



Published in final edited form as:

J Bone Joint Surg Am. 2025 June 04; 107(11): e57. doi:10.2106/JBJS.24.01305.

Predicting Post-Fracture Recovery with Smartphone Mobility

Data:

A Proof-of-Concept Study

Brian M. Shear, MD¹, Dane J. Brodke, MD¹, Gregory R. Hancock, PhD², Patrick McGlone, MD³, Haley Demyanovich, MPS¹, Vivian Li, BA¹, Alice Bell, BA¹, David Okhuereigbe, MS¹, Gerard P. Slobogean, MD, MPH¹, Robert V. O'Toole, MD¹, Nathan N. O'Hara, PhD, MHA¹

¹Department of Orthopaedics, University of Maryland School of Medicine, Baltimore, Maryland

²Department of Human Development and Quantitative Methodology, University of Maryland College of Education, College Park, Maryland

³Department of Orthopaedic Surgery, Walter Reed National Military Medical Center, Bethesda, Maryland

Abstract

Background: After a lower-extremity fracture, the patient's priority is to regain function. To date, our ability to measure function has been limited. However, high-fidelity sensors in smartphones continuously measure mobility, providing an expansive pre- and post-injury gait history. We assessed whether pre-injury mobility data, combined with demographic and injury data, reliably predicted post-fracture mobility.

Methods: We enrolled 107 adult patients (mean age, 45 years; 43% female, 62% White, 36% Black, 1% Asian, 1% more than one race) ≥ 6 months after the surgical treatment of a lower-extremity fracture. Consenting patients exported their Apple iPhone mobility metrics, including step count, walking speed, step length, walking asymmetry, and double-support time. We integrated these mobility measures with demographic and injury data. Using nonlinear modeling, we assessed whether pre-injury mobility metrics combined with baseline data predicted post-fracture mobility.

Results: All models were well calibrated and had model fits ranging from an adjusted R^2 of 0.18 (walking asymmetry) to 0.61 (double-support time). Pre-injury function strongly predicted post-injury mobility in all models. After the injury, the average daily step count increased by 65 steps each week (95% confidence interval [CI], 56 to 75). Weekly gains were significantly greater within 6 weeks after the injury (92 daily steps per week; 95% CI, 58 to 127) than 20 to 26 weeks post-injury (19 daily steps per week; 95% CI, 11 to 27; $p < 0.001$). Greater pre-injury steps were associated with increased post-injury mobility (301 daily steps post-injury per 1,000 steps

corresponding author: nohara@som.umaryland.edu.

Written work prepared by employees of the Federal Government as part of their official duties is, under the United States Copyright Act, a 'work of the United States Government' for which copyright protection under that Act is not available. As such, copyright protection does not extend to the contributions of employees of the Federal Government prepared as part of their employment.

The **Disclosure of Potential Conflicts of Interest** forms are provided with the online version of the article (<http://links.lww.com/JBJS/I582>).

pre-injury; 95% CI, 235 to 367). Mean walking speed declined by 0.200 m/s (95% CI, -0.257 to -0.143) from injury to 8 weeks post-injury. From 12 to 26 weeks post-injury, the average walking speed increased by 0.071 m/s (95% CI, 0.044 to 0.097).

Conclusions: These proof-of-concept findings highlight the value of high-fidelity pre-injury mobility data in predicting recovery. Individualized recovery projections can provide patient-friendly counseling tools and useful clinical insight for surgeons.

Level of Evidence: Prognostic Level III. See Instructions for Authors for a complete description of levels of evidence.

After a lower-extremity fracture, the patient's priority is to regain function^{1,2}. However, options for measuring patient recovery are limited and include in-office examinations, evaluating pain levels, and collecting patient-reported outcomes measures (PROMs). Each has inherent flaws related to subjectivity, measurement error, and recency bias³⁻⁵. Furthermore, these evaluations only capture single time-points and lack comparison with pre-injury function. Ideally, an objective and longitudinal method would be available to understand patient recovery. Creating recovery curves tailored to patient-specific factors could enable more effective patient-centered counseling and clinical decision support.

Over half of adults in the United States use an Apple iPhone equipped with sensors that collect mobility data, including step count, walking speed, and walking asymmetry^{6,7}. The accuracy and reliability of these mobility metrics have been validated with instrumented carpet and inertial sensor assessments^{7,8}. Research has demonstrated that iPhone-collected mobility metrics are sensitive to mobility changes after a lower-extremity fracture and during recovery. Without requiring user setup, the devices provide continuous, non-intrusive collection and cataloging of years of data, yielding previously unavailable insight into patients' pre-injury function and post-injury mobility.

We utilized these digital mobility metrics, combining patients' pre-injury function with patient and injury characteristics, to better understand and model functional recovery up to 6 months post-injury. We assessed whether baseline mobility and patient characteristics could be used to develop stratum-specific algorithms that reliably predicted post-injury mobility.

Materials and Methods

Study Design

We performed a retrospective cohort study at a single academic trauma center, enrolling patients from January 2024 through May 2024. The local institutional review board approved the protocol, and all patients provided written informed consent.

Patient Population

The study included patients ≥ 18 years who underwent operative fixation of ≥ 1 fracture of the pelvis or lower extremity (i.e., a pelvic, hip, femoral shaft, distal femoral, tibial plateau, pilon, ankle, and/or hindfoot fracture) at a United States trauma center and were seen for clinical follow-up ≥ 6 months after injury. Patients were required to have had an iPhone

with the Apple Health app for ≥ 1 year before recruitment. Apple Health was introduced to iPhones in 2014 and automatically logs mobility metrics without requiring activation.

The research staff screened follow-up clinical appointments to identify eligible patients. Consenting patients exported their Apple Health data from their iPhones to a secure database. The export transfers all Apple Health data recorded since 2019 or on their first iPhone, whichever occurred later. Demographic, injury, and surgical data were collected from the medical record and were linked to the mobility data. Race and ethnicity were self-reported at the time of index hospitalization and obtained from the medical record.

Outcomes

The outcome measures included 5 mobility metrics recorded multiple times daily on patients' smartphones, including step count, walking speed, step length, walking asymmetry, and walking double-support percentage, up to 6 months post-fracture. With the exception of step count, these data are screened by the device's quality system in real time, removing poor-quality data related to the phone's proximity to the person's center of mass or insufficient episodes of motion.

The primary outcome was the step count, measured using the patient's smartphone pedometer, capturing the steps taken while the device was on their person⁸. In the United States, the median daily step count for adults is 4,354 (interquartile range [IQR], 2,868 to 6,178)⁹. Research has demonstrated mortality benefits in association with step counts of 6,000 to 8,000 for patients ≥ 60 years of age and of 8,000 to 10,000 for patients < 60 years of age, providing support for the 10,000 daily steps target^{10,11}. We selected step count as the primary outcome as it best aligns with patients' primary recovery aspiration as shown in preference research^{1,12,13}.

Walking speed measures how quickly the patient walks on flat ground, modeled according to the patient's center of mass⁸. Walking speed has been suggested to be "the sixth vital sign" due to its sensitivity and specificity for detecting future health status and decline^{14,15}. Comfortable gait speeds in the population range from 1.3 to 1.5 m/s, varying considerably by age and gender¹⁶. Research suggests that a 0.1-m/s decline in walking speed is associated with an 8% increase in fall risk and a 12% increase in mortality among individuals ≥ 65 years of age^{17,18}.

Walking asymmetry estimates the time during which asymmetric steps are detected while walking, presented as a percentage of walking time. Zero percent indicates perfect symmetry, and 100% indicates perfect asymmetry⁸. Walking asymmetry increases when a patient favors 1 limb, making this measure pertinent to understanding recovery after unilateral injuries¹⁹. Studies have suggested that walking asymmetry of $> 10\%$ has negative clinical implications^{20,21}, including a modest increase in fall risk among older adults and reduced function after lower-limb amputation^{17,22}.

Step length measures the distance between alternating steps during the gait cycle and is derived from the patient's height, step cadence, and speed estimation⁸. Step length population norms range from 0.55 to 0.88 m, are correlated with height ($r = 0.45$), and

decline with age²³. Decreasing step length is associated with a twofold increase in the fear of falling²⁴. While the relationship between step length and fall risk is unclear, research has suggested that reduced step length is associated with increased dependency, mortality, and institutionalization^{24–27}.

Finally, double-support time is the percentage of the patient's gait cycle on both feet, ranging from 0% when running to 100% when shuffling. A typical double-support time falls between 20% and 40%, with lower percentages indicating better balance⁸.

Statistical Analysis

We parameterized the outcomes on a weekly basis for the analysis to mitigate the impact of extreme mobility outliers. For step count, the weekly sum was divided by 7 for a daily average. We extracted the 90th percentile of walking speed and step length for the model. Double-support time and walking asymmetry were modeled as a weekly average. We calculated pre-injury means and standard deviations for each mobility parameter, using data from the 6 months before injury to account for seasonal variation in mobility patterns.

We estimated post-fracture step count with use of a generalized additive model with a monotonic growth constraint on the main effects and interactive effects of time from injury and pre-injury mean step count. The other outcomes were estimated with use of generalized linear models interacting a polynomial spline-fit post-injury time covariate with the pre-injury mean for the specific outcome and bilateral injury. All models were adjusted for age, sex, open fracture, body mass index, fracture location, and outcome-specific pre-injury mobility variance, with continuous covariates fitted using polynomial splines. The time of injury was set as time zero for all models. The reported marginal effects were adjusted on the basis of the weighted distribution of sample covariates, with standard errors being estimated with use of the delta method.

Within the observation period, weeks with missing step-count data were rare (<2%). However, because of data-quality bounding of the other outcomes, which required minimum amounts of motion for accurate calculation, missingness was more frequent for some measures (22% for walking speed and step length, 25% for double-support time, and 38% for walking asymmetry). We did not impute missing data in these analyses and assumed the missing data to be related to poor data quality.

All analyses were performed with use of R (version 4.2.2; R Foundation for Statistical Computing) with the packages *scam*, *splines*, *marginal effects*, and *ggplot2*. All comparisons used an alpha of 0.05 to indicate significance. We did not adjust the alpha for multiple comparisons.

Results

Study Population

Of the 139 patients who met the eligibility criteria and were approached for consent, 11 declined to participate, 2 of whom expressed data-privacy concerns. We excluded 21 consenting patients because of insufficient pre- and post-injury mobility data. In the group of

107 patients who were included in the analysis, the mean age (and standard deviation) was 45 ± 17 years and 46 patients (43%) were female (Table I) (see Appendix Table S1). Thirty-nine patients (36%) had an open fracture, and 20 (19%) had a bilateral lower-extremity fracture. Patients most commonly had a periarticular fracture (69%), followed by diaphyseal fracture (32%) and then by pelvic or acetabular fracture (16%). In the 6 months before injury, the average daily step count was $4,366 \pm 1,373$, and the 90th percentile walking speed was 1.300 ± 0.069 m/s.

Step Count

After injury, the average daily step count increased by 65 steps (95% confidence interval [CI], 56 to 75) week over week. Weekly gains were significantly greater within 6 weeks post-injury (92 daily steps per week; 95% CI, 58 to 127) as compared with 20 to 26 weeks post-injury (19 daily steps per week; 95% CI, 11 to 27) ($p < 0.001$) (Fig. 1). Greater pre-injury steps were associated with increased post-injury steps (301 daily steps post-injury per 1,000 steps pre-injury; 95% CI, 235 to 367) (Fig. 2). Post-injury daily step count decreased by 10 steps per 1-year increase in age (95% CI, -19 to -2). Bilateral injuries were associated with 879 fewer steps per day (95% CI, 21,191 to -568) in the 26 weeks after the injury. Figure 3 demonstrates predicted post-injury daily step counts for 3 hypothetical patients.

Walking Speed

We estimated an average decline in walking speed of 0.200 m/s (95% CI, -0.257 to -0.143) from injury to 8 weeks post-injury. From 12 to 26 weeks post-injury, we estimated a 0.071 m/s increase (95% CI, 0.044 to 0.097) in walking speed (Fig. 1). Post-injury walking speed was predicted by pre-injury walking speed, with a 0.1-m/s-faster pre-injury speed associated with a 0.057-m/s increase (95% CI, 0.005 to 0.109) in post-injury speed (see Appendix). Post-injury walking speed was 0.022 m/s slower (95% CI, -0.030 to -0.013) for every 10-year increase in age. Post-injury walking speed did not significantly differ in patients with bilateral compared with unilateral injuries (difference, -0.026 m/s [95% CI, -0.076 to 0.023]; $p = 0.30$).

Walking Asymmetry

Average walking asymmetry worsened by 25.0% (95% CI, 17.3% to 32.6%) from injury to 8 weeks post-injury and improved by 5.9% (95% CI, 2.4% to 9.4%) from 12 to 26 weeks post-injury (Fig. 1). Post-injury walking asymmetry varied significantly by pre-injury asymmetry, with a 5% increase in pre-injury asymmetry associated with a 3.7% increase (95% CI, 2.5% to 5.0%) in post-injury asymmetry (see Appendix). Every 10-year increase in age was associated with a 2.7% increase (95% CI, 1.6% to 3.8%) in post-injury asymmetry. We did not find a significant association between bilateral fractures and walking asymmetry (difference, 2.3% [95% CI, -3.0% to 7.6%]; $p = 0.40$).

Step Length

Step length declined an average of 0.040 m (95% CI, -0.064 to -0.016) in the first 8 weeks after injury and then increased by 0.025 m (95% CI, 0.013 to 0.036) from 12 to 26

weeks post-injury (Fig. 1). Pre-injury step length did not significantly predict post-injury step length (0.034 m increase [95% CI, -0.061 to 0.128] post-injury per 0.05 m pre-injury; $p = 0.48$) (see Appendix). Bilateral injuries were associated with a 0.041-m reduction (95% CI, -0.062 to -0.020) in step length; ($p < 0.001$).

Double-Support Time

Average double-support time increased by 1.51% (95% CI, 1.13% to 1.90%) within the first 8 weeks post-injury and then declined by 0.36% (95% CI, -0.54% to -0.18%) from 12 to 26 weeks post-injury (Fig. 1). A 1% higher pre-injury double-support time was associated with an increased post-injury double-support time (0.24%; 95% CI, 0.14% to 0.35%) (see Appendix). Every 10-year increase in age predicted a 0.19% increase (95% CI, 0.13% to 0.25%) in double-support time. Double-support time was similar between bilateral and unilateral injuries within 8 weeks after the injury (difference, 0.05% [95% CI, -0.79% to 0.88%]; $p = 0.91$) but was higher in association with bilateral injuries 12 to 26 weeks post-injury (difference, 0.53% [95% CI, 0.17% to 0.89%]; $p < 0.01$).

Model Diagnostics

A visual comparison of observed versus predicted values suggested that the models were well calibrated from 1 to 26 weeks post-injury. The fit of the models, as measured with the adjusted R^2 , ranged from 0.18 for walking asymmetry to 0.61 for double-support time. In Table II, we report the root-mean-squared error as a measure of accuracy for each model. All model parameter estimates are available in Appendix Tables SII to SVI.

Discussion

The present study demonstrated that smartphone data for patients with lower-extremity fractures can be used to develop personalized functional recovery curves. Pre-injury mobility, a marker absent from previous risk models, was an important factor in predicting post-injury recovery. This finding was consistent across all of our mobility models. The observed magnitude of relative post-recovery change was greatest in terms of step count, walking speed, and walking asymmetry, underscoring the clinical importance of these data as recovery metrics.

The post-fracture trends for each mobility parameter create a multidimensional recovery narrative. Step-count gains were linear until 20 weeks and then reached an asymptote. Walking speed, asymmetry, and double-support time gradually worsened for approximately 8 weeks after injury. The use of walking aids presumably masked the true initial decline of these metrics, which were progressively uncovered as patients relinquished their reliance on such devices. These gait parameters improved after the 8-week mark, reaching a similar plateau at about 20 weeks after injury. Step length followed a similar pattern with less change in magnitude.

The observed relationship between pre- and post-injury mobility offers unique clinical insight. For example, we estimated that patients with higher pre-injury mobility (e.g., 6,000 daily steps) achieved better mobility 26 weeks after injury than patients with lower pre-injury mobility (e.g., 2,000 daily steps), reaching about 3,200 steps versus 1,800 steps,

respectively. However, on a relative scale, patients with greater pre-injury mobility were doing worse, walking just over 50% of their pre-injury levels. In comparison, patients with lower pre-injury mobility regained over 90% of their pre-injury mobility. Calibrating patients' expectations for these substantial changes in post-injury mobility might aid patients in recovery planning.

Our findings suggest that mobility data continuously captured through high-fidelity smartphone sensors could be processed through algorithms derived in this research to support real-time feedback to the patient and clinical care team. The patient-centered nature of these data supports recovery expectations and shared decision-making. Numerous smartphone-based activity and behavior-modification applications exist today and have successfully incentivized activity among patients^{28,29}.

Similar mechanisms could be developed with our algorithms, encouraging patient engagement in their recovery. We envision these as clinical "guardrails" for monitoring recovery, with negative deviations potentially indicating complications. Patients meeting expectations may elect for telemedicine follow-up, reducing patient burden and allowing clinicians to allocate more attention to patients with compromised recovery. The probability of successfully implementing these strategies into clinical workflow is profoundly increased because it does not require new technology to be given to the patient or for the patient to change their use behavior. These data are already being collected but have not yet been used to their full and considerable potential.

This study had several strengths. Movement data were collected automatically whenever the device was in motion and captured real-world mobility on uneven surfaces that cannot be replicated in gait laboratories. This approach also incorporated previously unknown pre-injury data, which were demonstrably crucial in our understanding of patients' overall recovery. In addition, enrolling only patients with iPhones created a closed hardware and software environment, decreasing variability in sensor output. This design feature benefits from Apple sensors' data quality filters, improving the internal validity of our results⁷.

Despite these strengths, we acknowledge that our study also had limitations. At its core, this is a proof-of-concept study assessing the feasibility of constructing recovery models with smartphone data. The 107-patient sample yields wide uncertainty in many estimates. Larger, more homogenous samples are required to improve the specificity and reliability of individualized recovery projections. The study was performed at a single center; variation across hospitals is unknown. Furthermore, enrollment required ≥ 6 months of follow-up to ensure sufficient post-injury data. This decision introduced selection bias toward patients with more severe injuries or those with prolonged follow-up. Therefore, we likely underestimated the average magnitude of post-fracture recovery. Instances of motion when patients were without their phones lead to step-count underreporting. However, comparing pre-injury data with U.S. population norms suggests that the scale of underreporting was minimal and likely non-differential between pre- and post-injury⁹. Finally, we restricted the study to patients with iPhones only. While the benefits of an iPhone-only sample have been described, the socioeconomic differences between Apple and Android users are unclear, but we anticipate these patients experience similar biological healing.

Conclusion

Mobility data from the smartphones of patients with lower-extremity fractures can produce reliable recovery curves. All models had acceptable model fit and were well calibrated from 0 to 26 weeks after injury. This proof-of-concept study demonstrates the feasibility of developing patient-specific recovery models, which may provide clinical utility in patient-centered counseling and as clinical decision-support tools.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Disclosure:

This study was supported by an AO Trauma North America fellows grant, an Orthopaedic Trauma Association resident research grant, and the National Institute of Arthritis and Musculoskeletal and Skin Diseases (K24AR076445).

References

1. Richards JT, O'Hara NN, Healy K, Zingas N, McKibben N, Benzel C, Slobogean GP, O'Toole RV, Sciadini MF Fix or replace? Patient preferences for the treatment of geriatric lower extremity fractures: a discrete choice experiment. *Geriatr Orthop Surg Rehabil*. 2024 Feb 28;15:21514593241236647.
2. O'Hara NN, Mulliken A, Joseph K, Slobogean GP, Johal H, Cunningham BP, Olaya S, Levy J, Pollak AN, Klazinga NS. Valuing the recovery priorities of orthopaedic trauma patients after injury: evidence from a discrete choice experiment within 6 weeks of injury. *J Orthop Trauma*. 2019 Nov;33(Suppl 7):S16–20. [PubMed: 31596779]
3. Brodke DJ, Saltzman CL, Brodke DS. PROMIS for orthopaedic outcomes measurement. *J Am Acad Orthop Surg*. 2016 Nov;24(11):744–9. [PubMed: 27661391]
4. Brodke DJ, Hung M, Bozic KJ. Item response theory and computerized adaptive testing for orthopaedic outcomes measures. *J Am Acad Orthop Surg*. 2016 Nov; 24(11):750–4. [PubMed: 27623193]
5. Chauhan D, Ahmad HS, Subtirelu R, Mannam S, Turlip R, Bryan K, Bathula S, Ghenbot Y, Yang AI, Wang MY, Basil G, Ali ZS, Yoon JW. Defining the minimal clinically important difference in smartphone-based mobility after spine surgery: correlation of survey questionnaire to mobility data. *J Neurosurg Spine*. 2023 May 26;39(3):427–37. [PubMed: 37243547]
6. Braun BJ, Histing T, Menger MM, Herath SC, Mueller-Franzes GA, Grimm B, Marmor MT, Truhn D; AO Smart Digital Solutions Task Force(Andrew M Hanflik, Peter H Richter, Sureshan Sivananthan, Seth R Yarboro). Wearable activity data can predict functional recovery after musculoskeletal injury: Feasibility of a machine learning approach. *Injury*. 2024 Feb;55(2):111254.
7. Werner C, Hezel N, Dongus F, Spielmann J, Mayer J, Becker C, Bauer JM. Validity and reliability of the Apple Health app on iPhone for measuring gait parameters in children, adults, and seniors. *Sci Rep*. 2023 Apr 1;13(1):5350. [PubMed: 37005465]
8. Apple, Inc. Measuring Walking Quality Through iPhone Mobility Metrics. 2022. Accessed 2024 Aug 14. https://www.apple.com/healthcare/docs/site/Measuring_Walking_Quality_Through_iPhone_Mobility_Metrics.pdf
9. Althoff T, Sosič R, Hicks JL, King AC, Delp SL, Leskovec J. Large-scale physical activity data reveal worldwide activity inequality. *Nature*. 2017 Jul 20;547(7663):336–9. [PubMed: 28693034]
10. Inoue K, Tsugawa Y, Mayeda ER, Ritz B. Association of daily step patterns with mortality in US adults. *JAMA Netw Open*. 2023 Mar 1;6(3):e235174.
11. Paluch AE, Bajpai S, Bassett DR, Carnethon MR, Ekelund U, Evenson KR, Galuska DA, Jefferis BJ, Kraus WE, Lee IM, Matthews CE, Omura JD, Patel AV, Pieper CF, Rees-Punia E, Dallmeier D, Klenk J, Whincup PH, Dooley EE, Pettee Gabriel K, Palta P, Pompeii LA, Chernofsky A,

- Larson MG, Vasan RS, Spartano N, Ballin M, Nordström P, Nordström A, Anderssen SA, Hansen BH, Cochrane JA, Dwyer T, Wang J, Ferrucci L, Liu F, Schrack J, Urbanek J, Saint-Maurice PF, Yamamoto N, Yoshitake Y, Newton RL Jr, Yang S, Shiroma EJ, Fulton JE; Steps for Health Collaborative. Daily steps and all-cause mortality: a meta-analysis of 15 international cohorts. *Lancet Public Health*. 2022 Mar;7(3):e219–28. [PubMed: 35247352]
12. McKibben NS, Marchand LS, Demyanovich HK, Healey KM, Zingas N, O'Connor K, Slobogean GP, O'Toole RV, O'Hara NN. Patient preferences for physical therapy programs after a lower extremity fracture: a discrete choice experiment. *BMJ Open*. 2023 Oct 5;13(10):e072583.
 13. Patterson JT, Parry JA, Working ZM, McKibben NA, Baca J, Duong A, Senior J, Kim A, Marchand LS, O'Hara N. Patient preferences for operative versus nonoperative treatment of LC1 pelvis fracture: a discrete choice experiment. *J Orthop Trauma*. 2024 Jun 1;38(6):291–8. [PubMed: 38442188]
 14. Fritz S, Lusardi M. White paper: “walking speed: the sixth vital sign”. *J Geriatr Phys Ther*. 2009;32(2):46–9. [PubMed: 20039582]
 15. Middleton A, Fritz SL, Lusardi M. Walking speed: the functional vital sign. *J Aging Phys Act*. 2015 Apr;23(2):314–22. [PubMed: 24812254]
 16. Bohannon RW. Comfortable and maximum walking speed of adults aged 20–79 years: reference values and determinants. *Age Ageing*. 1997 Jan;26(1):15–9.
 17. Verghese J, Holtzer R, Lipton RB, Wang C. Quantitative gait markers and incident fall risk in older adults. *J Gerontol A Biol Sci Med Sci*. 2009 Aug;64(8):896–901. [PubMed: 19349593]
 18. Studenski S, Perera S, Patel K, Rosano C, Faulkner K, Inzitari M, Brach J, Chandler J, Cawthon P, Connor EB, Nevitt M, Visser M, Kritchevsky S, Badinelli S, Harris T, Newman AB, Cauley J, Ferrucci L, Guralnik J. Gait speed and survival in older adults. *JAMA*. 2011 Jan 5;305(1):50–8. [PubMed: 21205966]
 19. Di Stasi SL, Logerstedt D, Gardinier ES, Snyder-Mackler L. Gait patterns differ between ACL-reconstructed athletes who pass return-to-sport criteria and those who fail. *Am J Sports Med*. 2013 Jun;41(6):1310–8. [PubMed: 23562809]
 20. Patterson KK, Gage WH, Brooks D, Black SE, McIlroy WE. Evaluation of gait symmetry after stroke: a comparison of current methods and recommendations for standardization. *Gait Posture*. 2010 Feb;31(2):241–6. [PubMed: 19932621]
 21. Hodt-Billington C, Helbostad JL, Vervaat W, Rognsvåg T, Moe-Nilssen R. Criteria of gait asymmetry in patients with hip osteoarthritis. *Physiother Theory Pract*. 2012 Feb;28(2):134–41. [PubMed: 21722001]
 22. Seth M, Coyle PC, Pohlig RT, Beisheim EH, Horne JR, Hicks GE, Sions JM. Gait asymmetry is associated with performance-based physical function among adults with lower-limb amputation. *Physiother Theory Pract*. 2022 Nov;38(13):3108–18. [PubMed: 34657569]
 23. Herrero-Larrea A, Miñarro A, Narvaiza L, Gálvez-Barrón C, León NG, Valldosera E, Felipe E, Valverde RA, Kruse L, Sabater JB, Rodríguez-Molinero A. Normal limits of home measured spatial gait parameters of the elderly population and their association with health variables. *Sci Rep*. 2018 Sep 4;8(1):13193. [PubMed: 30181569]
 24. Maki BE. Gait changes in older adults: predictors of falls or indicators of fear. *J Am Geriatr Soc*. 1997 Mar;45(3):313–20. [PubMed: 9063277]
 25. van Schooten KS, Pijnappels M, Rispens SM, Elders PJM, Lips P, Daffertshofer A, Beek PJ, van Dieën JH. Daily-life gait quality as predictor of falls in older people: a 1-year prospective cohort study. *PLoS One*. 2016 Jul 7;11(7):e0158623.
 26. Woo J, Ho SC, Yu AL. Walking speed and stride length predicts 36 months dependency, mortality, and institutionalization in Chinese aged 70 and older. *J Am Geriatr Soc*. 1999 Oct;47(10):1257–60. [PubMed: 10522962]
 27. Doi T, Nakakubo S, Tsutsumimoto K, Kim MJ, Kurita S, Ishii H, Shimada H. Spatio-temporal gait variables predicted incident disability. *J Neuroeng Rehabil*. 2020 Jan 30;17(1):11. [PubMed: 32000793]
 28. Islam MM, Poly TN, Walther BA, Jack Li YC. Use of mobile phone app interventions to promote weight loss: meta-analysis. *JMIR Mhealth Uhealth*. 2020 Jul 22;8(7):e17039.

29. Whittaker R, McRobbie H, Bullen C, Rodgers A, Gu Y. Mobile phone-based interventions for smoking cessation. *Cochrane Database Syst Rev*. 2016 Apr 10;4(4):CD006611.

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

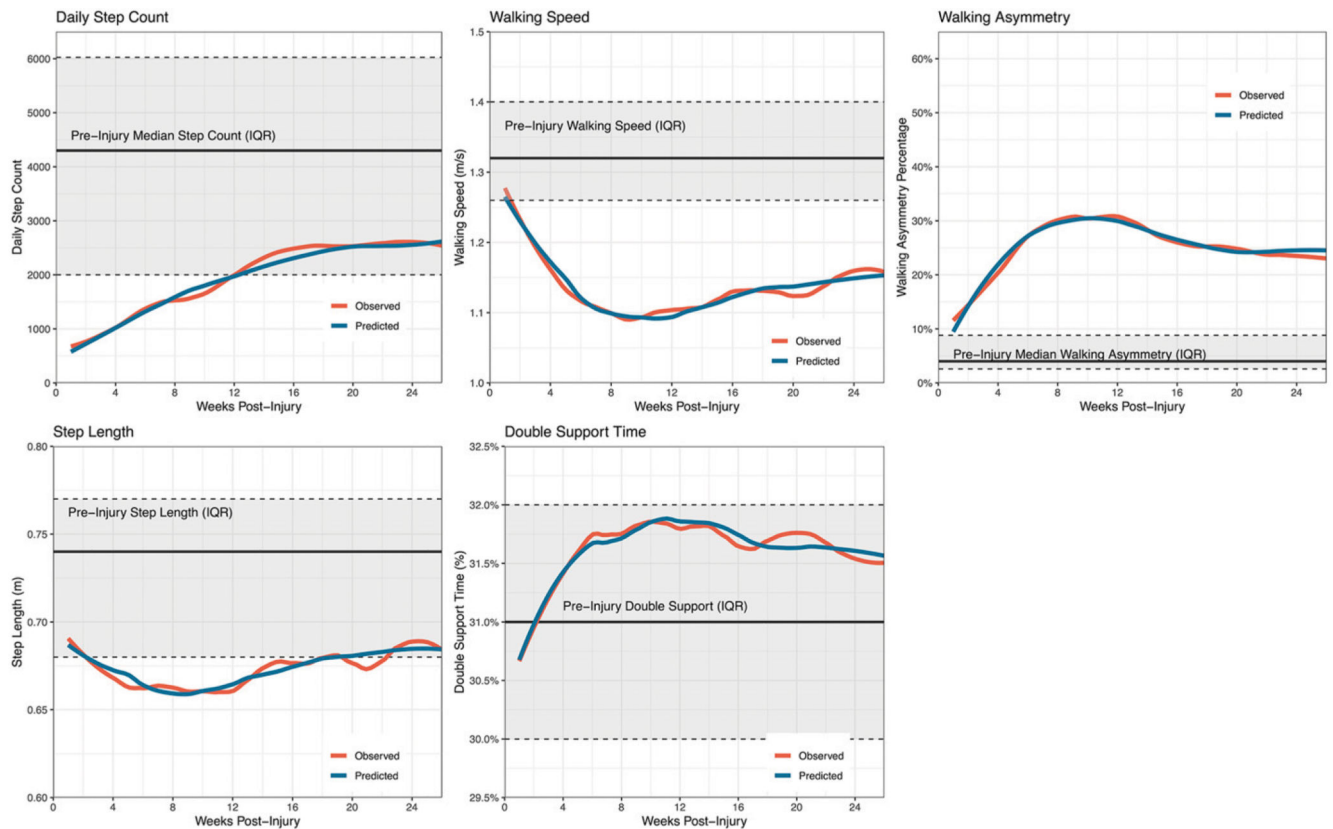


Fig. 1.

Graphs illustrating post-injury mobility as measured by step count, walking speed, walking asymmetry, step length, and double-support time. The graphs report predicted versus observed recovery for each outcome. The horizontal line and shading indicate the pre-injury median and interquartile range (IQR) for each parameter.

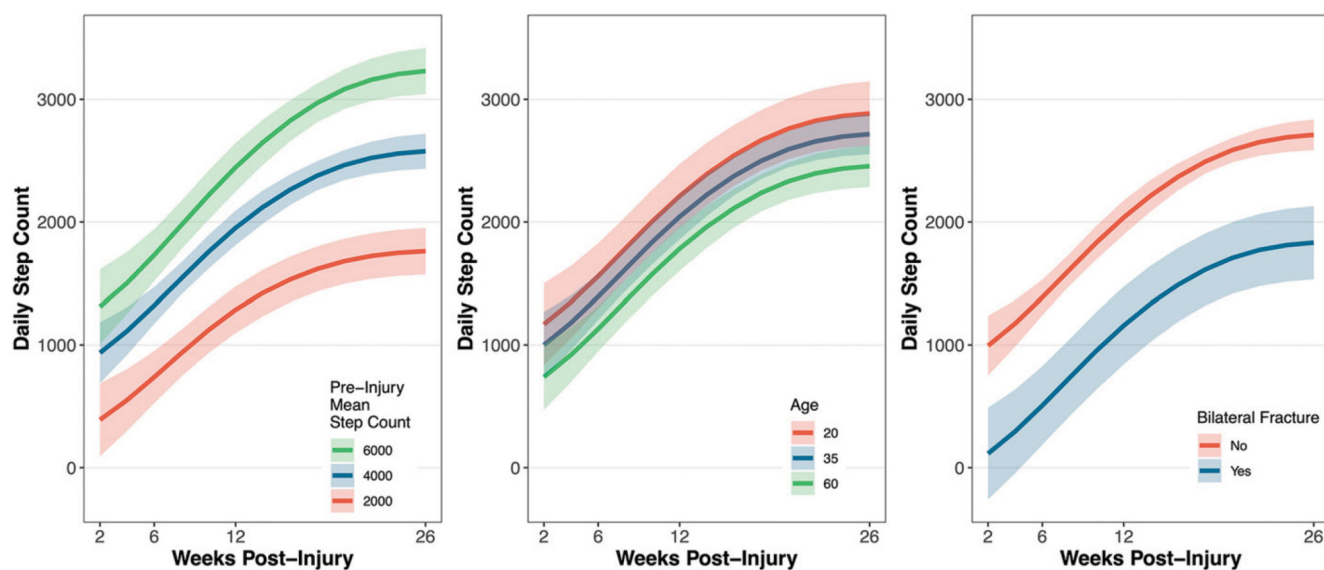


Fig. 2. Graphs illustrating post-injury mobility as measured by step count and stratified by pre-injury mobility, age, and bilateral versus unilateral fractures. The shaded areas represent 95% confidence intervals.

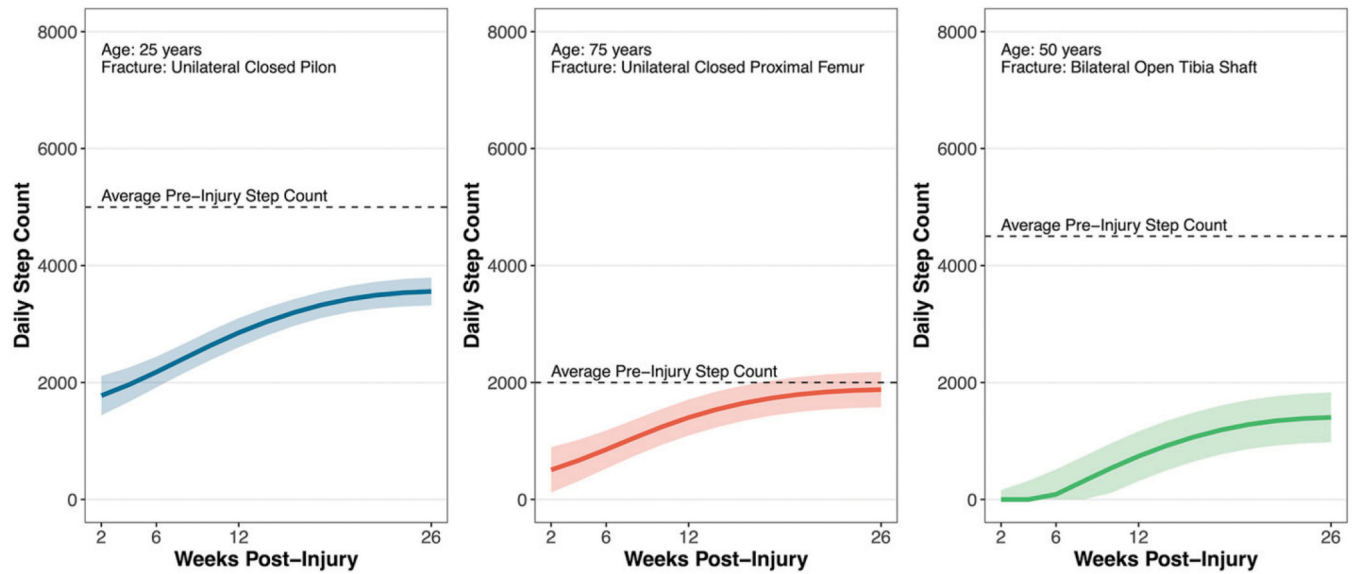


Fig. 3. Graphs illustrating predicted post-injury daily step count for 3 hypothetical patients as described by age, fracture type, and pre-injury mobility. The shaded areas represent 95% confidence intervals.

TABLE I

Patient and Injury Characteristics (N=107)

Age [*] (yr)	45 ± 17
Female sex (no. of patients)	46 (43%)
Ethnicity (no. of patients)	
Hispanic or Latino	4 (4%)
Not Hispanic or Latino	103 (96%)
Race (no. of patients)	
Asian	1 (1%)
Black or African American	39 (36%)
More than 1 race	1 (1%)
White	66 (62%)
Body mass index [†] (kg/m ²)	27 (24 to 33)
Bilateral injury (no. of patients)	20 (19%)
Open fracture (no. of patients)	39 (36%)
Fracture type (no. of patients)	
Periarticular	74 (69%)
Diaphyseal	34 (32%)
Pelvic or acetabular	17 (16%)
Pre-injury mobility [*]	
No. of steps per day	4,366 ± 1,373
Walking speed (m/s)	1.300 ± 0.069
Walking asymmetry (%)	8.6 ± 5.6
Step length (m)	0.722 ± 0.031
Double-support (%)	30.6 ± 0.3

^{*} The values are given as the mean and the standard deviation.

[†] The values are given as the median, with the interquartile range in parentheses.

TABLE II

Model Diagnostics

Outcome	Adjusted R ²	Root-Mean-Squared Error
Step count	0.40	1,544 steps
Walking speed	0.35	0.171 m/s
Walking asymmetry	0.18	23.5%
Step length	0.40	0.072 m
Double-support time	0.61	1.2%