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Conceptualizing a Dynamic Fall Risk Model Including Intrinsic Risks and Exposures

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A B S T R A C T

Falls are a major cause of injury and disability in older people, leading to serious health and social consequences including fractures, poor quality of life, loss of independence, and institutionalization. To design and provide adequate prevention measures, accurate understanding and identification of person's individual fall risk is important. However, to date, the performance of fall risk models is weak compared with models estimating, for example, cardiovascular risk. This deficiency may result from 2 factors. First, current models consider risk factors to be stable for each person and not change over time, an assumption that does not reflect real-life experience. Second, current models do not consider the interplay of individual exposure including type of activity (eg, walking, undertaking transfers) and environmental risks (eg, lighting, floor conditions) in which activity is performed. Therefore, we posit a dynamic fall risk model consisting of intrinsic risk factors that vary over time and exposure (activity in context). eHealth sensor technology (eg, smartphones) begins to enable the continuous measurement of both the above factors. We illustrate our model with examples of real-world falls from the FARSEEING database. This dynamic framework for fall risk adds important aspects that may improve understanding of fall mechanisms, fall risk models, and the development of fall prevention interventions.

Falls are a major cause of injury and disability in older people. Serious health and social consequences including fractures, subsequent poor quality of life, loss of independence, and institutionalization are common.[1] One in 3 community-dwelling people aged 65 years or older fall at least once a year, one-half of these fall multiple times.[2,3] Five percent to 10 percent of such falls lead to fractures, and about 90% of all hip fractures are the result of a fall.[2–4] For high-risk populations including nursing home residents or patients in geriatric rehabilitation units, fall incidence is even higher with 0.6–3.6 falls per person-year and in residential care, up to 25% of fallers sustain a fracture.[1] For those with certain neurologic condition such as Parkinson disease, falls are up to 20 times more frequent.[5] Falls and fractures also have an important economic impact with annual costs between 0.85% and 1.5% of total health care expenditure.[6] With the aging of populations in both developed and developing nations, numbers of fallers and costs will increase, accentuated by the large “baby boomer” generation, born between 1946 and 1964, now entering old age. Therefore, fall prevention is one of the most important public health challenges in older persons. While we will focus on this age group in our report, falls also have major impact on the lives of working age people[7] and children,[8] thus, fall prevention is relevant throughout the life span.

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The current Cochrane Review on fall prevention in community-dwelling older persons lists several effective interventions.[9] However, there is limited impact at the population level with the risk of falls being reduced between 15% for multiple component group exercises and 25% for multiple component home-based exercises.[9] Even less effective are interventions in residential aged care[10] where more than 50% of residents fall yearly. Clearly, more progress is required in fall prevention; it is likely more effective strategies would be informed by a more comprehensive understanding of the causal mechanisms of falling and fall risk.

Analyses of fall risk factors also show that we do not fully understand the causal mechanisms of falling. Epidemiologic studies identify at least 18 (nursing homes and hospitals[11]) to 30 (community living[12]) fall risk factors such as prior fall, balance and gait problems, and medical conditions such as Parkinson's disease.[11,12] Fall risk models based on the presence of such risk factors and their interplay have been used to predict an individual's risk of falling. However, current models are limited in this regard as the predictive accuracy of externally validated prediction models for falls in community-dwelling older adults is weak compared with models estimating the risk of cardiovascular events (Figure 1). Furthermore, prior fall is usually the most important risk factor, meaning that prevention of the first fall is difficult using these models.

A systematic prospective evaluation of 4 fall prediction tools in residential care showed that each one was unsuitable because of poor precision.[23] Sensitivity and specificity ranged from 0.50 to 0.80 and 0.32 to 0.80, respectively. Similarly, the FRAT-up tool used with frail older people has an area under the curve (AUC) of about 0.65, showing heterogeneity in results from different populations.[15] The operationalization of these fall risk models into prediction of falls in individuals has been disappointing and is not sufficient to direct practice or policy.

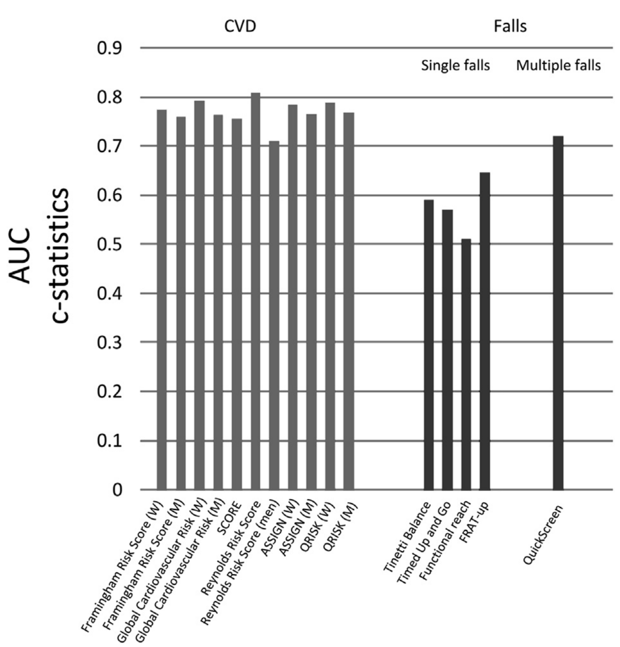

Fig. 1. Comparison of the predictive accuracy of fall risk factor models with risk models of cardiovascular events (CVD).[13] The AUC and the C-statistics represent the ability of the model to correctly discriminate those that sustain the event related to the risk factor profile: ASSIGN, SCORE, QRISK,[14] FRAT-Up,[15] Framingham Risk Score, Global Cardiovascular Risk, Reynolds Risk Score,[14] Tinetti Balance,[16–18] Timed-Up and Go,[16,19–21] Functional Reach,[16] and QuickScreen.[22] *ASSIGN*, Assessing Cardiovascular Risk to SIGN to assign preventive treatment; CVD, cardiovascular events; *FRAT-Up*, falls risk assessment tool; *M*, men; *W*, women; *QRISK*, QRESEARCH Cardiovascular Risk Algorithm; *SCORE*, Systematic Coronary Risk Evaluation; *SIGN*, Scottish Intercollegiate Guidelines Network.

Most data about fall risk factors to date are based on self-report and functional measures gathered during baseline assessments, often quite distant in time from fall events.[24] Fall event information is usually collected sometime after the event itself and verifiable proxy information is rarely available since less than 20% of falls are observed by other persons.[25,26] Self-report may be affected by recall problems or social report bias.[27–29] Even the reporting of date and time of falls is problematic. While the consequences of a fall such as injuries can usually be ascertained, most fallers cannot accurately report what happened before and during the fall.

With the rapid development of eHealth including body-worn sensor technology over the last decade, small wearable devices are now available that can provide objective measures of physical activity and the kinematics of human movement.[30] Thus, the combination of clinical characteristics with sensor technology in fall risk models has the potential to further improve falls prediction. Van Schooten et al added sensor-based measures including gait complexity, gait intensity, and gait smoothness to clinical risk factors and improved the AUC for falls prediction from 0.68 to 0.82.[31] The best AUC yielded sensitivity and specificity of 70.0% and 80.9%, and a positive and negative predictive value of 66.0% and 82.6%, respectively. However, the most important risk factor continues to be history of prior fall. Other studies using information and computer technology (ICT) to predict falls showed similar results. But, internal and external validity is not yet established as some models have been developed and validated on the same samples, thus replication is required.[24,32] Furthermore, most of the above ICT studies have limitations in that they have used fall history, clinical fall risk assessment, or both to define fall risk, instead of the gold standard measure of prospective fall ascertainment.[33]

The aim of this article is to discuss possible reasons for the observed limitations of current fall risk models and to suggest a new approach that may improve our understanding of fall mechanisms and better identify individuals at risk of falls.

Conceptualizing a Dynamic Fall Risk Model

We hypothesize, that the main reasons for the lack of precision are (1) the measurement of fall risk factors is static; and (2) the context in which falls occur is not considered. Intrinsic risk factors may change over time, and their interaction with contextual factors can vary. For example, physical function varies with acute intermittent illnesses, but is usually only measured at 1 time point.

Furthermore, in most studies, fall risk models do not consider individual exposure to hazardous situations, including activity (eg, walking, transfers) and environmental factors (eg, lighting, floor conditions) in which the fall occurs, nor the idiosyncratic nature of surroundings and unexpected events. Many older people fall during habitual daily activities, like walking or rising from a chair or a bed.[2,34] Other activities undertaken at the same time are not assessed, such as talking to another person, also known as dual tasking, and neither are other transient environmental factors such as distracting noises or visual stimuli. For those with intact cognitive capacity, adaptation is possible, but for people with reduced cognitive capacity, distractions may result in loss of balance and a fall. The interaction of cognitive capacity of the individual and the activity context makes the fall more or less likely. Together the activity and the environment (and their interaction) represent the exposure.

Rubenstein and Josephson[35] drafted a conceptual model which includes intrinsic risk factors, extrinsic risk factors and precipitating causes. We further develop this concept by structuring the components and adding the dynamic nature of fall risk and suggest a new model that includes intrinsic risk factors and the exposure. The components of the model are illustrated in more detail in following.