Dynamic Performance-exposure Algorithm for Falling Risk Assessment and Fall Prevention in Community-dwelling Older Adults

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Abstract

Background: Several models and algorithms were designed to identify older adults at risk of falling supported on an intrinsically and extrinsically traditional approach. However, the dynamic interaction between multiple risk factors for falls must be considered. The present study aimed to design a dynamic performance-exposure algorithm for falling risk assessment and fall prevention in community-dwelling older adults.

Methods: The study involved 1) a cross-sectional survey assessing retrospective falls, performance-related risk factors for falls (sociodemographic such as gender and age, cognitive, health conditions, body composition, physical fitness, and dual-task outcomes), exposure risk factors (environmental hazards and (in)physical activity), and performance-exposure risk factors (affordance perception), and 2) follow-up survey assessing prospective falls. Participants were Portuguese community dwellings (≥ 65 years). Data were reported based upon descriptive statistics, curve estimation regression, binary logistic regression, and ROC curve.

Results: The selected and ordered outcomes included in the algorithm and respective cutoffs were: **(1)** falls in previous year (high risk: n>1, moderated: n=1, low risk: n=0); **(2)** health conditions (high risk: n >3, moderated: n=3, low risk: n<3); **(3)** multidimensional balance (high risk: score <32 points, moderated risk: 32 points ≤ score ≤33 points, low risk: score>33); **(4)** lower body strength (high risk: rep/30s< 11, moderated risk: 11≤ rep/30s ≤14, low risk: rep/30s >4); **(5)** perceiving action boundaries (high risk: overestimation bias, moderated risk: not applied, low risk: underestimation bias); **(6)** fat body mass (high risk: % fat >38, moderated risk: 37≤ % fat ≤38, low risk: % fat <7); **(7)** environmental hazards (high risk: n>5, moderated risk: n=5, low risk: n<5); **(8)** rest period (high risk: hours/day >4.5, moderated risk: 4≤ hours/day ≤4.5, low risk: hours/day <4); **(9)** physical activity metabolic expenditure (high risk: MET-min/week <2300 or >5200, moderated risk: 2300≤ MET-min/week <2800, low risk: 2800≤ MET-min/week ≤5200).

Conclusions: Results demonstrated a dynamic relationship between older adults' performance capacity and the exposure to falls opportunity, supporting the build algorithm's conceptual framework. Fall prevention measures should consider the above factors that most contribute to the individual risk of falling, relative weights, and their distance from low-risk value, as proposed in the dynamic algorithm.

Background

Falls cause injury, fear, loss of independence, placement in assisted-living facilities, and premature mortality [1, 2]. Medical costs related to falls is too high. For instance, in the United States, the estimated costs of fatal and nonfatal falls totalled approximately $50.0 billion [3], while in China, the hospitalisation costs resulting from falls totalled more than 100 million RMB [4]. In Europe, the number of disability-adjusted life years (DALYs) due to fall-related injury in older adults increased by 54% from 1990 to 2017 [5].

Fall prevention has been a subject studied by science for some time, and effective recommendations have been designed [6–8]. Interventions shall be continued and attended in community and facilities settings [9]. Such literature suggests that about 50% of potential falls relating to older adults are avoided due to ongoing fall prevention interventions [10]. However, falls remain an increasing problem for older adults, families, society, and governments [11].

Literature usually points the main risk factors for falling as advancing age, female gender, history of previous falls, chronic health conditions (e.g., cardiovascular diseases, disorders of the nervous system, poor vision, or foot impairment), cognitive deficits, poor body composition, low lower limb strength, impaired balance and gait, impaired dual-task performance, environmental hazards and lifestyle habits such as physical (in)activity [7, 12–16]. In addition, a recent study found that the bias of overestimation of the perceived maximum performance for the stepping-forward task is also an important risk factor for falling [17].

Traditionally, fall risk factors have been proposed according to extrinsic (related to surrounding spaces or environment-related) and intrinsic factors (human body or individual related causes, such as age, cognition, physical fitness, chronic health conditions, or body composition) [16, 18]. Several models and algorithms were designed to identify older adults at increased risk of falling and suggest fall implementation measures for fall prevention [19–21]. Some include the traditional assessment of risk factors for falls, such as the STEADI algorithm [20]. Others include a more technological approach, such as the robotic multifactorial fall-risk predictive model developed and validated by Cella and colleagues [21]. Nonetheless, these and other researchers [22] evidenced that the occurrence of an effective fall results from the interaction among multiple risk factors, suggesting that different approaches might be considered.

Hence, in the present research is proposed a performance-exposure paradigm to explain fall occurrence. According to this paradigm, falls avoidance would depend on personal competence to maintain a positive balance between individual performance capacity and the demands of tasks, counterbalanced by the accuracy of action boundary perception. An accident (fall) would occur when a particular task demands exceed the personal capability to perform that task, particularly if there is an action-perception mistake. The task demands depend on the task difficulty and the environmental hazards: in a hostile environment, the demands of a given task increase. Subjacent to this approach is the dynamic system theory [23], advocating that the interaction of various constraints sources drives the nature of movement variability (personal, task, and environmental) on the action. Also, the ecological *affordance* theory developed by Gibson [24, 25] advocates that opportunities for actions emerge under a particular set of conditions and body characteristics, such as a successful and safe action performance (e.g., without accidental fall), that would depend on personal accuracy of the self-perceived action boundaries [26, 27]. In accordance, the conceptual model proposed (figure 1) considers performance-related risk factors for falls (sociodemographic such as gender and age, cognitive, health conditions, body composition, physical fitness outcomes, and dual-task), exposure risk factors (environmental hazards and (in)physical activity), and performance-exposure risk factors (affordance perception).

We have hypothesised that 1) the identification of the key performance-related, exposure, and performance-exposure risk factors for falling, and 2) the purpose of their respective high-low risk cutoffs, would help the easy access to older adults` falling risk profile and the design of more effective falling prevention measures.

Thus, the present study aimed to design a dynamic performance-exposure algorithm for falling risk assessment and fall prevention, proposing: 1) a weight-ordered set of key tests (outcomes) to easily assess the risk of falling in community-dwelling older adults and establish the individual risk profile; 2) the cutoffs destringing the low, moderated and high risk of falling for each outcome (measuring the key performance-related, exposure, or performance-exposure risk factors for falling) and respective low-high risk range values; and 3) recommendations for interventions design based on the individual risk profile and supported on the dynamic performance-exposure paradigm.

Methods

Study design

The present study integrated the ESACA (Aging safely in Alentejo – understanding for action - preventing falls and violence against older people) project and had a twofold design as a cross-sectional study involving a retrospective fall survey and a prospective fall survey. The retrospective survey was carried out side-by-side with the cross-sectional survey and assessed fall occurrences in the previous 12 months as well as the circumstances surrounding each fall. The prospective survey was performed 6 and 12 months after the first screening to record the falls occurrence and the circumstances surrounding each fall.

Participants

Voluntary participant recruitment was conducted in the Alentejo region, Portugal, by invitation sent to the list of the regional community settings (health, recreational, sports, cultural and senior centres). Some volunteers were also enrolled by means of pamphlets distribution and radio advertisements. The sample was drawn in a similar fashion within each study location. The minimum representative sample size was estimated as 384 (95% CI) using the statistical calculator for public health OpenEpi (Open Source Epidemiologic Statistics for Public Health, EUA, version 3.01) [28] and considering the population ≥ 65 years registered by the National Census [29].

The inclusion criteria for community-dwelling participants were: (i) aged ≥ 65 years old, (ii) independent mobility; (iii) absence of recent injuries that have caused temporary immobilisation, deafness or blindness, and (iv) absence of cognitive impairment in accordance with the Folstein Mini-Mental State Examination (MMSE: scoring >24 points) which would have impaired questionnaire comprehension and/or functional test [30, 31].

Participant's recruitment and evaluations were performed in 3 stages. In stage I, 832 volunteers were accessed for eligibility, 517 of them were eligible according to the inclusion criteria (i) and (ii), but five did not meet the inclusion criteria (iii), and four did not meet the inclusion criteria (iv). There remained 508 participants who were assessed for the cross-sectional study and for the fall retrospective survey. Nonetheless, in this first stage, only 398 completed the measurements. One year after the first evaluation, 280 of the above participants were assessed and completed the fall prospective survey measurements in stage II. While the prospective survey took place, 179 additional volunteers were recruited to participate in the cross-sectional study and the fall retrospective survey (stage III). Of those, 119 were eligible and met the inclusion criteria, but only 112 completed the measurements. After this third stage, 500 participants (398 + 112) were analysed regarding the cross-sectional and the retrospective falls data, and 293 were also analysed regarding the prospective falls data.

Participants from the cross-sectional and retrospective surveys were 72.2 ± 5.4 years old, with 5.2 ± 3.9 years of school. Of them, 72.4% were women. They showed 3.9 ± 2.7 health conditions number, were mainly overweight (body mass index: 28.5 ± 4.2) and revealed a somehow compromised balance (multidimensional balance: 31.1 ± 6.2 points in 40) (see Table 1). All participants showed high cognitive capacity, as all those revealing cognitive impairments were excluded from the study. From these participants, the ones involved in the prospective survey were identical characteristics.

All participants provided written informed consent to participate in the present study, which followed the Declaration of Helsinki ethical principles. The University of Évora Ethics Committee for research in the areas of Human Health and Well-being approved this study (reference number 16012).

Procedures

Some procedures were followed to minimize eventual errors associated with the measurements. The raters, who were graduated in sports sciences or nursing, received training in the assessment procedures and the tests` protocols. The same rater always performed each test throughout the data collection period. Questionnaires were filled by a rater based on each participant's oral answers to the questions performed in the form of an interview. Either the raters or the participants were blind to the study objectives. The intra-rater reliability tests were estimated using data collected from ten participants at a one-week interval between the test and retest, ranging from 0.722 to 0.999.

Data collection was performed between 2016 and 2020. For the cross-sectional and the fall retrospective surveys, each participant started the assessment with the interview to fill in the questionnaires. After that, body composition was assessed, and affordance perception and functional physical fitness tests were performed. Evaluations lasted approximately one and a half hours per participant. An individual report with the testing results and rating was provided to each participant. The prospective survey recording the rate of falls (6 and 12 months) and the circumstances surrounding each fall was achieved by phone calls made by the rater who performed the initial screening.

Outcome measures

Falls

A fall was defined as "*an event which results in a person coming to rest inadvertently on the ground or floor or other lower level*" [11]. As explained above, retrospective falls (occurred in the previous 12 months) were assessed by a rater who completed a questionnaire based on the participants` verbal responses to the interview. The date of the event and circumstances surrounding each fall (e.g., the reason for the fall, outdoor/indoor fall, the action that was taken, and the consequences of the fall-severe injury: serious abrasion, strained muscles, torn muscles, sprains, dislocations and fractures; light injuries: slight scratches and/or edema) [32] were assessed as double-checks for false-positive, and false-negative answers. Prospective falls were assessed by means of telephone calls 6 and 12 months after the initial screening, and the double-checks for false-positive and false-negative answers were repeated. Prospective falls data concerned fall occurrence in the 12 months. A non-faller (retrospective or prospective) was defined as a subject who had not fallen in the previous 12 months, a faller (retrospective or prospective) was defined as a subject who had fallen at least once in the same period [32, 33].

Performance-related outcomes

Sociodemographic characteristics and cognitive function

Participants` gender, chronological age, and education (school years) were assessed by a questionary. The presence of cognitive impairment was assessed by the MMSE Portuguese version [34].

Health-related outcomes

Health-related outcomes were also assessed by a questionnaire completed by the interviewer based on the participant answers. Each participant listed his/her diagnosed chronic diseases from 24 chronic diseases and reported the other diagnosed diseases. Physical impairments were assessed: frequent dizziness, foot problems, involuntary loss of urine, hearing problems, poor vision, and occasional loss of balance [35]. This information was confirmed by means of crossing the reports heath conditions` answers to the current medication. The number of health conditions was computed by summing the number of chronic diseases and of physical impairments.

Anthropometric measures and body composition

Standing height (cm) and weight (kg) were measured by a stadiometer (Seca 770, Hamburg, Germany) and an electronic scale (Seca Bella 840, Hamburg, Germany) respectively, and were used to compute body mass index (kg/m^2). Body fat mass (%) and lean body mass (kg) were assessed by bioimpedance (Omron BF 511, USA) [36].

Physical Fitness

Functional fitness was assessed by using the Senior Fitness Test. Agility/dynamic balance, lower and upper body strength, lower and upper body flexibility and aerobic endurance were assessed by the following tests: 8-foot up-and-go (s), 30-s chair stand (repetitions), arm curl (repetitions), chair sit-and-reach (cm), back scratch (cm) and 6-minute walk test (m), respectively [37].

Multidimensional balance was assessed by the Fullerton Advanced Balance (FAB) Scale [38], in which the total score ranges from 0 (worst) to 40 (best) points.

Dual-task

Dual-task performance was assessed by the cognitive 8-foot up-and-go (Dual TUG) test following the methodology proposed by Tomas-Carus and colleagues [15]. The variables included the time spent on the dual-task (s), the number of cognitive stops (n), and the number of motor stops (n).

Retrospective falls

The history of retrospective falls (a reported risk factor for falls associated with frailty [39]), namely the number of retrospective falls, was also considered and assessed.

Exposure to falls opportunity outcomes

Physical (in)activity

Habitual physical activity and sedentary behaviour were assessed using the short version of the International Physical Activity Questionnaire (IPAQ) [40]. Physical activity metabolic expenditure (metabolic equivalent of task: MET-min/week) was calculated by summing the metabolic expenditure of walking (3.3 MET), moderate activity (4.0 MET) and vigorous activity (8.0 MET), which in turns, were computed as regard the time (min/day) and frequency (day/week) spent on each one of these activities. The weekday and the weekend day rest period (hour/day) other than night sleeping was also assessed, and the respective mean value was calculated.

Environmental Hazards

Environmental hazards were assessed by checking a list of environmental hazards, including interior and exterior dwelling hazards and the presence of animals and habitual footwear [6, 14]. The total number of the reported hazards was counted (minimum: 0, maximum: 34).

Performance-exposure outcome

Affordance perception

The perception and stepping-forward boundaries were accessed by using the Stepping-Forward Affordance Perception Test (SF-APT) [41]. The SF-APT measurements are based on the relationship between the “estimated/perceived” stepping-forward distance (cm) and the “real” stepping-forward

distance performed (cm). The error between real and estimated (cm) was computed (real performance – estimation), and the error tendency was categorized as underestimated (estimated < real) or overestimated (estimated > real).

Statistical analysis

An exploratory data analysis was performed. The analysis included descriptive analysis and univariate binary regression analysis to characterize the main potential risk factors for falling reported in the literature and assessed in the present study. Extreme outliers were excluded. Data were shown as means and standard deviations (SD), as absolute frequency or percentage in case of prevalence or incidence, and as univariate Odds Ratio (OR).

Then, multivariate binary regression analysis [42] was performed to identify the key risk factors for falling. For this, it was considered retrospective falls occurrence (retrospective faller vs non-faller) and prospective falls occurrence (prospective faller vs non-faller). The fittest and most parsimonious model explaining retrospective or prospective falls was determined by using the traditional approach [43], as did Pereira and colleagues [32], and the Hosmer-Lemeshow goodness-of-fit test was used to analyse each overall model fit. In addition, each model's (retrospective or prospective) ability to discriminate fallers from non-fallers was examined using ROC analysis based on the area under the curve (AUC). The internal validation of prospective and retrospective models was tested by using the resampling or cross-validation procedure [44]. In accordance, participants included in each model were clustered into ten equal groups by random sampling without replacement, and the probabilities generated by cross-validation were used to calculate the AUC through ROC analysis.

Posteriorly, the cutoff points for the probability of falling (π) stratifying the risk of falling as low, moderated, or high were established. The cutoff for π distinguishing people at high risk of falling was established by maximizing sensitivity and specificity [45]. The cutoff of π: 0.25 was also considered to distinguish people at low risk of falling. Thus, the probabilities of falling between these two cutoffs would distinguish people at moderated risk of falling. In accordance, the risk of falling was stratified as low (π: < 0.25), as moderated (0.25 ≤ π: < cutoff, which maximizes both sensitivity and specificity) and high (π: ≥ cutoff, which maximizes both sensitivity and specificity). These were done for the retrospective model and the prospective model.

Then, following a similar procedure of Pereira and colleagues [45], the regression equation (first from the retrospective model) was solved successively using each selected key factor outcome value from the 1st to 99th percentiles to find the values marching the above-outlined π cutoff points. Thus, each factor outcome value that equal the falling probability cutoff (π) described above (point estimation) were identified as the risk of falling factor cut-offs usable for the risk level stratification as low, moderate, or high. The same was done for the prospective model.

Data analysis observed that the relationship between physical activity and fall occurrence did not follow a linear relation. The function (quartic) which best fit this relation (showing high R^2, significant p-value,

and high F-statistic) was determined using the curve estimation regression, and the probability of falling was calculated depending on the amount of physical activity i.e., metabolic expenditure [46, 47]. The sensitivity and specificity of this model were determined using ROC analysis [48]. The physical activity values equalling a probability of falling such as $\pi = 0.25$, and such as π = cutoff maximising both sensitivity and specificity, were identified as the values/cutoffs usable for the risk level stratification as low, moderate, or high.

For last, as soon as the key risk factors for falling were established, scatter plots were drawn whit respective fit lines, showing the rate of fallers variation (percentage) according to each risk factor for falling variation. For that, the categories on categoric risk factors were considered and equal range values for each numeric risk factor were established. The range values were established, such as each one included at least 10 participants. Consequentially, extremes outliers were excluded. The scatter plots were used on the design of the “Dynamic model explaining the risk of falling depending on the relationship between the subject performance capacity and the exposure to the fall occurrence opportunity”.

All the above resulted in the design of the “Dynamic performance-exposure algorithm for falling risk assessment and fall prevention in community-dwelling older adults”.

Analyses were performed using the SPSS software package (version 24.0 for Windows, IMB Statistics) and Excel software (version16.24 for Mac). A value of $p \leq 0.05$ was considered statistically significant for all analyses.

Results

Exploratory results

Retrospective data showed that 37.2% of the participants had fallen at least once in the previous 12 months. Of those, 14.0% suffered a retrospective falls-related severe injury (fracture, serious abrasion, strained muscles, torn muscles, sprains, or dislocation). On the other hand, prospective data showed that 33.4% of the assessed participants had fallen at least once in the 12 months prospective follow-up. From them, 13.6% suffered a prospective fall-related severe injury.

Table 1 shows the participants’ characteristics regarding potential risk factors for falling. Analysing the potential risk factors for falling, results from univariate binary regression analysis (analysed single) showed that most of the performance-related outcomes significantly explained retrospective falls occurrence. For example, a poor condition (e.g., a higher number of health conditions) or performance capacity (e.g., aerobic endurance, balance) increased the likelihood of falling (OR: $1.037_{\text{body fat mass}}$ - $1.182_{\text{agility/dynamic balance}}$, $p < 0.05$), and a better condition or performance capacity decreased the likelihood of falling (OR: $0.939_{\text{multidimensional balance}}$ - $0.977_{\text{aerobic endurance}}$, $p < 0.05$). On the other hand, the exposure outcomes showed a less straight relationship with the retrospective occurrence of falls. It was observed that the increase of rest period or environment hazards were associated with the increase of the

likelihood of falling (OR: 1.129, 95% CI: 1.021-1.247 and OR: 1.057, 95% CI: 1.020-1.096, respectively), but physical activity did not show to explain significantly retrospective falls occurrence by using binary regression analysis. As regards the performance-exposure outcome - the action boundaries perception - it was observed that this outcome significantly explains retrospective falls occurrence, such as an overestimated error on the perception of action boundaries increase the likelihood of falling almost twice (1.905, 95% CI: 1.213-2.992).

In what concerns prospective falls, univariate binary regression analysis showed that several potential risk factors lost their ability to explain significantly falls occurrence. Hence, regarding the performance-related outcomes, only health conditions, body fat mass, agility/dynamic balance (OR: 1.049-1.153), lower body strength, aerobic endurance, multidimensional balance (OR: 0.912-0.997) shown to explain falls significantly, $p < 0.05$. In addition, it was observed that the number of retrospective falls concerns a serious risk factor for future falls occurrence (OR: 1.523, 95% CI: 1.250-2.855). Regarding exposure outcomes, no risk factor was shown to explain prospective falls. The action boundaries perception (the performance-exposure outcome) also did not significantly prove its ability to explain prospective falls.

It would be important to story that the prospective fall data collection and the analysis of the risk factor ability to explain prospective falls were performed on the year posterior to the first evaluation. Each participant received an analytic report of the personal risk profile on the first evaluation. The report included the personal participant's results on each evaluated risk factor for falling, indicates each factor contributes to the individual risk of falling and is far from the safe value.

Table 1
Participant's characteristics regarding potential risk factors for retrospective and prospective falls

Potential risk factor	Mean ± SD or %	Retrospective OR (95%CI)	Prospective OR (95%CI)
Performance-related outcomes			
Age (years)	72.2 ± 5.4	1.025 (0.991-1.060)	1.031 (0.981-1.073)
Education (years)	5.2 ± 3.9	0.990 (0.946-1.035)	0.967 (0.908-1.029)
Sex			
Male	27.6%		
Female	72.4%	1.524 (1.002-2.318)	1.372 (0.769-2.446)
Health conditions (n)	3.9 ± 2.7	1.167 (1.088-1.251)	1.153 (1.063-1.251)
Body height (cm)	156.4 ± 8.7	0.969 (0.948-0.990)	0.990 (0.962-1.018)
Body weight (kg)	69.8 ± 12.4	0.997 (0.983-1.012)	1.005 (0.985-1.025)
Body mass index (kg/m^2)	28.5 ± 4.2	1.037 (0.993-1.082)	1.033 (0.972-1.097)
Body fat mass (%)	37.4 ± 7.4	1.037 (1.011-1.064)	1.049 (1.005-1.095)
Body lean mass (kg)	43.6 ± 9.1	0.982 (0.962-1.002)	0.993 (0.973-1.014)
Agility/dynamic balance (s)	6.0 ± 1.6	1.182 (1.049-1.331)	1.120 (1.003-1.251)
Lower body strength (rep/30-s)	15.6 ± 4.6	0.965 (0.954-0.976)	0.912 (0.851-0.979)
Upper body strength (rep/30-s)	16.6 ± 4.6	0.969 (0.959-0.980)	0.946 (0.894-1.002)
Lower and body flexibility (cm)	-2.6 ± 9.7	1.010 (0.991-1.029)	0.946 (0.975-1.021)
Upper body flexibility (cm)	-11.0 ± 11.0	0.975 (0.959-0.992)	0.993 (0.972-1.014)
Aerobic endurance (m)	493.1 ± 95.9	0.997 (0.995-0.999)	0.997 (0.995-0.999)
Multidimensional balance (points)	31.1 ± 6.2	0.939 (0.910-0.968)	0.940 (0.903-0.979)
Dual-task time (s)	10.0 ± 4.5	1.046 (1.003-1.092)	1.057 (0.984-1.137)
Dual-task cognitive stops (n)	0.8 ± 0.8	1.107 (0.874-1.403)	0.941(0.713-1.368)
Dual-task motor stops (n)	0.4 ± 0.6	1.072 (0.806-1.426)	1.021 (0.654-1.593)
Retrospective falls (n)	0.81 ± 2.074	---	1.523 (1.250-1.855)
Exposure outcomes			

SD standard deviation, *OR* odds ratio, [a] *OR* odds ratio, computed for each 100 MET-min/wk.

Potential risk factor	Mean ± SD or %	Retrospective OR (95%CI)	Prospective OR (95%CI)
Physical activity (MET-min/week)	3065.6 ± 2340.7	0.998 (0.990-1.006) [a]	0.999 (0.985-1.014) [a]
Rest (hr/day)	4.4 ± 1.8	1.129 (1.021-1.247)	1.001 (0.872-1.149)
Environmental hazards (n)	7.3 ± 5.0	1.057 (1.020-1.096)	1.033 (0.930-1.147)
Exposure-ability outcome			
Action boundaries perception			
Underestimated error tendence	79.2 (%)		
Overestimated error tendence	20.8 (%)	1.905 (1.213-2.992)	1.127 (0.574-2.114)

SD standard deviation, *OR* odds ratio, [a] *OR* odds ratio, computed for each 100 MET-min/wk.

Algorithm design based on the models explaining fall occurrence

A dynamic performance-exposure algorithm for falling risk assessment and fall prevention in community-dwelling older adults was conceived based on four models. Each model included the risk factor(s) selected as key risk factors/outcomes for falls (figure 2). The first model concerned retrospective falls, was built using multivariate binary logistic regression, and selected health conditions, multidimensional balance, fat body mass, environmental hazards, and rest period as the key risk factors explaining falls ($p < 0.05$). A second model also concerning retrospective falls was built using multivariate binary logistic. This model was computed based on literature evidence pointing to strength as a key risk factor for falling and emerged as an alternative and/or complemental model explaining retrospective fall occurrence. The key risk factors for falls selected by this second model were lower body strength, perceived action boundaries, and environmental hazards ($p < 0.05$). A third model concerning prospective falls was built using multivariate binary logistic and selected the number of falls in the previous year (retrospective falls) and health conditions as the key risk factors explaining falls ($p < 0.05$). The above three multivariate models` Hosmer and Lemeshow goodness-of-fit tests were not significant ($p = 0.570$, $p = 0.133$, and $p = 0.472$, respectively). Testing each model predictive capacity, the first model AUC was 0.690 (95% CI: 0.642-0.738), and the cut point for π maximizing specificity (0.650) and sensitivity (0.688) was 0.3550 (~35.5%). The second model AUC was 0.611 (95% CI: 0.554-0.668) and the cut point for π maximizing specificity (0.571) and sensitivity (0.618) was 0.3699 (~37%). The third model AUC was 0.698 (95% CI: 0.633-0.762), and the cut point for π maximizing specificity (0.683) and sensitivity (0.617) was 0.3117 (~31.2%). The AUCs computed by cross-validation were for the first model of 0.680 (CI 95%: 0.631-0.729), for the second model of 0.600 (CI 95%: 0.542-0.658), and for the third model of 0.684 (0.619-0.749). Lastly, a fourth model was built by using the curve estimation statistic technical. This model showed that

metabolic expenditure on physical activity performance also explains retrospective fall occurrence, following a quartic function (p = 0.026, R^2= 0.562). From these four models, nine key risk factors emerged to include in the algorithm, which are shown in accordance with their preponderance to the risk of falling: 1st number of falls in the previous year, 2nd health conditions number, 3rd multidimensional balance (points), 4th lower body strength (rep/30s), 5th perceiving action boundaries, 6th fat body mass (%), 7th environmental hazards number, 8th rest period (hour/day), and 9th physical activity metabolic expenditure (MET-min/week).

The above four models' analysis evidenced that, besides the single relationship between each key risk factor and the occurrence of falls, there is an interaction among the risk factors contributing to the risk of falling. Figure 3 illustrates the fallers rate (%) variation under each risk factor variation. In the figure, it can be observed that as poor performance-related factors are, the higher is the rate of fallers. In what concerns to exposure factor risk factors, as environmental hazards, rest period, or the number of retrospectives falls (falls occurred in the year previous to the first assessment) increased, the higher was the fallers rate. As regards physical activity, the fit line configures a wave with a low fallers rate for low physical activity, an increase in fallers rate associated with the increase of physical activity until ~1500 Mets-min/week of metabolic expenditure, followed by a decrease in fallers rate between ~1500 and ~4500Mets-min/week of metabolic expenditure, and an increase in falls rate above ~4500 Mets-min/week of metabolic expenditure. Figure 3 also illustrates how falls depend on a balance between individual health, fitness performance capacity, and exposure to fall occurrence opportunities. It shows how as better health, fitness, and performance capacity decrease the risk of fall occurrence when the individual is exposed to the opportunity of falls (when performing a physical activity because a person does not fall when do not move) even if in a hazardous environment, and that the inverse is also true. Although people may not fall when they are at rest, it was observed that people who spend more time at rest are the ones who more fall when they move, particularly the ones who have a higher number of retrospective falls. In addition, it was observed that the risk of falling depending on the above risk factors interaction is mediated by the action boundary perception such as older people who underestimate their real performance (perceived < real) show a lower rate of faller than the ones who overestimate their real performance (perceived > real).

Figure 4 illustrates the dynamic performance-exposure algorithm for falling risk assessment and fall prevention in community-dwelling older adults. The fall risk stratification of each risk factor was established by solving each model equation according to the cutoff of π maximizing specificity and sensitivity (see above) and according to the cutoff of π = 0.25 as explained in statistical analysis item. In the figure are each risk factor cutoff and the reference values usable for the stratification of the risk of falling in the studied population; they were as follows: **number of falls in previous year** (high risk: n > 1, moderated: n = 1, low risk: n = 0); **number of health conditions** (high risk: n > 3, moderated: n = 3, low risk: n < 3); **multidimensional balance** (high risk: score < 32 points, moderated risk: 32 points ≤ score ≤ 33 points, low risk: score > 33; **lower body strength** (high risk: rep/30s < 11, moderated risk: 11 ≤ rep/30s ≤ 14, low risk: rep/30s > 14); **perceiving action boundaries** (high risk: overestimation bias, moderated risk:

not applied, low risk: underestimation bias); **fat body mass** (high risk: % fat > 38, moderated risk: 37 ≤ % fat ≤ 38), low risk: % fat < 37; **environmental hazards** (high risk: n > 5, moderated risk: n = 5, low risk: n < 5); **rest period** (high risk: hours/day > 4.5, moderated risk: 4 ≤ hours/day ≤ 4.5, low risk: hours/day < 4); **physical activity metabolic expenditure** (high risk: MET-min/week < 2300 or > 5200, moderated risk: 2300 ≤ MET-min/week < 2800, low risk: 2800 ≤ MET-min/week ≤ 5200). The figure also includes the recommendations for assessment and the design of intervention measures for fall prevention.

Discussion

Present study results support the conceptual framework used to build the dynamic performance-exposure algorithm by demonstrating the dynamic relationship between performance-related and exposure risk factors for falling with the personal risk of falling. Corroborating this issue, the results showed that, to some extent, a high-performance capacity - made possible by good health and fitness, mainly if there is no history of retrospective falls - may prevent falls, even if the older person is highly exposed to fall occurrence opportunity by performing physical activity (do the tasks) in hazardous environments. Besides, results showed that the opposite is also true. Independently of age and gender, the risk performance-related risk factors selected as the main factors explaining falls were 1st, the number of falls that occurred in the previous year, 2nd, the number of health conditions, 3rd, multidimensional balance, 4th, lower body strength, and 6th, body fat mass. The exposure risk factors selected as the main factors explaining falls were 7th, environmental hazards number, 8th, rest periods, and 9th physical activity metabolic expenditure. The performance-exposure risk factor for falling “perceived action boundaries”, namely the overestimation of action boundary, was also selected as significantly explaining fall occurrence (in 5th order). The respective high-moderated-low risk cut-offs and respective reference values were determined (see results) for these selected risk factors as recommended by the Centers for Disease Control and Prevention [49]. In addition, a methodology for using of this acknowledgement in fall risk assessment and the design of falling prevention measures was defined and illustrated as the dynamic performance-exposure algorithm (see figure 4 in results).

Regarding performance-related risk factors for falls, it was observed that as healthier and fitter were the older adults (smaller number of health conditions, higher balance and lower body strength, lower fat mass, and not showing a history of previous falls), as lower was the risk of falling, even in the older ones. These results were expected because they were similar to the ones observed in previous and more traditional research [12, 13, 16]. On the other hand, if the cut-offs established to the history of previous falls (0, 1 and 2 or more falls) are equal to the ones observed in other studies [20], some differences are found in the other established cut-offs. For example, the study of Cho and colleagues [50] used a cut of 15 rep on the 30-s chair stand test to distinguish fallers from non-fallers older adults, while the present study used the cut-off > 14 rep to identify people at low risk of falling, the range 11-14 rep to identify people at moderated risk of falling, and the cut-off of < 11 rep to identify people at high risk of falling. Another example is the study of Hernandez and Rose [51], which found a cutoff of ≤ 25 points on the Fullerton Advanced Balance scale as identifying older adults at high risk of falling. While the present study found the cut-off > 33 points to identify people at low risk of falling, the range 32-33 points to

identify people at moderated risk of falling, and the cut-off of < 32 points to identify people at high risk of falling. These and other differences are expected because, in the present study, the established cut-off considered three categories (low vs moderate vs high risk), while the other studies [50, 51] considered two categories (high vs low risk, or fallers vs non-fallers). Besides, results showed in the present study for each risk factor were controlled for the co-effect of the other risk factors as is characteristic of multivariate binary regression modelling [42]. Thus, studies establishing cut-offs using models that include other risk factors are expected to find different cutoffs.

Concerning the exposure risk factors for falling, either physical activity, rest period, or environmental hazards sowed to contribute to the risk of falling. It is known that, along time, physical activity/exercise engagement habits improve health and fitness, which, in turn, decrease the risk of falling [7, 37]. However, at immediate time physical (in)activity concerns the exposure/non-exposure to fall occurrence opportunity. Thus, physical activity metabolic expenditure was shown to significantly explain fall occurrence, which is expected because if the person does nothing, not moving at all, will not fall [14]. Nonetheless, the present study observed that there is no direct relationship between the likelihood of fall occurrence and the amount of physical activity. Contrary to other studies results suggesting somehow that as much physical activity the better [14, 52], the present study showed that, in these community-dwelling older adults, the relation between physical activity expenditure and fall occurrence fit a line configuring several waves. According to our results, community-dewing older people with very low physical activity levels show a high fallers rate that increases until physical activity achieves ~1500 Mets-min/week of metabolic expenditure. A metabolic expenditure ranging from ~1500 to ~4500Mets-min/week configure a decrease in fallers rate (achieving a low rate), and a metabolic expenditure above ~4500 Mets-min/week is connected to an increased fallers rate (achieving a high rate). In accordance, the present study found that either lower levels (< 2300 Mets-min/week) of physical activity or very high levels (> 5000 Mets-min/week) were associated with a high risk of falling. Sedentary time has been reported as a risk factor for several health outcomes [53]. The present study showed that habits of high day rest periods (night sleeping excluded) are also a risk factor for falling and recommends daily rest periods totalling less than 4 hours to avoid falls. This result is controversial because if people are at rest, they are not expected to fall. However, we hypothesized that people with a high level of sedentary time may lose some awareness of the safe way to perform tasks (without falling). Thus, when they get up to perform a task, they are more susceptible to falling. Regarding environmental hazards, like other studies [18], the present study also showed that an increased number of hazards increases the likelihood of falling. However, the present study complemented this acknowledgement by founding the cut-offs to distinguish low (< 5 hazards), moderated (5 hazards) and high risk (6 or more hazards) of falling.

With respect to the perceived action boundary, the performance-related and exposure risk factor, the present study results confirmed previous findings [17], showing that the stepping-forward action perceived overestimation is a serious risk for falling.

The great advantage of the algorithm built in the present study is that, besides proposing the assessment of an ordered set of key performance-related and exposure risk factors for falls, it addresses cut-offs and

reference values for these risk factors divided into “high, moderate, and low risk”, as recommended by the Centers for Disease Control and Prevention [49]. Moreover, these risk factors are assessed by very accessible tests and very easy to interpret outcomes, being an issue of particular importance because many older adults lack the perception of their fall risk [54]. Thus, if a report with the risk profile is provided, the older person would strongly engage in fall prevention measures [18] once they became aware of their risk of falling and the changes needed to reduce it. Note that, in the present study, the percentage of retrospective fallers was 37.2%. In comparison, the rate of prospective fallers was 33.4%, showing a reduction in fallers percentage after the study participants received their risk profile analytic report.. Moreover, the establishment of a risk profile, where it is clear which factors contribute most to the risk of falling and how far each one is of the safe value, would allow the definition of fall prevention interventions, prioritizing individual needs (as recommended in literature) [55–57]. Individualized risk profile reports allow establishing very operational and concrete goals, particularly in the recommended [57] modifiable outcomes: Do I need to reduce environmental hazards? How many points should I increase in the balance test, how much should I increase or decrease my physical activity?

Some major strengths of this study are the representative and large sample size (500 older adults) and the inclusion of retrospective and prospective data. Strengths confer high external validity and a high level of statistical power to the study, despite the limitation of a higher proportion of women in the sample than men. One limitation pointed in the literature is using a questionnaire to assess physical activity instead of objectively measures (accelerometery) because people tend to overvalue the amount of performed physical activity in IPAQ [14]. Another limitation concerns the definition of a faller as a person who has fallen at least once in the previous 12 months, not as a person who has fallen recurrently, as recommended by some researchers [51]. Nevertheless, in the present study exploratory analysis, single/multiple fall-faller models showed a higher explanatory power and goodness of fit than recurrent-faller models. The models capacity for discriminating fallers were not high (AUC: 0.611; 0.690; and 0.693), but they were comparable to the ones observed in other studies, even when focusing exclusively on recurrent fallers (AUCs of 0.68 and 0.71) [35, 58], and the AUCs computed by cross-validation were similar results (AUC Ranging from 0. 600-0.684). At last, to ensure data accuracy and that participants live independent in the community setting, the inclusion criterion of an absence of cognitive impairment was defined, and, therefore, this important risk factor [7, 19] was not included in the fall risk assessment. The gait pattern, another reported risk factor for falls [57] was not considered either. Thus, future studies complementing the present study should examine the contribution of these two and other additional risk factors for falling on the individual risk of falling.

Conclusions

This study results demonstrated a dynamic relationship between older adults’ performance capacity and the exposure to falls opportunity supporting the conceptual framework underlying the dynamic performance-exposure algorithm build. The high-moderated-low risk cut-offs and respective reference values were determined (see results) for the ordered key risk factors explaining falls, either performance-related: 1st, the number of falls occurred in the previous year, 2nd, the number of health conditions, 3rd,

multidimensional balance, 4th, lower body strength, and 6th, body fat mass; exposure: 7th, environmental hazards number, 8th, rest period, and 9th, physical activity metabolic expenditure; or performance-exposure: 5th, bias of overestimation the action boundary in a stepping-forward. Fall prevention programs shall attend informed older adults and consider the above factors that most contribute to the individual risk of falling (with particular attention to the modifiable ones) and their relative weights and their distance from low-risk values. Health, exercise, and social professionals should consider these study findings and the proposed dynamic algorithm for fall assessment and prevention in the community.

Abbreviations

DALYs: Disability-adjusted life years; MMSE: Mini-Mental State Examination; FAB: Fullerton Advanced Balance; IPAQ: International Physical Activity Questionnaire; MET: Metabolic equivalent of task; SF-APT: Stepping-Forward Affordance Perception Test; SD: Standard deviation; OR: Odds ratio; AUC: Area under the curve.

Declarations

Ethics approval and consent to participate

All participants provided written informed consent to participate in the present study, which followed the Declaration of Helsinki ethical principles. The University of Évora Ethics Committee for research in the areas of Human Health and Well-being approved this study (reference number 16012).

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author upon reasonable request.

Competing interests

The authors have declared that no competing interests exist.

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Authors' contributions

Study conception and design: CP. Data collection: CP, HR, and JB. Data Analysis: CP, GA, and JB. Prepared figures 1 - 4: CP and JB. Write the main manuscript text: CP, HR, GA and JB. All authors read and approved the final manuscript.

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Figures

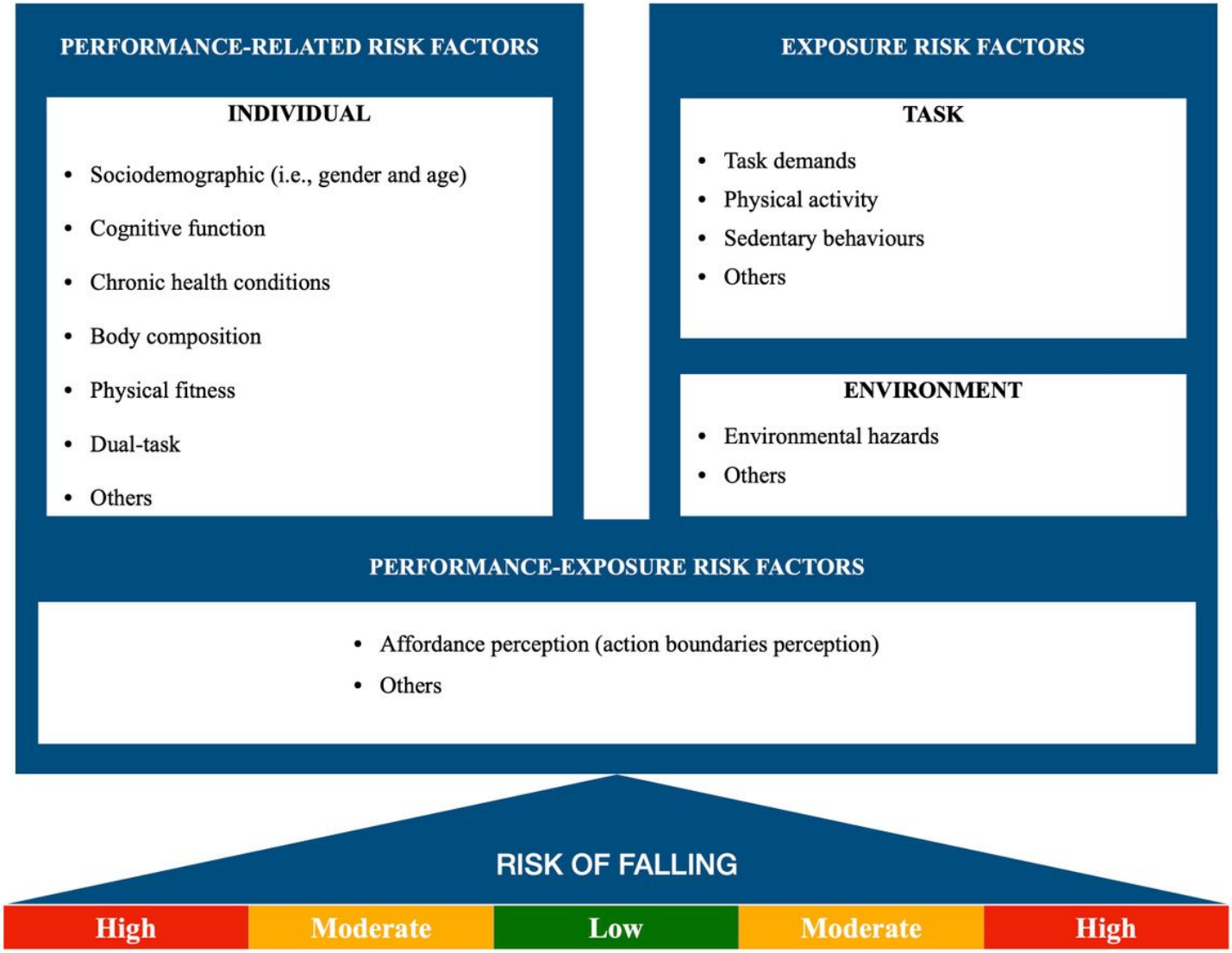

Figure 1

Performance-exposure conceptual framework explaining fall occurrence

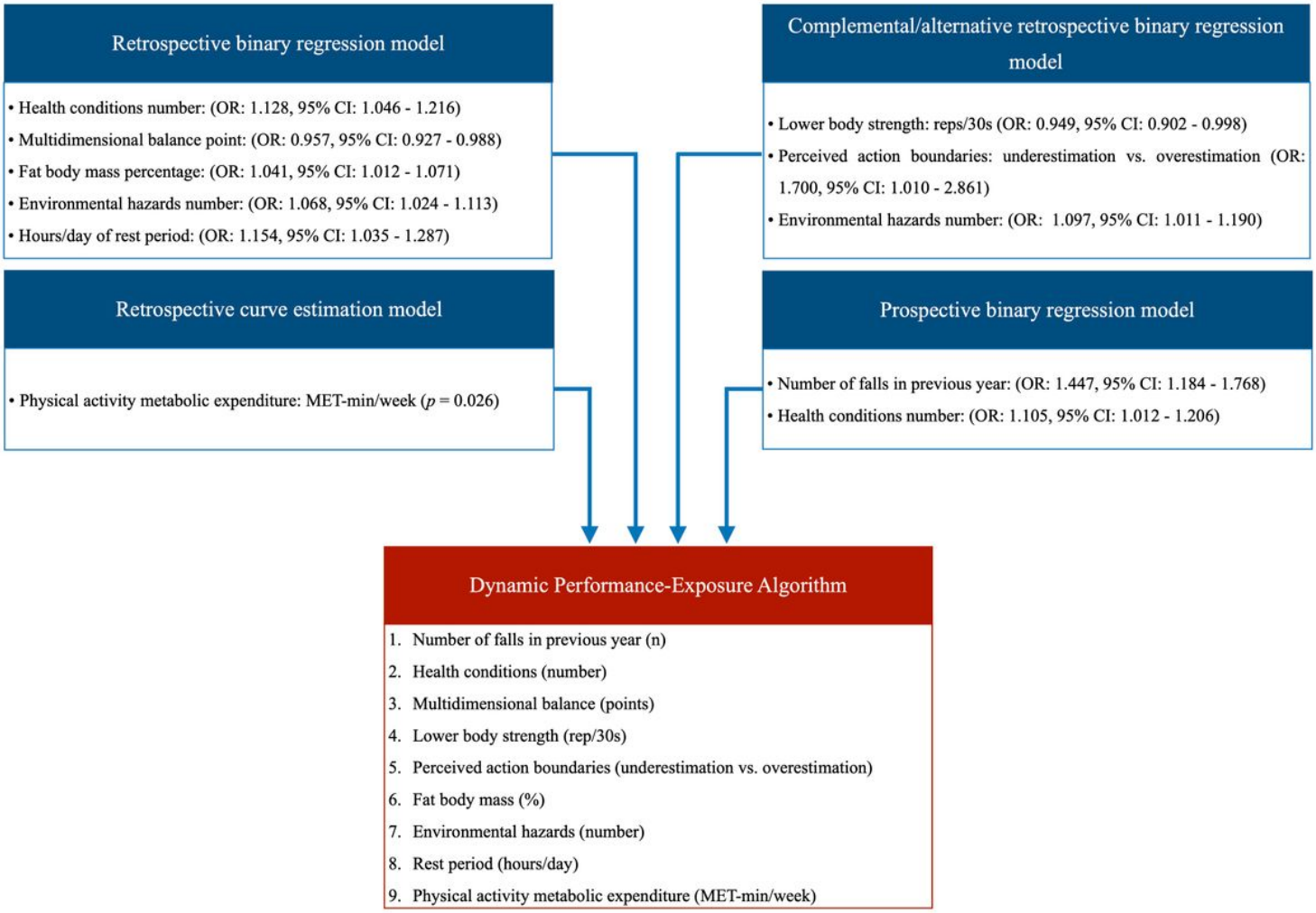

Figure 2

Illustration of the algorithm design. Data are shown as multivariate odds ratio (OR)

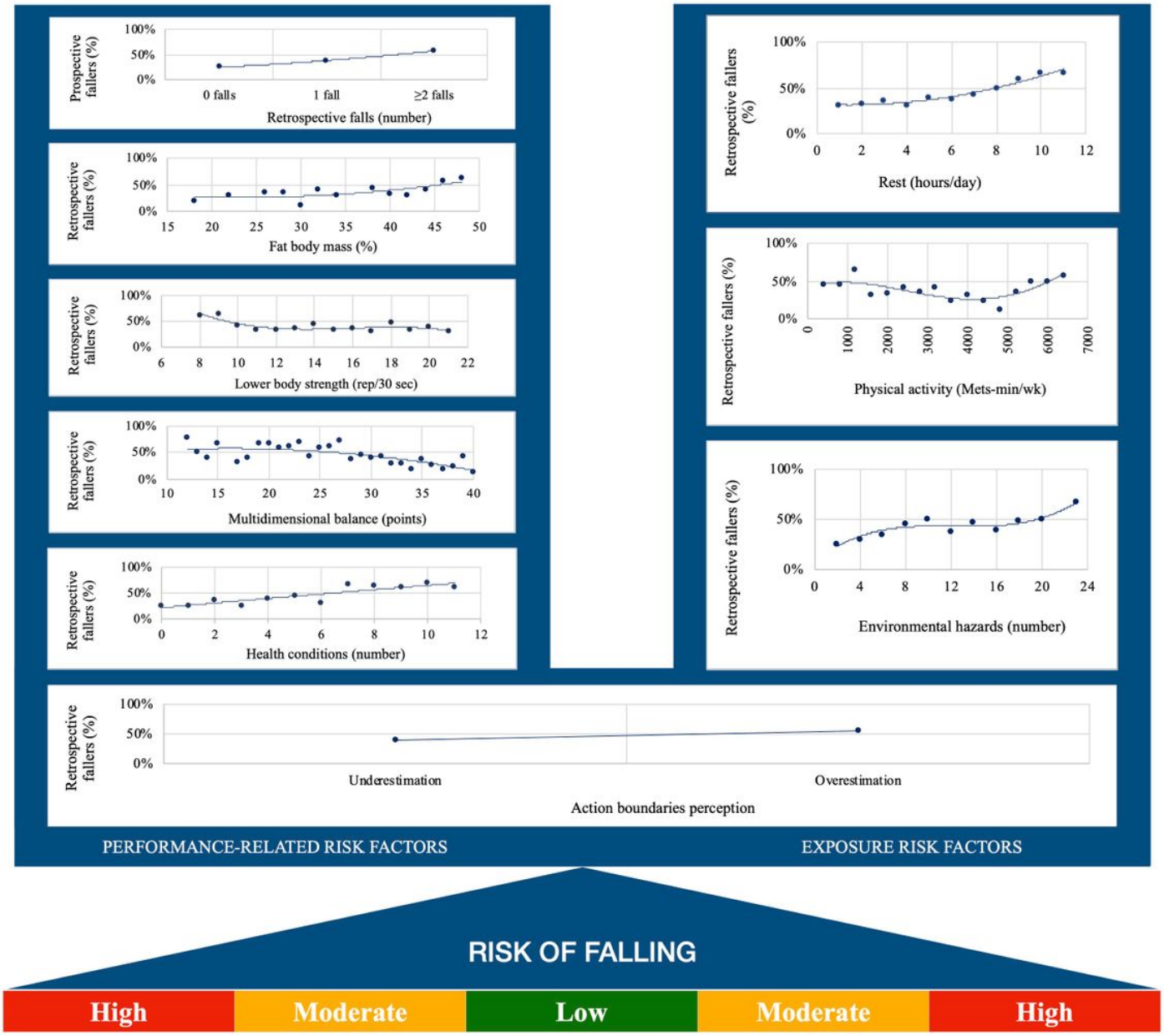

Figure 3

Dynamic model explaining the risk of falling depending on the relationship between the subject performance capacity and the exposure to the fall occurrence opportunity. Each graphic illustrates the variation in the fall rate (%) depending on each risk factor value. Retrospective faller percentage data concerns the occurrence of retrospective falls (see participants recruitment stages I and II). Prospective fallers percentage data concerns prospective falls occurrence (see participants recruitment stage II)

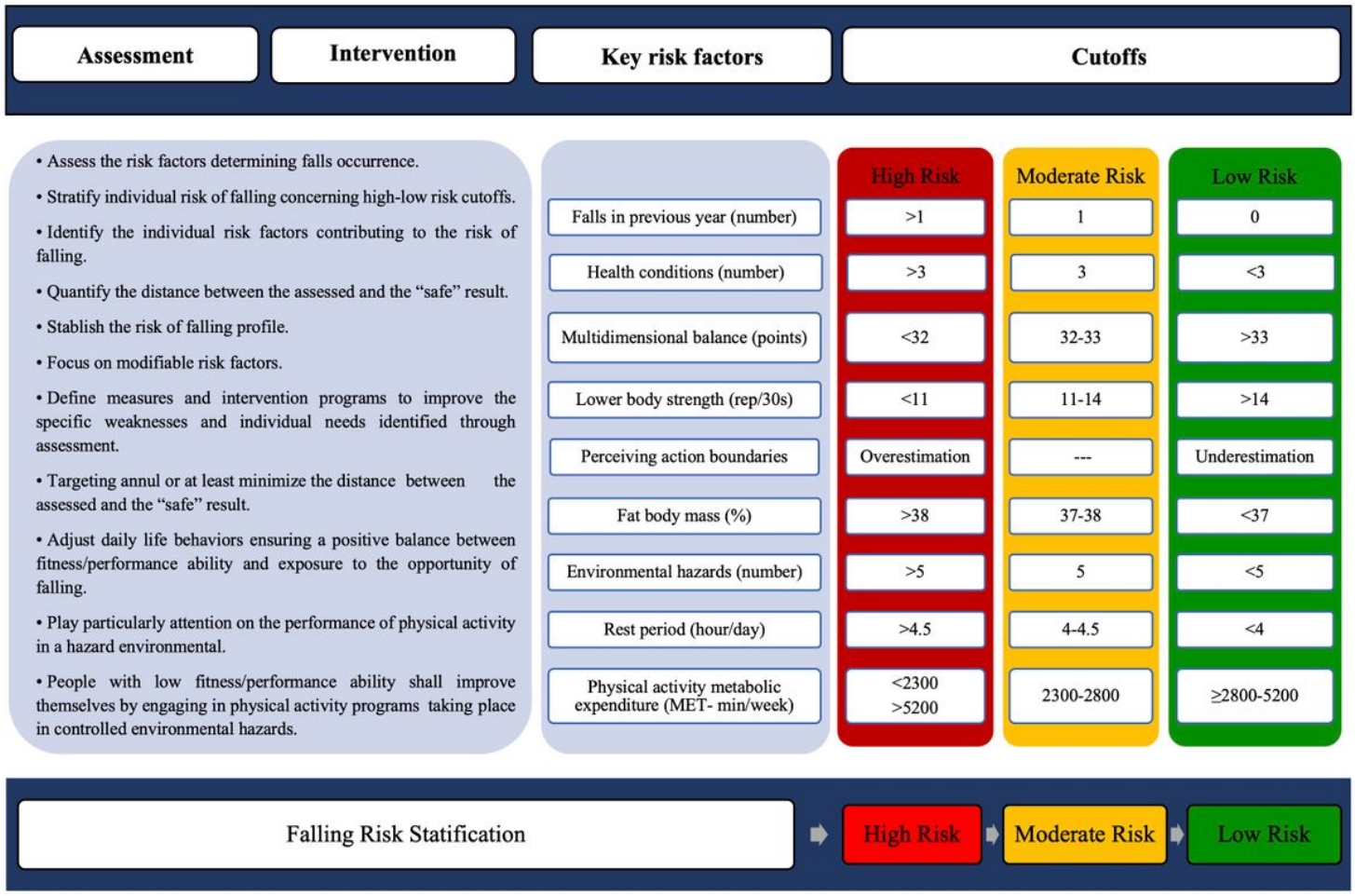

Figure 4

Dynamic performance-exposure algorithm for falling risk assessment and fall prevention in community-dwelling older adults