The Journal of Frailty & Aging 15 (2026) 100179

Contents lists available at ScienceDirect

The Journal of Frailty & Aging

journal homepage: www.elsevier.com/locate/tjfa

Brief Report

Comparing two methods to quantify physical resilience

Heather E. Whitson [a,b,c,*], Marissa Ashner [a,d], Virginia B. Kraus [a,b], Sarah Peskoe [a,b], Janet L. Huebner [a,b], Corey B. Simon [a,e], Katherine Hall [a,b,c], Cathleen Colon-Emeric [a,b,c]

[a] Duke Aging Center, Duke University School of Medicine, Durham, NC, USA
[b] Department of Medicine, Duke University School of Medicine, Durham, NC, USA
[c] Geriatrics Research Education and Clinical Center (GRECC), Durham Veterans Administration Medical Center, Durham NC, USA
[d] Department of Biostatistics and Bioinformatics, Duke University School of Medicine, Durham, NC, USA
[e] Department of Orthopedics, Duke University School of Medicine, Durham, NC, USA

A R T I C L E I N F O

Keywords:
Resilience
Surgery
Aging
Measurement
Knee arthroplasty
Stressor
Recovery

A B S T R A C T

Physical resilience, conceptualized as the extent of observed recovery after a health stressor, is an important construct in research on aging and frailty. Various methods have been proposed to quantify physical resilience using repeated measures of health or function following a stressor. The purpose of this analysis is to directly compare two alternative approaches to quantifying physical resilience – the recovery trajectory (RT) and the expected recovery differential (ERD) – using data from 170 older adults in an observational study of elective knee replacement surgery. Each participant's resilience, based on repeated measures of pain interference over 6 months after surgery, was determined using both the RT and the ERD method. The 10 individuals classified as high resilience based on RT also had better-than-expected recovery based on ERD. However, ERD scores were more variable among individuals classified by RT as moderate resilience (n = 82). Of those classified as low resilience (n = 78) by RT, most (85.9%) also had worse-than-expected recovery based on ERD. In this head-to-head comparison of two conceptually distinct approaches for quantifying resilience after a health stressor, the results were most comparable in individuals at extremes of high or low recovery patterns. Each approach has merit for quantifying physical resilience after a health stressor, and factors that may influence the choice of method and interpretation of results are discussed.

1. Introduction

Physical resilience—the extent of recovery after an acute health stressor such as infection or surgery—is a determinant of future health [1–3]. Over the past decade, physical resilience has been advanced as an important construct in clinical research in older adults, both because late life is associated with increased exposure to health stressors and because aging biology alters one's capacity to respond to stressors [4–6]. Physical resilience, which manifests after a health stressor, is linked to the concept of frailty, which refers to a state of diminished physiological reserves that results in vulnerability to stressors [7,8]. Even among individuals who are not "frail," heterogenous outcomes are observed after exposure to similar health stressors, with age and comorbidity linked to poorer physical resilience [9–11]. To validate biomarkers and interventions that improve physical resilience across the lifespan, the field needs reliable ways to measure physical resilience [4,12].

We previously described two approaches to quantify physical resilience: the recovery trajectory (RT, also previously referred to as "recovery phenotype") and the expected recovery differential (ERD) [13]. Both RT and ERD approaches utilize repeated measures of health at multiple timepoints before and after a given health stressor. The RT approach quantifies each individual's resilience based on observed recovery trajectories j(e.g., area under the curve, time to full recovery, or slope of recovery), without incorporating information about an individual's risk factor profile. The RT can be calculated for any individual without knowledge of how similar individuals have responded to the same stressor, or researchers can apply methods such as latent class or factor analysis to identify common patterns of recovery in a population. In contrast, the ERD approach explicitly incorporates information about known risk or protective factors, and defines resilience as the extent to which a person's actual recovery compares to their predicted recovery. The ERD addresses a common clinical question: "how much better or worse did this patient recover, relative to other patients of similar age and pre-stressor health status?"

* Corresponding author at: DUMC Box 3003, Durham, NC 27710, USA.
E-mail address: Heather.whitson@duke.edu (H.E. Whitson).

https://doi.org/10.1016/j.tjfa.2026.100179
Received 4 January 2026; Received in revised form 10 April 2026; Accepted 3 June 2026
Available online 20 June 2026
2260-1341/

The RT and ERD are not proposed as two measures of the same latent variable; rather, they represent two different ways of operationalizing resilience that yield different types of information. For example, consider two surgical patients: one is an 86-year-old with features of frailty and multiple comorbidities who undergoes a prolonged surgery time, whereas the other is a fit 61-year-old with no comorbid conditions who undergoes an uncomplicated procedure. If both patients exhibit the same, "average" pace and degree of functional recovery after surgery, they would both be classified as moderate resilience according to the RT method, However, under the ERD method, the older, higher-risk patient would be considered more resilient because recovery exceeds expectations based on the risk profile. In this way, ERD highlights resilience as a relative, risk-adjusted construct, whereas RT reflects absolute recovery performance. If the investigator is most interested in asking "Is this biomarker or intervention associated with faster recovery after a stressor?" then the RT method is an appropriate and straightforward way to quantify and compare how quickly patients recover. If the investigator is more interested in identifying pathways or mechanisms that may protect against age- or disease-related vulnerabilities, then the ERD approach will help identify individuals who may possess a protective or risk-modifying factor.

Although both approaches are used in physical resilience research [11,14–16], it is unknown if the two approaches generally classify the same individuals as "resilient". We aimed to directly compare these two approaches in a patient population exposed to the same stressor: elective total knee arthroplasty. The degree of recovery after knee arthroplasty is typically indicated by performance measures or patient-reported measures of function and symptoms. Here, we defined resilience – according to the RT and ERD method – based on measures of "pain interference," a validated tool by which patients rate the impact of pain on work and daily activities [17]. Pain interference was selected because it is an outcome that matters to patients, reflects both symptoms and function, and is a precise and responsive indicator of recovery after knee arthroplasty [18,19]. It is the patient-reported measure that has been most strongly correlated with chronic poor pain outcomes after knee surgery [20]. Measures of pain interference were available at multiple time points in the dataset, which allowed for the construction of detailed trajectories.

2. Methods

2.1. Study population

We quantified physical resilience in the Physical Resilience Indicators and Mechanisms in the Elderly Study of elective total knee arthroplasty (PRIME-KNEE), a prospective study of older adults evaluated before and 1, 2, 4, and 6 months after elective knee arthroplasty in the Duke University Health System. Methods of the PRIME-KNEE study have been previously described [21]. Briefly, the study included participants aged 60+ years who were community-dwelling and scheduled for elective knee arthroplasty with planned admission or overnight observation. Participants were required to be English-speaking and ambulatory (assistive device allowed). Exclusion criteria included diagnosis of dementia or failed telephone cognitive screen, treatment for non-skin cancer in the last 12 months, hearing or vision impairments that impeded electronic survey completion or telephone interviews after best accommodation. PRIME-KNEE was approved by the Duke Health Institutional Review Board and all participants provided informed consent.

2.2. Measures

Our primary indicator of physical resilience in this analysis is self-reported pain interference using the PROMIS short form 6a; this validated health indicator in orthopedic surgical rehabilitation quantifies the impact of pain on work and social activities over the past week [17]. **Supplementary Table 1** summarizes all other variables from the PRIME-KNEE database that are used in the present analysis.

2.3. Analysis

The goal of this analysis is to compare definitions of resilience after surgery using the RT and ERD approaches [13]. For the RT, we modeled recovery trajectories from pain interference scores at timepoints before and after the stressor and applied latent class trajectory analysis to identify similar "classes" of recovery patterns (TRAJ procedure, SAS, Cary, NC). RT class emphasizes the magnitude and speed of individual recovery experiences. Models were iteratively tested with varying numbers of latent classes and polynomial representations of time, with final model selection based on Bayesian Information Criterion (BIC) and minimum class size thresholds.

The ERD approach calculated the difference between observed verses predicted pain interference at the 6-month postoperative timepoint. The predicted values were derived using an elastic net penalized regression model. Predictors of 6-month pain interference score included baseline pain interference, demographics, comorbidities, physical and cognitive function, psychological resilience, and surgical/anesthesia characteristics. Continuous variables were centered and scaled. Leave-One-Out Cross Validation was used to select optimal penalty parameters. The ERD score (observed minus predicted value) is continuous, with scores above zero representing better than predicted recovery.

With the RT approach, three resilience classes were identified (**Supplemental Figure 2**). Posterior probabilities from the RT models were used to assign individual participants to best-fit RT trajectory class. This empirical method resulted in three RT-defined resilience groups of unequal sizes (n = 10, 82, 78). Next, the cohort was subdivided into three quantiles based on the continuous ERD score, such that ERD-defined quantile size matched those of the RT classes (n = 10, 82, and 78) . To visualize how similarly the two metrics assign individuals to resilience groups in the same population, we generated histograms and an Alluvial plot.

3. Results

Our analytical sample included 170 (of 203) PRIME-KNEE participants who had complete data to construct both RP- and ERD-based resilience metrics. Four individuals enrolled in PRIME-KNEE did not undergo surgery and 29 individuals did not have a 6-month rating of pain interference (so ERD could not be calculated). Table 1 summarizes the analytic cohort, according to defined resilience groupings. A majority of the cohort were female (N = 102, 60%) and White (N = 141, 82.9%), and only seven participants (4.2%) identified as Latino. Ten participants (5.9%) were assigned to the high resilience RT class; 82 (48.2%) to the moderate resilience class; 78 (45.9%) to low resilience class. ERD quantiles were constructed to be the same size as the RT classes. People in higher RT classes tended to have better ERD scores (Fig. 1A). No individual in the high resilience RT class had an ERD in the low quantile, and all individuals in the high resilience RT had ERD scores above 0, indicating better-than-predicted recovery. Most people in the low resilience RT class had low ERDs and 67 (85.9%) had negative ERD (i.e., worse-than-predicted recovery), with 63 (81%) in the lowest quantile of ERD scores. However, one individual in the low RT class had an excellent ERD score (Fig. 1B). This individual had poor pain interference scores at all timepoints, except for a much-improved score at 6 months. People in the moderate RT class had a wide distribution of ERD scores.

4. Discussion

The RT and ERD approaches to resilience measurement comparably identified individuals with low or high resilience patterns after knee

Table 1
Characteristics of the Cohort at Baseline.

Character-istic	Entire Cohort	Recovery Trajectory Class			Expected Recovery Differential		
	Overall (N = 170)	High (N = 10) (5.9%)	Moderate (N = 82) (48.2%)	Low (N = 78) (45.9%)	High (N = 10) (5.9%)	Moderate (N = 82) (48.2%)	Low (N = 78) (45.9%)
Age at Surgery Date (years) Mean (SD)	71.4 (6.20)	74.5 (7.11)	71.6 (6.30)	70.8 (5.91)	71.1 (5.11)	71.8 (6.54)	70.9 (5.98)
Race							
White	141 (82.9%)	9 (90.0%)	76 (92.7%)	56 (71.8%)	6 (60.0%)	74 (90.2%)	61 (78.2%)
Black or African American	22 (12.9%)	0 (0%)	5 (6.1%)	17 (21.8%)	3 (30.0%)	7 (8.5%)	12 (15.4%)
Asian	2 (1.2%)	1 (10.0%)	0 (0%)	1 (1.3%)	0 (0%)	1 (1.2%)	1 (1.3%)
More than one race or Unknown	5 (3.0%)	0 (0%)	1 (1.2%)	4 (5.1%)	1 (10.0%)	0 (0%)	4 (5.1%)
Sex							
Female	102 (60.0%)	4 (40.0%)	51 (62.2%)	47 (60.3%)	5 (50.0%)	51 (62.2%)	46 (59.0%)
Male	68 (40.0%)	6 (60.0%)	31 (37.8%)	31 (39.7%)	5 (50.0%)	31 (37.8%)	32 (41.0%)
Years of Education Mean (SD)	16.2 (2.36)	17.0 (2.31)	16.2 (2.37)	16.1 (2.35)	15.4 (1.58)	16.3 (2.59)	16.2 (2.18)
Body Mass Index Mean (SD)	32.0 (5.34)	29.8 (5.00)	31.9 (5.39)	32.4 (5.31)	33.2 (5.73)	32.2 (5.46)	31.7 (5.20)
Vascular Disease, N %)	44 (25.9%)	2 (20.0%)	20 (24.4%)	22 (28.2%)	3 (30.0%)	18 (22.0%)	23 (29.5%)
Chronic Liver Disease, N (%)	5 (2.9%)	0 (0%)	2 (2.4%)	3 (3.8%)	0 (0%)	2 (2.4%)	3 (3.8%)
Heart Disease, N (%)	9 (5.3%)	1 (10.0%)	3 (3.7%)	5 (6.4%)	0 (0%)	4 (4.9%)	5 (6.4%)
Diabetes, N (%)	35 (20.6%)	2 (20.0%)	21 (25.6%)	12 (15.4%)	1 (10.0%)	19 (23.2%)	15 (19.2%)
History of Cancer, N(%)	11 (6.5%)	2 (20.0%)	4 (4.9%)	5 (6.4%)	1 (10.0%)	6 (7.3%)	4 (5.1%)
3MS Cognitive Score, Mean (SD)	93.1 (6.49)	95.7 (5.23)	93.8 (5.42)	92.1 (7.50)	90.2 (6.68)	93.6 (6.16)	93.1 (6.78)
Gait Speed (m/sec), Mean (SD)	1.00 (0.256)	1.02 (0.259)	1.03 (0.221)	0.973 (0.288)	0.947 (0.245)	0.987 (0.244)	1.03 (0.271)
PHQ-9, Mean (SD)	3.25 (3.66)	1.80 (2.74)	2.78 (3.51)	3.93 (3.82)	5.00 (7.35)	2.72 (2.95)	3.59 (3.64)

3MS = Modified Mini-Mental State Examination (score out of 100)
PHQ-9 = Patient Health Questionnaire-9 depression screen.

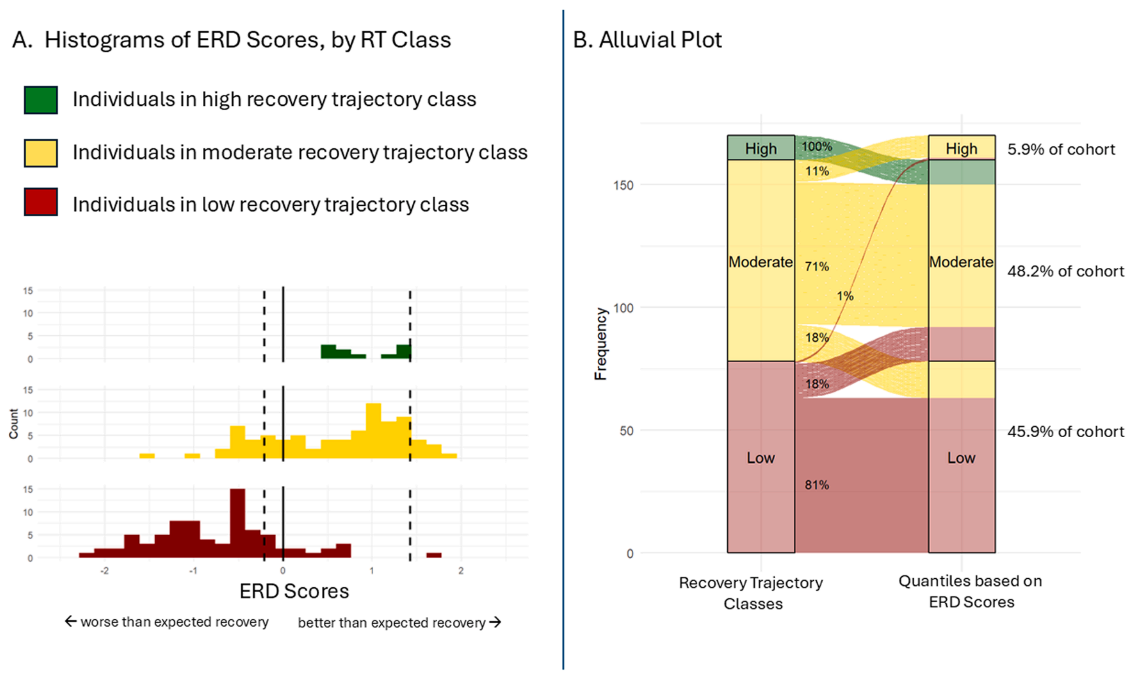

Fig. 1. Graphical displays comparing two resilience metrics: Recovery Trajectory (RT) Classes compared to Expected Recovery Differential (ERD) scores.
Legend: This figure compares two approaches for quantifying resilience among 170 individuals participating in the PRIME-KNEE study. All individuals completed questionnaires to assess PROMIS™ pain interference before and at 1, 2, 4, and 6 months following elective knee arthroplasty. The **recovery trajectory (RT)** is based on individuals' observed trajectories of pain interference. Latent class analysis identified three classes of recovery trajectories, and individuals were assigned to the class that most closely fit their own recovery pattern. The **Expected Recovery Differential (ERD)** captures how much better or worse a participant's self-reported measure of pain interference was at 6 months, compared to the predicted value based on a multivariable model to predict pain interference at 6 months in this cohort. The cohort was subdivided into three quantiles based on ERD score, such that quantile size matched those of the RT classes. **Panel A** provides the histograms (count of individuals) across ERD scores, stratified by RT class. ERD scores above 0 indicate that pain interference at 6 months was better than predicted, whereas scores less than 0 indicate pain interference at 6 months was worse than predicted. The dashed lines indicate the ERD scores used to subdivide the cohort into three ERD quantiles. **Panel B** is an Alluvial plot, with a ribbon from the left to right sides for each of the 170 individuals in the sample. The left side depicts the three groups according to best-fit class of the three latent classes of recovery trajectory. The right side depicts the three groups defined by ERD score.

surgery. However, individuals whose RT was classified as "moderate resilience" exhibited a wider range of ERD scores. ERDs may help distinguish among the plurality of patients whose trajectory of recovery is moderate, or "average." An average recovery trajectory and above-zero ERD score identifies a person for whom average recovery is better than predicted, based on a myriad of clinical factors measured before or at the time of the stressor. Both approaches provide relevant outcomes for testing an intervention's effectiveness, and the choice of which physical resilience measure to use should be driven by context and the clinical question.

ERDs may be helpful in identifying surrogate indicators – such as biomarkers or clinical traits – that distinguish patients likely to recover better or worse than predicted, which can inform future clinical decision-making. Because the derivation of the ERD score accounts for many clinical features that influence recovery after a stressor by including these variables in the prediction model, the ERD score may reflect unmeasured phenomena that are important drivers of resilience. These drivers might include biological or genetic factors that support metabolism or immune responses during physical stress, psychosocial traits such as grit or self-efficacy, or contextual factors such as health-care access and social support. One previous study identified a small number of molecular biomarkers that accounted for almost 30% of the variance in the ERD score after hip fracture [14]. By shedding light on mechanisms associated with better-than-predicted recovery, biomarkers and protective factors may point toward new treatments that improve resilience for all.

Both the RT and ERD approaches can be adapted for different clinical scenarios or data availability. The recovery trajectory for pain-limited function after elective joint replacement is typically measured in months, whereas resilience after other stressors may be more appropriately measured in days or weeks. We used pain interference as the indicator of resilience in this analysis, but the RT and ERD could just as easily be calculated from other metrics of recovery after knee surgery (e.g., daily step counts, self-reported function). While the adaptability of RT and ERD scores is useful, the methodological choices influence whether a given individual is categorized as resilient or not. For example, in the present analysis, one individual had highly discrepant RT and ERD measures, with low resilience by RT but very high ERD score. The discrepancy was explained by the fact that our derivation of RT classes considered the full trajectory of recovery (pain interference measures across multiple timepoints over 6 months), whereas the ERD was calculated from pain interference at one timepoint (6 months). The individual in question had poor recovery at initial time points and a marked improvement at 6 months. The choice to calculate ERD scores based on pain interference level at 6 months was based on prior data and precedents from research on total knee arthroplasty recovery [19,22]. However, had we derived ERD scores from predicted vs. observed recovery levels at 4 months or based on area-under-the curve measurements, the RT and ERD methods would render more compatible resilience assessments for this case.

Several limitations impact the interpretation of findings from this analysis. First, the data are drawn from a single-site study focused on one type of health stressor (elective knee arthroplasty) and should be validated in additional and more diverse clinical populations. Second, our head-to-head comparison of RT and ERD methods utilized "pain interference" as the sole indicator of recovery. It has been suggested that physical resilience is necessarily defined by the system (e.g., whole person vs. organ-based), the state (e.g., measure that defines recovery), and the stressor [23]. Thus, future research should more fully operationalize the quantification of resilience by further comparing the ERD and RT methods when incorporating alternative measures of whole-person recovery (e.g., mobility) and considering resilience in specific systems (e.g., wound healing, cognitive recovery, immune resilience).

5. Conclusions

Despite these limitations, this analysis constitutes the first direct comparison of two complementary approaches for measuring resilience after health stressors [13]. Although these approaches were developed to capture different latent constructs regarding resilience, the findings here suggest that individuals at high and low ends of the resilience spectrum are generally categorized similarly by these two approaches. The RT approach is more clinically intuitive, while the ERD approach may have an advantage in identifying biomarkers or clinical factors associated with unexpected resilience in older adults with frailty or multiple morbidities. Both approaches should be adopted in future research aimed at understanding and optimizing physical resilience.

Data sharing statement

De-identified datasets and statistical code are available upon request to Dr. Whitson. PRIME-KNEE participants were not consented for sharing of identifiable data.

Author contributions

All authors had access to the data and take responsibility for data integrity and accuracy of analysis.

Conceptualization and funding acquisition

Whitson, Colon-Emeric, Kraus.

Acquisition, curation, interpretation and visualization of data

All authors.

Formal analysis

Ashner and Peskoe.

Writing (original draft)

Whitson.

Writing (review and editing)

All authors.

Conflict of interest

None reported.

Funding support

This study received funding support from the National Institute on Aging grants UH2AG056925, UH3AG056925, and P30AG028716 (the Duke Claude D Pepper Older Americans Independence Center). The original UH2/UH3 (cooperative grant) included input on concept and study design from assigned program officers. The funders had no role in the conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication.

Declaration of generative AI and AI-assisted technologies in the writing process

No AI was used in the writing process.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Heather Whitson reports financial support was provided by Durham VA Health Care System. Heather Whitson reports a relationship with National Institutes of Health that includes: funding grants. Heather Whitson reports a relationship with American Geriatrics Society that includes: board membership. Heather Whitson reports a relationship with University of California San Diego that includes: speaking and lecture fees. Heather Whitson reports a relationship with Ohio University that includes: speaking and lecture fees. Heather Whitson reports a relationship with Yale School of Medicine that includes: consulting or advisory. Heather Whitson reports a relationship with Wake Forest University School of Medicine that includes: consulting or advisory and non-financial support. Heather Whitson reports a relationship with Driven Data that includes: consulting or advisory. Heather Whitson reports a relationship with UptoDate Inc that includes: consulting or advisory. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We wish to thank the research staff and administrative team that supported the PRIME-KNEE study. We heartily thank the participants and their care partners who shared time, energy, and data to make these analyses possible.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.tjfa.2026.100179.

References

[1] Gijzel SMW, Whitson HE, van de Leemput IA, Scheffer M, van Asselt D, Rector JL, Olde Rikkert MGM, Melis RJF. Resilience in clinical care: getting a grip on the recovery potential of older adults. J Am Geriatr Soc 2019;67:2650–7.
[2] Sauro KM, Smith C, Ibadin S, Thomas A, Ganshorn H, Bakunda L, Bajgain B, Bisch SP, Nelson G. Enhanced recovery after surgery guidelines and hospital length of stay, readmission, complications, and mortality: a meta-analysis of randomized clinical trials. JAMA Netw Open 2024;7:e2417310.
[3] Ahuja SK, Manoharan MS, Lee GC, McKinnon LR, Meunier JA, Steri M, Harper N, Fiorillo E, Smith AM, Restrepo MI, Branum AP, Bottomley MJ, Orru V, Jimenez F, Carrillo A, Pandranki L, Winter CA, Winter LA, Gaitan AA, Moreira AG, Walter EA, Silvestri G, King CL, Zheng YT, Zheng HY, Kimani J, Blake Ball T, Plummer FA, Fowke KR, Harden PN, Wood KJ, Ferris MT, Lund JM, Heise MT, Garrett N, Canady KR, Abdool Karim SS, Little SJ, Gianella S, Smith DM, Letendre S, Richman DD, Cucca F, Trinh H, Sanchez-Reilly S, Hecht JM, Cadena Zuluaga JA, Anzueto A, Pugh JA, South Texas Veterans Health Care System C-t, Agan BK, Root-Bernstein R, Clark RA, Okulicz JF, He W. Immune resilience despite inflammatory stress promotes longevity and favorable health outcomes including resistance to infection. Nat Commun 2023;14:3286.
[4] Hadley EC, Kuchel GA, Newman AB, Workshop S. Participants, report: NIA workshop on measures of physiologic resiliencies in human aging. J Gerontol A Biol Sci Med Sci 2017;72:980–90.
[5] Whitson HE, Duan-Porter W, Schmader KE, Morey MC, Cohen HJ, Colon-Emeric CS. Physical resilience in older adults: systematic review and development of an emerging construct. J Gerontol A Biol Sci Med Sci 2016;71:489–95.
[6] Abadir PM, Bandeen-Roche K, Bergeman C, Bennett D, Davis D, Kind A, LeBrasseur N, Stern Y, Varadhan R, Whitson HE. An overview of the resilience world: proceedings of the american geriatrics society and national institute on aging state of resilience science conference. J Am Geriatr Soc 2023;71:2381–92.
[7] Fried LP, Tangen CM, Walston J, Newman AB, Hirsch C, Gottdiener J, Seeman T, Tracy R, Kop WJ, Burke G, McBurnie MA. Cardiovascular Health Study Collaborative Research, frailty in older adults: evidence for a phenotype. J Gerontol A Biol Sci Med Sci 2001;56:M146–57.
[8] Varadhan R, Walston JD, Bandeen-Roche K. Can a link Be found between physical resilience and frailty in older adults by studying dynamical systems? J Am Geriatr Soc 2018;66:1455–8.
[9] Colon-Emeric C, Whitson HE, Pieper CF, Sloane R, Orwig D, Huffman KM, Bettger JP, Parker D, Crabtree DM, Gruber-Baldini A, Magaziner J. Resiliency groups following hip fracture in older adults. J Am Geriatr Soc 2019;67:2519–27.
[10] Klop M, Melis RJF, Peeters G, Geuzebroek GSC, Heijmen RH, van Wezel RJA, Claassen J. Preoperative physical resilience indicators and their associations with postoperative outcomes. Geroscience 2025;47:4857–70.
[11] Peeters G, de Munck I, Tooth L, Melis R. Quantifying physical resilience after knee or hip surgery in older Australian women based on long-term physical functioning trajectories. Gerontology 2024;70:950–61.
[12] Colon-Emeric C, Walston J, Bartolomucci A, Carroll J, Picard M, Salmon A, Suglia S, Whitson H, Abadir P. Stress tests and biomarkers of resilience: proceedings of the second state of resilience science conference. J Am Geriatr Soc 2025;73:1017–28.
[13] Colon-Emeric C, Pieper CF, Schmader KE, Sloane R, Bloom A, McClain M, Magaziner J, Huffman KM, Orwig D, Crabtree DM, Whitson HE. Two approaches to classifying and quantifying physical resilience in longitudinal data. J Gerontol A Biol Sci Med Sci 2020;75:731–8.
[14] Parker DC, Colomicronn-Emeric C, Huebner JL, Chou CH, Kraus VB, Pieper CF, Sloane R, Whitson HE, Orwig D, Crabtree DM, Magaziner J, Bain JR, Muehlbauer M, Ilkayeva OR, Huffman KM. Biomarkers associated with physical resilience after hip fracture. J Gerontol A Biol Sci Med Sci 2020;75:e166–72.
[15] Xue QL, Laskow T, Alzahrani MK, Varadhan R, Walston JD, Schrack JA, Newman AB, Sieber F, Bandeen-Roche K. Multivariate profiling of physical resilience in older adults after total knee replacement surgery: results from a prospective observational study. J Gerontol A Biol Sci Med Sci 2025;80.
[16] Whitson HE, Crabtree D, Pieper CF, Ha C, Au S, Berger M, Cohen HJ, Feld J, Smith P, Hall K, Parker D, Kraus VB, Kraus WE, Schmader K, Colón-Emeric C. A template for physical resilience research in older adults: methods of the PRIME-KNEE study. J Am Geriatr Soc 2021;69:3232–41.
[17] Stone AA, Broderick JE, Junghaenel DU, Schneider S, Schwartz JE. PROMIS fatigue, pain intensity, pain interference, pain behavior, physical function, depression, anxiety, and anger scales demonstrate ecological validity. J Clin Epidemiol 2016;74:194–206.
[18] Dhollander O, Roorda LD, Diarra S, Ghijselings I, Demurie A, Terwee CB, Cornu O, Van den Wyngaert H. Psychometric properties and feasibility of PROMIS computerized adaptive tests compared with disease-specific measures in knee arthroplasty. J Bone Joint Surg Am 2025;107:2371–88.
[19] Kagan R, Anderson MB, Christensen JC, Peters CL, Gililland JM, Pelt CE. The recovery curve for the patient-reported outcomes measurement information system patient-reported physical function and pain interference computerized adaptive tests after primary total knee arthroplasty. J Arthroplasty 2018;33:2471–4.
[20] George SZ, Rubenstein D, Bolognesi MP, Horn ME. Can patient-reported outcome measurement information system measures estimate high impact chronic pain after total joint arthroplasty? J Arthroplasty 2023;38:S47–51.
[21] Whitson HE, Crabtree D, Pieper CF, Ha C, Au S, Berger M, Cohen HJ, Feld J, Smith P, Hall K, Parker D, Kraus VB, Kraus WE, Schmader K, Colon-Emeric C. A template for physical resilience research in older adults: methods of the PRIME-KNEE study. J Am Geriatr Soc 2021;69:3232–41.
[22] Starring H, Waddell WH, Steward W, Schexnayder S, McKay J, Leonardi C, Bronstone A, Dasa V. Total knee arthroplasty outcomes in patients with Medicare, Medicare advantage, and commercial insurance. J Knee Surg 2020;33:919–26.
[23] Chhetri JK, Xue QL, Ma L, Chan P, Varadhan R. Intrinsic capacity as a determinant of physical resilience in older adults. J Nutr Health Aging 2021;25:1006–11.