoces, S. V., Garcés-Pina, E., & Molés-Julio, M. P. (2022). Validity and reliability of an android device for the assessment of fall risk in older adult inmates. *Nursing Open*, 00, 1–8. <https://doi.org/10.1002/nop2.1532>

## APPENDIX A

### Characteristics of the sample studied

	All	Castellón I	Madrid III	Zuera	Picassent
<b>Demographic characteristics</b>					
Participants: <i>n</i> (%)	81 (100.0)	20 (24.7)	16 (19.8)	21 (25.9)	24 (29.6)
Age (years): Median (IQR)	70.8 (67.6–74.5)	70.4 (67.4–71.9)	73.6 (68.1–74.7)	67.8 (66.5–71.7)	72.9 (69.8–77.8)
<b>Sex: <i>n</i> (%)</b>					
Male	72 (88.9)	17 (85.0)	16 (100)	21(100)	18 (75.0)
Female	9 (11.1)	3 (15.0)	0 (0.0)	0 (0.0)	6 (25.0)
<b>Anthropometric characteristics</b>					
Weight (kg): Mean (95% CI)	78.6 (75.7–81.4)	78.2 (71.5–84.9)	80.9 (73.7–88.0)	80.1 (74.1–86.2)	75.9 (71.4–80.4)
Height (cm): Median (IQR)	170 (164–174)	170 (162–174)	171 (169–175)	172 (168–178)	166 (159–173.5)
BMI (kg/m <sup>2</sup> ): Median (IQR)	26.9 (24.2–30.1)	26.6 (24.5–29.8)	25.9 (24.1–31.6)	26.8 (23.7–28.4)	27.7 (24.1–31.4)
<b><i>n</i> (%)</b>					
Normal weight	28 (34.6)	6 (30.0)	6 (37.5)	8 (38.1)	8 (33.3)
Overweight	32 (39.5)	9 (45.0)	5 (31.3)	10 (47.6)	8 (33.3)
Obese	21 (25.9)	5 (25.0)	5 (31.3)	3 (14.3)	8 (33.3)
<b>Limitations</b>					
Falls in the past year: <i>n</i> (%)	25 (30.9)	5 (25.0)	6 (37.5)	9 (42.9)	8 (33.3)
Hearing problems: <i>n</i> (%)	25 (30.9)	5 (25.0)	9 (56.3)	5 (23.8)	6 (25.0)
Visual problems: <i>n</i> (%)	24 (29.6)	8 (40.0)	6 (37.5)	9 (42.9)	1 (4.2)
<b>Charlson Comorbidity Index: <i>n</i> (%)</b>					
Absent	51 (63.0)	15 (75.0)	12 (75.0)	8 (38.1)	16 (66.7)
Low	11 (13.6)	1 (5.0)	2 (12.5)	5 (23.8)	3 (12.5)
High	19 (23.5)	4 (20.0)	2 (12.5)	8 (38.1)	5 (20.8)

Abbreviations: IQR: Interquartile range (25th Percentile – 75th Percentile).