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Defining the concept of physical resilience and quantifying recovery during standing balance in middle-aged and older adults

John Manning[1], Hyeon Jung Heselton[2], Dawn M. Venema[3], Julie B. Boron[2] & Jennifer M. Yentes[1]✉

Physical resilience is the ability to recover from an external perturbation, an integral aspect of functional adaptability and healthy behavior. Techniques that quantify behavior over multiple time scales offer a solution to quantifying resilience. As people age, they tend to lose functional adaptability and resilience. However, age-related declines in resilience between middle-aged and older adults is unclear. This study compared the difference in the ability to recover to baseline following standing balance perturbations between middle-aged and older adults, and between those that do or do not recover to baseline. Thirty-eight middle-aged and thirty-one older adults stood on a force platform during five, 60-sec trials. The platform moved posteriorly a specified distance during each trial (2.54 to 12.7 cm). Detrended fluctuation analysis (DFA) was calculated on anteroposterior center of pressure with moving windows of five seconds. Baseline DFA alpha (BA) was obtained by averaging windows before the perturbation. Directly after the perturbation, windows were analyzed until the DFA recovered within a set criterion of BA, called recovery Alpha (RA). If DFA didn't meet the criterion, DFA of the last window was taken as the RA. Trials were coded as recovery and non-recovery. There was a significant interaction between age and Recover or No recovery on RA. Older adult non-recoverers had a significantly lower RA than middle-aged adults and older adult recoverers. Older adults who did not recover to baseline exhibited less persistent sway, evidenced by decreases in RA. Older adult non-recoverers demonstrating decreased DFA indicates decreased resilience.

Keywords Aging, Recovery, Robustness, Biomechanics, Fractals

Standing balance and perturbations to standing balance have received a great deal of study in biomechanics literature[1–3]. Displacement of the center of pressure (COP) reflects body sway, which is thought to be indicative of physiological influences and neurological control mechanisms[4,5]. There are a wide variety of methods utilized to test the standing balance system[1,6,7], and to analyze the digital signals that are produced[6–11]. Common techniques include linear methods which characterize the physical displacement of COP, such as sway velocity and total sway area, and nonlinear methods which include measures of regularity, statistical self-similarity, the rate of divergence, and more[2,12–17].

The human body is known to exhibit fractal like structure, meaning it is irregular, but exhibits self-similarity[18–20]. The overall shape or pattern of a fractal structure can be broken down into smaller components, which are statistically similar to the whole structure, regardless of the scale at which they are observed[20]. This fractal structure provides redundancy to the human body and its subsystems, and it is this redundancy which in turn provides the human body with a set of possible states which can be assumed (i.e. state space), as opposed to a single state[20,21]. Being able to access many different system states is beneficial in the sense that it allows the human body to adapt to varying demands, and to switch to a different state in the case that the current one becomes disadvantageous or inaccessible[22].

This redundancy, which exists across different physical scales of organization in the human body (e.g. whole-body scale, organ scale, tissue scale), gives rise to long-range correlations in physiological and biomechanical

[1]Department of Kinesiology & Sport Management, Texas A&M University, College Station, TX, USA. [2]Department of Gerontology, University of Nebraska at Omaha, Omaha, NE, USA. [3]Department of Health and Rehabilitation Sciences, College of Allied Health Professions, University of Nebraska Medical Center, Omaha, NE, USA. ✉email: jyentes@gmail.com

time-series data[17,23–26]. Long-range correlations are measurable through nonlinear analysis techniques, such as the detrended fluctuation analysis (DFA)[23]. When DFA is applied to COP time series in the anteroposterior direction, the output value, termed the alpha value (α), tends to be between 1 and 2, indicating that the time series is persistent and unbounded, with higher α values indicating greater persistence[17]. In a persistent signal, increases or decrease in the values at any specific time scale are likely to be followed by increases or decreases at other time scales, respectively[17,26,27]. This persistence is indicative of self-similarity in time, which is accompanied by self-similarity in the system's physical structure[28]. Older adults tend to exhibit greater α values than middle-aged and young adults, indicating a degradation (i.e. greater persistence) in the postural control system[6,29]. However, it is unclear how age and perturbations affect COP persistence. Measuring a system's persistence in time is an indirect way of measuring its physical redundancy and fractal structure, with which the set of possible system states can be inferred[30].

Related is the concept of physical resilience[31–33]. The National Institutes of Health recently started a new initiative to define a research framework using the concept of resilience as a theoretical underpinning[34]. Previous researchers have opted to operationally define physical resilience, as no attempt, that these authors know of at the time of writing, has been made to make explicit statements about how it is the phenomenon is believed to exist (i.e. its ontological status), which is a major shortcoming of many concepts in the behavioral sciences[35]. The general similarities between previous research seem to indicate that physical resilience involves a system existing in some baseline state, being perturbed from that state to a state of lower functional ability, then recovering to the baseline state[31]. It is currently unclear how to appropriately measure these three components of resilience (i.e. baseline, perturbation, recovery), however the DFA seems to be a promising avenue for measuring the current state of a complex system, such as the human body[29]. A previous study in the motor control literature measured continuous movement of the hand during a visuomotor adaptation task where perturbations were introduced to disrupt performance[36]. In this study, the hand movement data were analyzed using DFA, which demonstrated that resilient motor performance during the task was positively related to the DFA scaling exponent α[36]. Thus, it may be possible to use a sliding window approach to DFA to measure the current state of a complex system and its response to a perturbation.

The purpose of the present study was to evaluate the differences in COP persistence between middle-aged and older adults and their ability to recover from a perturbation by applying DFA to a series of sliding windows before and after the perturbation. This could be a potential measurement for resilience as defined earlier. To that end we postulated two main hypotheses relative to baseline state: (1) Older adults will exhibit decreased COP persistence in response to a perturbation; and (2) Those who are not able to recover to their baseline state from a perturbation will also exhibit decreased COP persistence.

Results

Sixty-nine participants completed the study; 38 middle aged adults and 31 older adults (Table 1.). Participants stood on a force platform and one backward perturbation was delivered at one of five magnitudes during five one-minute trials. DFA was calculated for windows of time before and after the perturbation. Baseline α (BA), α from the first window post perturbation, and recovery α (RA) were quantified. If RA was within two standard deviations of BA before the end of the trial, the trial was classified as recovery. Three separate three-way factorial ANOVAs with repeated measures were used to test the effects of three independent variables: (1) age group, (2) perturbation magnitude, and (3) recovery (i.e. recover or no recover status); on three separate dependent variables: (a) BA, (b) α from the first window after the perturbation, and (c) RA. No effect of perturbation magnitude was found in any model, so it was removed from further analysis and instead three separate two-way factorial ANOVA's with repeated measures were used to test the effects of the two independent variables: (1) age group and (2) recovery; on the three separate dependent variables: (a) BA, (b) α from the first window after the perturbation, and (c) RA.

BA and α from the first window after the perturbation were normally distributed. The original data and the log transformed data for RA were found to differ significantly from a normal distribution ($p < .001$). The RA values from two individual trials in the older adult's group were found to be extreme outliers, defined as being

Middle Age	***n*** **= 38**
Age, years	54.4 ± 7
Sex, male/female	21/17
Height, cm	173.3 ± 10.4
Mass, kg	86 ± 26.5
TUG, s	8.5 ± 1.4
Older Adult	***n*** **= 31**
Age, years	70 ± 4.1
Sex, male/female	14/17
Height, cm	169 ± 8.7
Mass, kg	86.1 ± 14.2
TUG, s	9 ± 1.3

Table 1. Participant demographics ($N = 69$). Values are presented as mean ± standard deviation. MOCA = Montreal Cognitive Assessment. TUG = Timed Up & Go.

Dependent Variable	Age Group	Mean	Standard Deviation	F-value	*p*-value	partial η^2
BA	MA	1.81	0.05	3.14	0.08	0.05
	OA	1.78	0.07			
First Window	MA	1.76	0.14	0.32	0.57	0.01
	OA	1.77	0.13			
RA	MA	1.79	0.09	5.3	0.02	0.08
	OA	1.75	0.10			

Table 2. Main effects of age group on alpha values from Follow-Up One-Way ANOVAs. Statistical summary of the main effects of age group on each dependent variable from one-way ANOVA tests. BA = baseline DFA alpha, RA = recovery DFA alpha, First window represents the DFA alpha value from the first 500 data points following the perturbation.

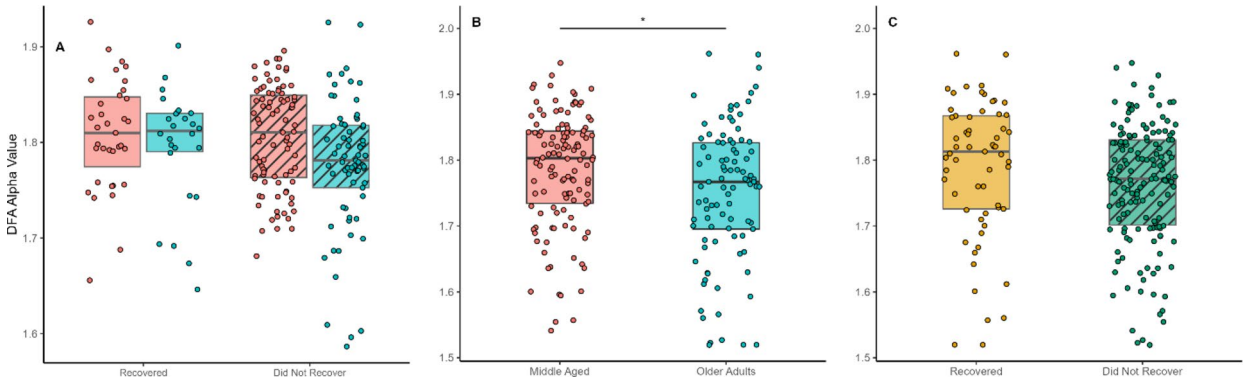

Fig. 1. Baseline mean alpha values (BA), calculated by taking the average of all sliding windows before the perturbation was applied for baseline means split by (**A**) the interaction of Age Group by recovery, (**B**) Age Group, and (**C**) recovery (i.e., whether or not the participant recovered to their baseline value within 60-seconds). Red indicates middle-aged and blue indicates older adults. Solid bars indicate recoverers and striped bars indicate non-recoverers. The horizontal bars with one asterisk (*) indicates significance at the $p < .05$ level.

Dependent Variable	Df	Sum of Squares	Mean Square	F-value	*p*-value
BA	1	0.0002	0.0002	0.02	0.9
First Window	1	0.02	0.02	1.58	0.21
RA	1	0.04	0.04	3.57	0.06

Table 3. Interaction effects for between age group and Recovery status from Two-Way repeated measures ANOVAs. Statistical summary of the interaction terms used in the two-way repeated measures ANOVA tests for each DFA alpha dependent variable. age group included individuals from middle-aged and older adults. Recovery status was true if the return alpha (RA) was within two standard deviations of baseline alpha (BA) before the end of the trial. First window represents the DFA alpha value from the first 500 data points following the perturbation.

more than three standard deviations away from the mean. These outliers were removed from further analysis. Following removal of the outliers, the data did not differ significantly from a normal distribution ($p = .43$).

Two-way factorial ANOVA found a nearly significant main effect of age group on BA ($n = 69$, $F(1,58) = 3.14$, $p = .08$), providing some evidence that there may be age differences (Table 2.). Tukey's HSD revealed a significantly less persistent BA in older adults compared to middle aged adults with a medium effect (p-adjusted = 0.005; mean difference = -0.02; 95% CI = [-0.04, -0.007]; partial $\eta^2 = 0.07$) (Fig. 1.). No significant main effects or interactions were found for perturbation magnitude or recovery on BA.

No significant differences were found between age groups, perturbation magnitudes, or recovery on the α of the first window post perturbation.

Two-way factorial ANOVA found a nearly significant interaction between age group and recovery ($n = 69$, $F(1,58) = 3.6$, $p = .06$) on RA (Table 3.). Tukey's HSD indicates that older adult non-recoverers have a significantly lower RA than middle-aged recoverers (p-adjusted = 0.04; mean difference = -0.05; 95% CI = [-0.10, -0.001]) and non-recoverers (p-adjusted = 0.02; mean difference = -0.04; 95% CI = [-0.08, -0.005]) (Fig. 2.). Main effects

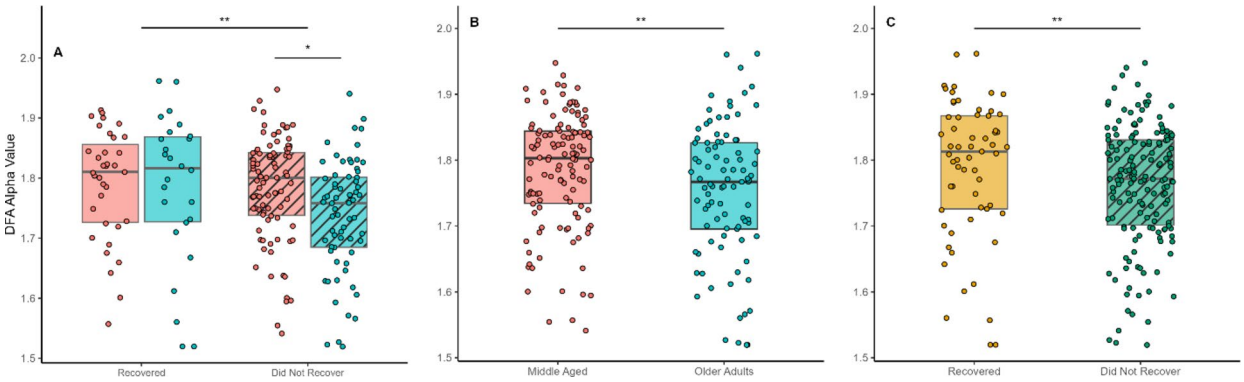

Fig. 2. Recover alpha (RA) values from the final sliding detrended fluctuation analysis window when the alpha value recovered to within two standard deviations of the baseline mean split by (**A**) the interaction of Age Group by recovery, (**B**) Age Group, and (**C**) recovery (i.e., whether or not the participant recovered to their baseline value within 60-seconds). Red indicates middle-aged and blue indicates older adults. Solid bars indicate recoverers and striped bars indicate non-recoverers. The horizontal bars with two asterisks (**) indicate a significant difference at the $p < .01$ level, and one asterisk (*) indicates significance at the $p < .05$ level.

Dependent Variable	Recover or No Recover	Mean	Standard Deviation	F-value	*p*-value	partial η^2
BA	Recover	1.80	0.06	0.97	0.33	0.01
	No Recover	1.79	0.06			
First Window	Recover	1.76	0.12	0.56	0.48	0.01
	No Recover	1.77	0.14			
RA	Recover	1.79	0.10	8.78	0.004	0.13
	No Recover	1.76	0.10			

Table 4. Main effects of recovery on alpha values from Follow-Up One-Way ANOVAs. Statistical summary of the main effects of recovery on DFA alpha values from one-way ANOVA follow-up tests. Recovery status was true if the return alpha (RA) was within two standard deviations of baseline alpha (BA) before the end of the trial. First window represents the DFA alpha value from the first 500 data points following the perturbation.

tests revealed a significant main effect of age group ($F(1,58) = 5.3$, $p = .02$; mean difference = -0.03; 95% CI = [-0.06, -0.008]; partial $\eta^2 = 0.08$) and recovery ($F(1,58) = 8.8$, $p = .004$; mean difference = -0.2; 95% CI = [-0.05, -0.003]; partial $\eta^2 = 0.13$) on RA (Table 4.). The main effects' significances seem to be driven by older adult non-recoverers. No significant main effect or interaction was found for perturbation magnitudes on RA.

Discussion

The purpose of the present study was to evaluate the differences between middle-aged and older adults in their ability to recover from a perturbation based on COP persistence. Two hypotheses were postulated: (1) Older adults would exhibit decreased COP persistence in response to a perturbation, and (2) Those who are not able to recover to baseline from a perturbation will also exhibit decreased COP persistence. The results support the first hypothesis, in that older adults had significantly lower COP persistence than middle-aged adults following a perturbation (Fig. 2B.). When successive increments in a time series are correlated, meaning that past events influence future events, the signal can be characterized as persistent. As demonstrated by these results, participants exhibited a highly persistent COP ($\alpha > 1$) before and after a perturbation, with older adults being significantly less persistent. However, this age difference was driven by older adult non-recoverers as the results of the interaction between Age Group and recovery demonstrate (Fig. 2A.). In opposition to our second hypothesis, this indicates that older adult recoverers do not differ from middle-aged recoverers and non-recoverers. This provides further evidence that some older adults retain physical resilience similar to their younger counterparts.

These α values over 1 indicate the time series is persistent, exhibiting correlations within itself over multiple time scales, and is unbounded[17]. Or simply put, increases in time series values are likely to be followed by additional increases and vice versa. As α continues to rise above 1, the signal becomes qualitatively smoother, indicating non-stationarity[37], and that correlations exist, but they stop being of a power-law form[17]. A value of $\alpha = 1.5$ indicates the signal is Brownian noise, which is dominated by lower frequency trends in the data[17]. Data from this study indicate highly persistent COP behavior — well into α values greater than 1.5, indicating extreme persistence. This is likely due to the biomechanical nature of anteroposterior balance control.

The control of balance in the anteroposterior direction is typically accomplished through ankle and hip strategies[4]. In this control scheme, the ankle and the hip work in opposition to one another through an inverse moment couple whereby a positive change in angular position in one joint (e.g. ankle) is met with a negative

change in angular position of the other joint (e.g. hip) in an attempt to maintain center of mass over the base of support. For example, if the ankles plantarflex, moving the center of mass posteriorly, the hips would have to flex moving the center of mass anteriorly to maintain center of mass over base of support. These responses are inversely coupled, but not phase locked, meaning changes in one will not cause immediate changes in the other. Instead, the reaction of the other will lag slightly. This non-phase locked inverse coupling of control in the anteroposterior direction may be what causes the COP signal in this direction to exhibit persistence. Anteroposterior COP DFA α values tend to be somewhere between 1 and 2, indicating that any given time the balance system is dependent upon its previous states, and becomes more dependent upon its previous states the higher the alpha value rises[6,38].

Based on the findings presented, the difference between age groups was driven by older adult trials in which the participants did not recover. During these trials, participants exhibited a significant decrease in signal persistence in response to a standing balance perturbation, which indicates they were less dependent upon their previous states and began exploring a larger state space. The pre-perturbation state space likely had a high degree of order, with constraints that limited the system to certain regions, indicating a lower-dimensional attractor within a high-dimensional space. Then, the perturbation may have induced a change in control over the degrees of freedom, and a new functional state was enacted which could no longer depend on the previous system states because they had become inaccessible.

The ability to access a large repertoire of possible states, which is known as the degrees of freedom problem, is a fundamental feature of the human motor control system[39]. It has been hypothesized that aging and loss of system complexity are complimentary. As aging progresses there may be either a decrease in the amount of system components and the interaction between them which would lead to rigid, predicable behavior, or there may be an overabundance of system components and interactions between them, which may lead to random unpredictable behavior[19]. In either case, when behavior becomes either too rigid or too random it may be characterized as losing complexity[18,19,40]. The amount of system components and interactions between those components contributes directly to the set of possible states the system has access to (i.e. state space). Currently, physical resilience is conceptualized as a decline in function followed by a recovery to baseline[33]. However, despite attempts to frame physical resilience in terms of dynamical systems theory, the concept of baseline state has not yet been framed through the concept of state space[41].

Defining physical resilience

There is not yet a clear consensus on how to define physical resilience at the whole-body level in the gerontological literature. Previous research endeavors have operationally defined physical resilience, which has led to inconsistencies in its conceptualization[31,32,41]. In this paper, we explore the concept of physical resilience, which is a whole-body level, biomechanical, human-movement based concept[31,32,41–44]. This is distinguished from the concept of resilience at any other given level (e.g. physiological[45] or psychological), or in the more general conceptualization of the term at the whole-system level (i.e. summation of all bodily systems – which is not to be confused with whole-body level), or across system levels.

There are a handful of general conceptual frameworks for defining physical resilience, which use terminology such as resistance, recovery, and robustness when attempting to define it. Whitson et al. (2015) defined physical resilience as a phenomenon that exists at the whole person level which determines the ability of an individual to *resist* functional decline or *recover* physical health following a stressor[31]. Ukraintseva et al. (2016) challenged this definition by differentiating the ability to *resist* functional decline from the ability to *recover* following a stressor[32]. In this view, the authors defined robustness as the ability to *resist* functional decline, and physical resilience as the ability to *recover* following a stressor[32]. Later, Whitson et al. (2016) agreed that it may be useful to differentiate between resilience and robustness[46]. To date, there is no general consensus on whether the concept of resilience ought to incorporate both *resistance* and *recovery*, or if *resistance* belongs to robustness and *recovery* to resilience.

The idea that resilience as a whole, not just specifically physical resilience, should be defined as a general positive adaptation has been challenged by Hill et al. (2024)[47]. The authors assert that resilience as a whole is a phenomenon which exists at the biopsychosocial level, and define it as the ability of such a system to recover to the previous level of functioning following a perturbation[42,47]. This definition of resilience has been contrasted with the concepts of resistance to, and growth following, a stressor, which are believed to be separate phenomena[47]. However, the concepts of resilience, resistance, and growth all seem to share the general components of baseline state, perturbation, and response to that perturbation, but each differs in its response to the perturbation. Hill et al. (2024) go further to state that recovering to a previous level of functioning may be a negative consequence, if the previous state is at a lower functional level than the current state[47]. Herein we note the importance of semantics in defining terminology, in opposition to the notion propounded by Whitson et al. (2016) that overemphasizing semantic differences hinders scientific progress[46]. The terms, 'return,' and 'recover,' are used in seemingly the same context between studies, obfuscating the path to a clear definition of resilience[31,32,41,42,46,47]. We operationally defined recovery as a special case of returning to a previous state following a perturbation, where the previous state is at a higher functional level, and propose that recovery, not simply returning, is an essential subcomponent of resilience.

To measure recovery, a perturbation must be introduced either experimentally or naturally, that diminishes the set of states the system has access to. In the present study, we perturbed the system experimentally using a moving platform and measured completeness of recovery through the resulting COP time-series persistence. The results indicate that older adult non-recoverers exhibit less persistent sway patterns than middle aged adults and older adult recoverers, meaning that the older adult non-recoverer's responses to physical perturbations are likely to take longer (Fig. 2.). It appears then, that whole-body level perturbations decrease COP persistence in

older adults when they are not able to recover to their baseline state. This provides evidence that older adults are sometimes less resilient to physical perturbations than middle-aged adults.

Future directions

Current literature lacks a consensus as to what it means for a human to be physically resilient. This lack of consensus arises as a result of not having an ontologically grounded formulation of physical resilience, which also provides definitions of its subcomponents (i.e. baseline state, perturbation, and recovery)[35]. An ontology of physical resilience, then, would allow a theory of physical resilience to make predictions that can be falsified experimentally by testing its subcomponents[35]. Future work should employ a tool such as the Ontology Development Toolkit[48] to develop an ontology of physical resilience, using the Web Ontology Language standards[49].

In line with the propositions made by Ukraintseva et al. (2018), we take the general stance that robustness and resilience ought to be differentiated. There is seemingly an agreement between Ukraintseva et al. (2016) and Varadhan et al. (2018) that robustness ought to be defined as the ability to *resist* functional decline following a perturbation by taking advantage of the redundancy build into the human motor control system to occupy different functional states while retaining the same level of performance. There is no consensus about how resilience exists (i.e. its ontological status), however, there is some agreement about what its three subcomponents are. Specifically, (1) there is some baseline state in which the system exists, (2) a time-dependent perturbation occurs which pushes the system outside of its baseline state into a state of lower function, and (3) there is a *recovery* from the perturbed state to the baseline state.

To define physical resilience, we believe that it is crucially important to define its subcomponents in a way that is falsifiable. First, we must be able to define some baseline state that the system exists in. Second, we must be able to define some perturbation that is able to be applied to the system, which has the capacity to push the system outside of its baseline state into a perturbed state of a lower functional level. Finally, we must be able to define what it means to recover from the perturbed state to a state with the same functional level as the baseline state. In this study, we operationally defined each subcomponent as follows; (a) baseline state was defined as the average alpha value from windows before the perturbation, (b) perturbation was defined as the movement of the plate the participants were asked to stand on, and (c) recovery was defined as the point at which the alpha value returned to within two standard deviations of the baseline mean.

When defining the subcomponents, it is likewise important to make explicit assertions about how the phenomena are believed to exist[35]. We conject that it is important to consider the set of possible states the system has access to when defining the baseline state, which is a direct reflection of the systems physical redundancy and fractal structure.

A common conception that appears to pervade the literature on physical resilience is that the baseline state should be defined as a homeostatic system, or a fixed-point attractor[41,47]. In the classical interpretation of both homeostasis and fixed-point attractors, it is assumed that there is a single state which the system fluctuates around or moves toward. We challenge this notion with the assertion that biological systems tend to fluctuate within acceptable limits (i.e. homeokinesis), as opposed to fluctuating around a single state (i.e. homeostasis)[50,51]. Instead of conceptualizing the baseline state as a single state, we propose to conceptualize it as the set of possible states the system can assume (i.e. its state space). In this conceptualization, the set of possible states contains the set of probable states as a proper subset. The actual state the system assumes at any given time, which may be conceptualized as a strange attractor, is a singleton subset of the set of probable states. Instead of simply pushing the system into a different state, a perturbation diminishes the set of possible states the system has access to, lowering its dimensionality in phase space. This diminishes the set of possible states the system is capable of assuming, which then diminishes the set of probable states the system is likely to assume. The actual state then, is necessarily dependent upon the set of probable states. Thus, recovery to baseline means recovering the set of possible states the system has access to, following a perturbation that resulted in the loss of possible states (Fig. 3.).

An adequate measure of physical resilience then, may include time to recovery or completeness of recovery, where recovery means the system has regained access to a set of system states that is equivalent to (not identical to) the set of system states that was present at baseline.

The individuals who participated in this study were all generally healthy, were not considered frail, and did not have any conditions that obviously affected balance. Still, there was variability in performance both within and between age groups for recovery to BA. Individuals who did not recover to BA exhibited a decreased COP signal persistence, a finding that was driven by older adult non-recoverers. It is unclear why some individuals, especially those in the older adult group, sometimes respond differently to standing balance perturbations than others. It is also unclear whether those differences in performance indicate anything of concern regarding someone's health. Future research might seek to compare specific patient groups using this experimental paradigm (e.g. those with frailty vs. those without frailty; fallers vs. non-fallers) and explore whether risk factors for common age-related syndromes such as frailty and falls relate to failure to recover to baseline.

Limitations

A main limitation of the present study is the type of measurements that were taken. COP were measured using a force plate, which reduces the 3-dimensional nature of the control of the center of mass into a 2-dimensional measurement. While related, center of mass and COP are not directly deducible from each other, and there is evidence that both are important in the control of balance[52]. Another limitation is that there were not a large enough number of parameters for performing transitive statistics or factor analysis. We also did not account for the effects of electrical muscle activity (e.g. electromyography), body segment mass distributions (e.g. center of

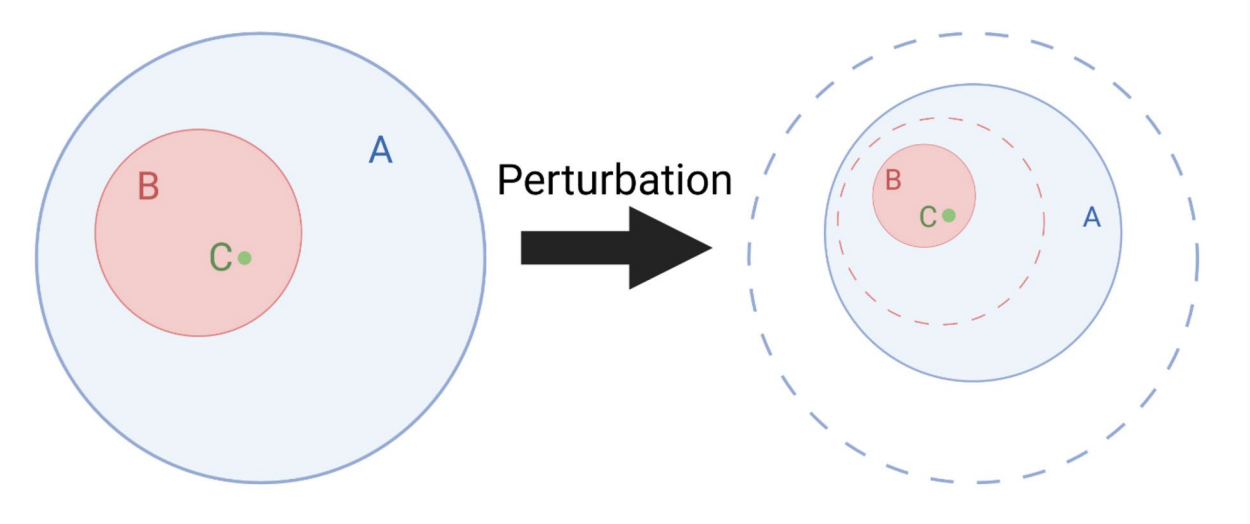

Fig. 3. A schematic of the set of possible states (A), the set of probable states (B), and the singleton set of the actual state (C) before (pre) and after (post) a perturbation. The perturbation results in the loss of possible states (A→A′), denoted by the outer dashed line, and the loss of probable states (B→B′), denoted by the inner dashed line. Note that the singleton set C does not diminish. Put formally; {C} ⊂ B ⊂ A→{C} ⊂ B′ ⊂ A′.

mass) or joint kinematics (e.g. ankle angular displacement) in the analysis, as measurements of these were not taken. These types of measurements would aid future work in the identification of key mechanisms responsible for the phenomena observed in this study.

A second limitation is the sampling rate that was used. Data were sampled at 100 Hz over five-seconds, meaning that there is likely redundancy in the signal. The DFA method is able to accurately estimate the Hurst exponent with 512 data points[17], but the redundancy may make the data appear to be smoother. When time series exhibit smooth, nonlinear structure, the DFA method is likely to provide an overestimated scaling value because the sample has an artificially light-tailed distribution[27]. On the other hand, down sampling the data would make it too short to obtain a valid α value[17]. Increasing the data length then might alleviate this issue. However, this would also lower the contribution of the higher frequency components in the signal to the α value, which are associated with the balance response to a perturbation. Future research using these methods should aim to find optimal sampling rates and data lengths which are able to both: (a) obtain valid α values, and (b) capture the relevant frequency content.

Conclusion

Perturbations and recovery from perturbations are important factors for maintaining upright posture, and ultimately health. The methods presented were able to distinguish between trials where participants were able to recover to baseline conditions following a perturbation, and trials where they were not. The main finding of the present study was that older adults who were not able to recover to their baseline state were less physically resilient than middle-aged adults and older adult recoverers. Physical resilience is considered to be vitally important to the health status of older adults[31]. Future studies should use these methods to determine physical resilience in older adults, and aim to discover how that physical resilience is driven by underlying physiological systems.

Methods

Ethics statement

The protocol of the present study was approved by an Institutional Review Board at the University of Nebraska Medical Center and complied with the Declaration of Helsinki (IRB Protocol #639-19-EP). Prior to study involvement, participants provided informed consent. Information about the purpose and procedures were purposefully withheld during the consent process to avoid the effects of anticipation and intention on balance performance during perturbation trials. Anticipation and intention have been shown to affect balance performance in previous literature[53,54], so blinding of participants was considered to be necessary. After completion of the study protocols, participants were debriefed about the true nature of the study.

Participants

We recruited a community-based sample of seventy apparently healthy participants from two different age groups[55]. Of those participants, one was not able to participate due to contraindications, for a grand total of 69 participants. Thirty-eight middle aged adults between the ages of 40–65 years, and 31 older adults 65 years or older completed all study protocols. Participants were excluded if they: (a) had lower extremity surgery within the past year; (b) were diagnosed with a condition that effects balance (e.g. vertigo); (c) used medication that is

known to affect balance or cause dizziness; (d) were older adults with a Frailty Index for Elders score > 4; and/or (e) were pregnant or breast feeding.

Experimental setup

Participants attended one visit that was approximately two hours long. We asked participants to stand on a force platform that could move quickly in the anteroposterior direction while they were secured in a safety harness (sampling rate: 100 Hz; Research Module for the NeuroCom Balance Master®, Natus Medical Inc., Pleasanton, California). Participants stood barefoot and feet were placed in accordance with the guidance regarding height from the manufacturer to standardize stance width. Five trials, all one-minute in length, were then administered to all participants in a randomized order while being video recorded. During each of the five trials the force plate moved at a constant velocity of 20 cm/s over five different fixed distances. For trial order and randomization see Table 5. Performance during all trials were recorded using a stationary video camera set on tripod behind the participant to determine loss of balance.

During all perturbation trials participants were asked to watch a video of a natural scene (e.g. trees in a forest) on an iPad set at eye level. The purpose of the video was to provide a distraction so they would not think about their standing balance. No instructions were given regarding the video and no eye tracking was recorded to quantify how much attention they devoted to it. In between trials, participants were asked to rest for five minutes during which time they were asked to complete either a questionnaire or a word search. The purpose of the questionnaire or word search was to keep the participant from thinking about the perturbations. Following the completion of all trials, participants were debriefed as to the true purpose of the study.

Data analysis

Trials where the participant lost their balance were removed from analysis. To do so, trial performance videos were analyzed visually, and trials were marked as to whether the participant lost their balance or not. Loss of balance was defined as either taking a step in any direction, grabbing onto the harness, or placing one's hands on the surrounding system to manipulate their center of mass to prevent a fall.

Anteroposterior COP positional data from the 60-second trials were exported from the NeuroCom. Custom MATLAB (The MathWorks Inc., Natick, Massachusetts) codes were used to mark the perturbation onset and calculate DFA. The output of DFA, α value, provided a measurement of time series persistence[26]. DFA α values above 0.5 indicated the signal was persistent, while values above 1 indicated the signal was persistent and unbounded[17]. In the present study, lower α values are interpreted as less persistent, and less desirable behavior. The MATLAB code was written to analyze a window length of 500 data points (five-seconds), then slide one-second forward, analyze the next five-second window, and complete this process for the first 15 s of each trial (Fig. 4.). Within the DFA calculation, the code used box sizes from 10 to 62 (the length of the 500 point input window divided by 8, rounded down), which resulted in a data length of 496 data points being used from the 500 data points[56]. Then, the average α values from the windows within this time interval were determined, which served as the baseline α (BA) for each respective trial.

Immediately after the perturbation the same method was used where windows of five-seconds (500 data points) were analyzed, followed by the window sliding forward one-second and analyzing the next five-second window. This continued until either; (a) the participant's DFA α recovered to within two standard deviations of their BA which was considered their recovery α (RA), or (b) the trial reached sixty seconds and ended, in which case the last DFA α was considered as the RA. DFA α from the first window immediately after perturbation was also recorded. Whether or not participants recovered to BA was then determined and individual trials were marked as either recover or no recover. Recovery indicated that the participant recovered to their BA value during the trial, while No recovery indicated that the participant was not able to recover to their BA value after the perturbation.

Statistical analysis

Data from 69 participants were used in the statistical analyses. Before the analysis, the first perturbation trial was removed for each participant. This was done to remove the potential confounding effect of shock associated with the first perturbation, as the participants were unaware that the platform would move. Thus, only four trials from each participant were subjected to statistical analysis. In total, this meant there were 276 samples for the statistical estimates, or 69 per condition for four conditions.

Order	Perturbation	Timing of perturbation
Randomized	2.54 cm	27 s
	5.08 cm	16 s
	7.62 cm	21 s
	10.16 cm	21 s
	12. 70 cm	18 s

Table 5. Perturbation magnitudes and randomization. Trials were conducted in a randomized order. During each trial the force plate moved backwards a set distance at a set time, timing of perturbation. The timing of the perturbation was different between trials, and the participant was unaware as to whether the plate would move during each trial.

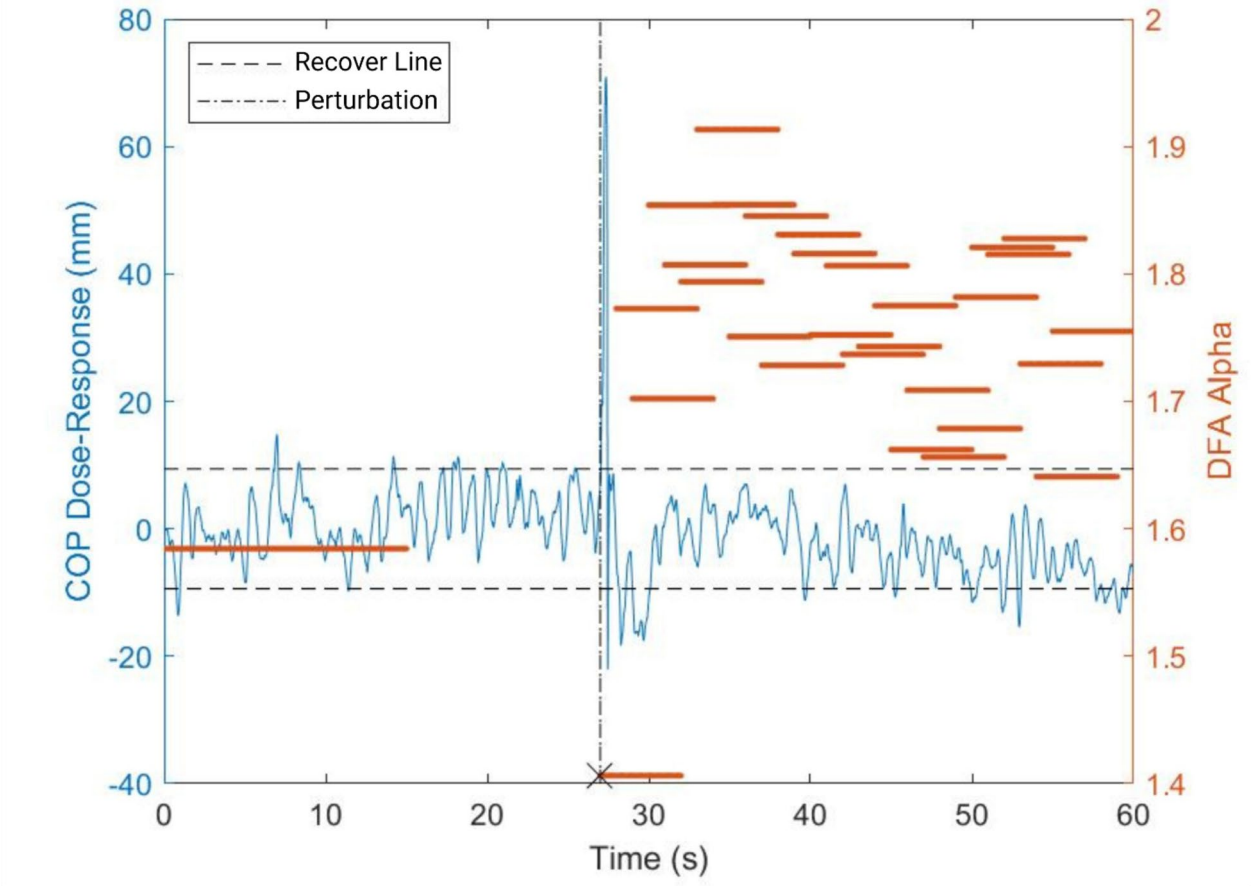

Fig. 4. Representative center of pressure (COP) data during the 2.54 cm condition in the anteroposterior direction presented in millimeters (left y-axis), with a representation of the detrended fluctuation analysis (DFA) alpha values (right y-axis) and window sizes as indicated by the orange lines overlayed on the COP position. The left-most orange line denotes the average baseline alpha value, while the horizontal dashed lines indicate the 95% confidence interval for the baseline alpha value. The vertical line denotes the timing of the perturbation, while the X denotes the first post-perturbation window. Orange lines to the right of the perturbation line indicate alpha values for windows that are the length of each line.

Normality of the data were tested through the Shapiro-Wilk test. If data were found to violate normality, they were log transformed. If the log transformed data still violated normality, then the original data were inspected for outliers. Outliers were then removed if they were greater than three standard deviations away from the mean. Demographic information for sample characterization, was analyzed using descriptive statistics.

A contingency analysis was used to determine the odds of recovering to baseline between age groups (results provided in Supplementary Fig. S1.).

Three separate three-way factorial mixed-effects ANOVAs with repeated measures were used to test the effects of three independent variables: (1) age group, (2) perturbation magnitude, and (3) recovery (i.e. recover or no recover); on three separate dependent variables: (a) BA, (b) α values during the first window after the perturbation, and (c) RA. The model included an interaction term between Age Group and recovery and accounted for within participant variability by including participant as a random effect.

The perturbation magnitude was found to have no effect on the outcome variables, so it was removed from analysis and instead three separate two-way factorial mixed-effects ANOVAs with repeated measures were used to test the effects of the two remaining independent variables: (1) Age Group and (2) recovery (i.e. recover or no recover); on the three separate dependent variables: (a) BA, (b) α values during the first window after the perturbation, and (c) RA. The model included an interaction term between Age Group and recovery and accounted for within participant variability by including participant as a random effect.

The two-way factorial mixed-effects ANOVA with repeated measures approach accounts for both fixed effects, representing differences across Age Group, recovery, and random effects, capturing subject-level variability. The fixed effects included the main effect of the between-subjects factor, which tested for differences in means across Age Groups, and the main effect of the within-subjects factor, which assesses whether mean responses differ across recovery. Additionally, the interaction term between Age Group and recovery was used to evaluate whether changes across recovery depend on Age Group. To model individual differences, random intercepts for

subjects were included. Fixed effects were estimated using least squares estimation, while random effects were estimated using restricted maximum likelihood.

The statistical model for a two-way factorial mixed-effects ANOVA with repeated measures can be expressed as:

$$Y_{\{ijk\}} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{\{ij\}} + S_k + (\beta S)_{\{jk\}} + \epsilon_{\{ijk\}}$$

where $Y_{\{ijk\}}$ is the observed response for subject *k*, Age Group *i*, and recovery *j*, μ is the grand mean, α_i represents the between-subjects effect, β_j denotes the within-subjects effect, and $(\alpha\beta)_{\{ij\}}$ is their interaction. The terms S_k and $(\beta S)_{\{jk\}}$ capture random intercepts and slopes for subjects, respectively, while $\epsilon_{\{ijk\}}$ represents residual error. Statistical significance was estimated using F-tests for main effects and interactions. Random effects were estimated through variance components and likelihood ratio tests.

Pairwise comparisons using Tukey's Honestly Significant Difference (HSD) were conducted as follow-up tests when a significant result was obtained in the global two-way ANOVA model. Partial η^2 was calculated to estimate the effect sizes (results provided in supplemental). A value between 0 and 0.099 was considered small, between 0.01 and 0.058 was considered medium, and between 0.059 and 0.138 was considered large[57]. Statistical analysis was performed using R (R Core Team, 2022), RStudio (Rstudio Team, 2022), the tidyverse package[58], and plots were created with the ggplot2 package[59]. Significance was set at $\alpha = 0.05$. Per journal guidelines, post-hoc power sensitivity analyses were conducted using G*Power version 3.1.9.7 (See Supplemental)[60].

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Author contributions

Conceptualization: JY, DV, JB; Methodology: JY, HJH; Formal analysis and investigation: JY, JM; Writing - original draft preparation: JM; Writing - review and editing: JM, JY; Funding acquisition: JY, DV, JB; Resources: HJH; Supervision: JY.

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Declarations

Competing interests

The authors declare no competing interests.

Ethical approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Statement of human rights

The study was approved by the Institutional Review Board at the University of Nebraska Medical Center (IRB Protocol #639-19-EP).

Informed consent

Informed consent was obtained from all individual participants included in the study.

Additional information

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1038/s41598-025-92746-7.

Correspondence and requests for materials should be addressed to J.M.Y.

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