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Development of a physical mobility prediction model to guide prosthetic rehabilitation

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Abstract

Background: Prosthetic rehabilitation decisions depend on estimating a patient's mobility potential. However, no validated prediction models of mobility outcomes exist for people with lower-limb amputation (LLA).

Objectives: To develop and test predictions for self-reported mobility after LLA, using the Prosthetic Limb Users Survey of Mobility (PLUS-M).

Study Design: This is a retrospective cohort analysis.

Methods: Eight hundred thirty-one patient records (1,860 PLUS-M observations) were used to develop and test a neighbors-based prediction model, using previous patient data to predict

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Author contributions
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the 6-month PLUS-M T-score trajectory for a new patient (based on matching characteristics). The prediction model was developed in a training data set (n = 552 patients) and tested in an out-of-sample data set of 279 patients with later visit dates. Prediction performance was assessed using bias, coverage, and precision. Prediction calibration was also assessed.

Results: The average prediction bias for the model was 0.01 SDs, average coverage was 0.498 (ideal proportion within the 50% prediction interval = 0.5), and prediction interval was 8.4 PLUS-M T-score points (40% improvement over population-level estimates). Predictions were well calibrated, with the median predicted scores falling within the standard error of the median of observed scores, across all deciles of the data.

Conclusions: This neighbors-based prediction approach allows for accurate estimates of PLUS-M T-score trajectories for people with LLA.

Keywords

prognosis; amputation; rehabilitation; data science; neighbors-based prediction; patient reported outcome measures

Background

People living with lower-limb amputation (LLA) are highly diverse, proving rehabilitation to be complex.[1] Age, amputation level, comorbidities, etiology of amputation, and mobility all influence a patient's mobility with a prosthesis.[2] Therefore, determining functional prognosis is difficult, often leaving patients under-informed about their recovery.[3–6] Conventional prosthetic rehabilitation decisions are driven by clinical experience and expertise, contributing to variability and subjectivity in care.[1,3,5,6] Variability in care contributes to inefficient healthcare utilization and can limit a patient's ability to maximize functional potential.[1] A method for estimating functional prognosis while incorporating patient-specific characteristics is needed to optimize prosthetic rehabilitation.[1]

There are currently no accepted methods for predicting an individual patient's future mobility after LLA.[1] Moreover, previous predictions have estimated outcomes at a single time point, such as 1 year after amputation, rather than the trajectory of functional mobility change over time.[7–11] Particularly during the initial months after the provision of a prosthesis, patient mobility is intended to improve,[12] warranting medical necessity for the prosthesis. Understanding the estimated trajectory of functional mobility change may support prosthesis justification, long-term care planning, and informing realistic expectations of both patients and providers throughout the course of recovery. Neighbors-based predictions, where historical data are used to construct the prognosis for a new patient, have been promoted as a method for creating realistic prognostic estimates while leveraging clinical data.[13,14] Neighbors-based predictions offer the potential to understand how a patient's current mobility status, based on specific characteristics, may inform projections of their future mobility trajectory.

The Prosthetic Limb Users Survey of Mobility (PLUS-M) is a patient-reported measure of mobility that is easy to administer in routine practice, thus offering a feasible means of tracking and predicting a patient's perceived mobility.[15,16] The purpose of this study was to develop and test a neighbors-based prediction approach for mobility recovery after LLA using the PLUS-M T-scores. PLUS-M T-scores are a standardized score with a mean of 50 and a SD of 10 established in a sample of 1,091 people with LLA, where a higher T-score of 60 would indicate higher function than 84% of people who the test was developed in.[17] We hypothesized that neighbors-based predictions of PLUS-M T-score would perform well, with small bias (small average distance on a z-scale between a patient's predicted and observed scores), accurate coverage (close to 50% of realized PLUS-M observations falling within the 50% prediction interval), and improved precision (average width of the 50% prediction interval) compared with population-level prognostic estimates. We further hypothesized that predictions would be well calibrated when tested in both the training data set (within-sample testing) and the test data set (out-of-sample testing).

Methods

Data source

This was a retrospective cohort analysis from a data set of clinic records provided by a private prosthetics practice, Hanger Clinics, with 341 clinic locations across the continental United States. Records included patients with LLA (distal to hip disarticulation) who were seen for a new or replacement prosthesis between April 2016 and March 2018. Only records containing PLUS-M scores were extracted. Records were excluded if they did not contain 2 or more time points of the PLUS-M primary outcome measure or if they were missing any required covariates (eg, age) (Figure 1). Records were de-identified and exported to Excel (Microsoft, Redmond, WA). Study procedures were approved by the Colorado Institutional Review Board.

Prosthetic limb users survey of mobility

The PLUS-M 12-item short form is a self-reported survey of patient-reported difficulty in performing tasks that require lower-limb use,[15] demonstrating construct validity, test–retest reliability [intraclass correlation coefficient (ICC) = 0.96], and low measurement error [standard error of measurement (SEM) = 1.93 T-score points with the 12-item paper short form].[15,16] Patients completed the 12-item short-form PLUS-M with T-scores[15] calculated (1) at baseline, (2) at a clinic visit (ranging from 2 weeks to 6 months after baseline administration), and (3) approximately 6 months after baseline.[16] Baseline was defined as the time the first PLUS-M was administered, either at the initial evaluation (for patients currently using a prosthesis) or the first appointment after receiving their first prosthesis. Resulting PLUS-M T-scores were routinely discussed with patients.

Patient matching characteristics

All variables available in the provided data set were evaluated for potential matching characteristics in neighbors-based predictions. Variables were included based on their association with function after LLA and included age,[2] sex,[18] adjusted body mass index (either patient-reported or clinical evaluation),[19] amputation level,[2] amputation laterality,[20] time since amputation,[21] etiology of amputation,[2,18] functional comorbidity index,[2,18] employment status,[22] Prosthesis Evaluation Questionnaire well-being subsection,[23] and PLUS-M T-scores.[2,18] The functional comorbidity index is a sum of 18 self-reported comorbid conditions with a score of 0–18,[24] whereas the Prosthesis Evaluation Questionnaire—Well-Being subsection is a 2-item survey of patient satisfaction and quality of life, with scores ranging from 0 to 10 for each question.[23,25] Both measures have demonstrated validity and have been used in populations with LLA.[23,24,26,27] Amputation levels were categorized as follows: (1) distal to the hip but at or proximal to the knee (ie, transfemoral and knee disarticulation), (2) distal to the knee but at or proximal to the ankle (ie, transtibial and ankle disarticulation), and (3) distal to the ankle (ie, partial foot). Cases with bilateral amputations were categorized as bilateral, and in the 19 cases with asymmetrical amputation levels, the most proximal amputation level was used as the level of amputation. Time since amputation was the date of the first amputation. Age and sex were self-reported.

Statistical analyses

Neighbors-based predictions were constructed using historical data; a new patient was matched to historical patients based on select matching characteristics (ie age, sex, amputation level, and baseline PLUS-M T-score), using an adaptation of predictive mean matching. Realized PLUS-M T-scores from these historical matches were then used to construct the new patient prognosis. The steps for neighbors-based prediction are summarized in Box 1.

Selection of matches by predictive mean matching—Because the data sets contained PLUS-M measurements at irregular time intervals, a PLUS-M T-score at 90 days after baseline PLUS-M was estimated for each patient using linear mixed-effects models through the brokenstick package (R statistical computing).[28,29] The 90-day T-score was selected due to the common time frame for clinical follow-up and due to the higher density of PLUS-M observations. The 90-day estimate was then used as the distal anchor for selecting matches by predictive mean matching. Briefly, a brokenstick model was fit to patients in the training data set with 3 knots in the time variable (k = 0, 45, and 90).[28,30] Patients in the training data set were then matched according to a predicted 90-day PLUS-M T-score by building a linear model with matching characteristics as predictors and the 90-day PLUS-M estimate as the outcome. Variable selection was determined by Akaike information criterion (stepAIC function, R statistical computing).[31] Other variables are known to contribute to functional performance after LLA[2]; therefore, it is possible that some variables (eg, etiology and comorbidities) demonstrate collinearity with PLUS-M T-scores. However, only variables that demonstrated a significant relationship with the 90-day PLUS-M T-score were selected as matching characteristics.

Flexible modeling of observed data—For each patient in the training data set, the observed PLUS-M T-scores from the patient's matches (m) were used to fit a Generalized Additive Model for Location, Scale, and Shape (GAMLSS).[32,33] The GAMLSS approach was chosen for its flexibility in modeling the median (location), variance (scale), skewness, and kurtosis (shape) of PLUS-M T-scores as a smooth function of time (i.e., time since baseline).[34] A cubic spline smoother with 3 degrees of freedom for the location parameter and 1 degree of freedom for the scale and shape parameters was used.

Model tuning through within-sample testing—The performance of prediction methodology was adjudicated based on 3 metrics: bias, coverage, and precision. Bias was operationalized as the average difference (on a z-scale) between patients' predicted PLUS-M T-scores and the observed PLUS-M T-scores in the first 6 months after patients' baseline PLUS-M (ideal bias = 0 SDs). Bias may be interpreted similar to effect size (i.e., Cohen's *d*, which is also reported in units of SD). Commonly reported benchmarks for effect size *d* are as follows: 0.2 = small, 0.5 = medium, and 0.8 = large.[35] Coverage was calculated as the proportion of observations within the 50% prediction interval (ideal coverage = 50%). Because the width of the prediction interval is allowed to vary with time (i.e., days after evaluation) and may also be asymmetrical about the point estimate (e.g., the prediction interval might be +4.4 points to −4 points), precision was evaluated as the average width (in PLUS-M T-score points) of the 50% prediction interval (narrower is better). Using these metrics, the optimal number of matches (m) was examined: (1) GAMLSS models were fit to the matches' observed data for each patient in the training data set, with the number of matches ranging from 10 to 552 (i.e., the total number of available patients in the training data set); (2) at each increment (ie, 10 matches; 11, 12, …; 552 matches), the average bias, coverage, and precision of the predictions were calculated; and (3) the optimal number of matches was determined by the solution that minimized bias while retaining accurate coverage along with improved precision over population-level estimates.

Internal and external validation—To examine predictions' validity, predicted versus observed PLUS-M T-scores were compared using calibration plots. For both the training and test data sets, the predicted PLUS-M T-scores were binned by deciles. The median and the standard error (95% confidence interval) of the observed data in each decile were calculated.

Results

The entire data set was separated (cut point January 2018) to form a within-sample training and new sample test set of records. In the training data set, data from 552 patients with 1274 PLUS-M observations were analyzed, and 279 patients (586 observations) were used in the test data set (Table 1). Time since amputation was positively skewed and thus collapsed into the following categories: (1) <1 year, (2) 1–5 years, and (3) >5 years since amputation to reduce the impact of skewness.

Selection of matches and model tuning

Predictive mean matching—Age ($\beta = -0.07$; $P = .02$), sex (reference = female; male: $\beta = 1.84$, $P = .002$), amputation level (reference = below knee; above knee: $\beta = -1.48$; $P = .023$, partial foot: $\beta = 5.53$, $P = .040$), time since amputation (reference = <1 year; >1 year and <5 years: $\beta = -2.43$; $P = .006$, >5 years: $\beta = -0.34$, $P = .70$), and baseline PLUS-M T-score ($\beta = 0.51$; $P < .001$) demonstrated statistically significant relationships with the 90-day PLUS-M scores. Therefore, these variables were selected as matching characteristics for use in subsequent neighbors-based predictions (Table 2). The baseline PLUS-M T-score carried the most weight in identifying matches.

Model tuning—The optimal number of matches was m = 45 based on the best performance in average bias (0.01 SDs) and coverage (the proportion of realized observations within the 50% prediction interval: 0.498). In addition, the average width of the 50% prediction interval with m = 45 matches was 8.4 points. For reference, with m = 552 matches (i.e., the full training data set), the average precision was 14.0 points. Therefore, the neighbors-based prediction with m = 45 matches resulted in a 40% improvement in precision of prognosis relative to estimates that reflect the whole population.

Calibration by within-sample and out-of-sample testing—Once the number of matches was determined (m = 45), within-sample (training data set) and out-of-sample (test data set) calibrations were examined. This process mimicked how development and testing would work in practice with prospective analysis. The median predicted PLUS-M T-score for each decile fell within the standard error of the median of observed scores, indicating accurate calibration (Figure 2).

Discussion

In this study, we developed and tested neighbors-based predictions for patient self-reported mobility after LLA. Using predictive mean matching for the 90-day PLUS-M T-score, baseline PLUS-M T-score, age, sex, amputation level, and time since amputation were identified as matching characteristics for an index patient. The observed data from these matches (ie, neighbors) were then used to generate an estimated trajectory of PLUS-M T-score recovery for the index patient. This same approach could be deployed clinically to estimate the mobility course for new patients, using existing patient records and outcomes within individual prosthetics practices. The neighbors-based approach offers an opportunity to support clinical practice by informing patient expectations and monitoring progress in prosthetic care.

To construct the neigbors-based predictions, we determined the optimal number of matches to be m = 45 by within-sample testing. Predictions with m = 45 matches for both the within-sample and out-of-sample calibrations resulted in small bias (0.01 SDs, on average), accurate coverage (49.8% of realized observations falling within the 50% prediction interval), and a 40% improvement in precision over population-level models. The clinical relevance of these findings is a topic worthy of future research. Ideally, to be useful in practice, predictions would be more accurate than the prognostic estimates of experienced prosthetists. This could be tested experiementally in future work. However, it is notable that differences in individual-level predictions were readily apparent (Figure 3), indicating that the precision was sufficient to distinguish prognostic trajectories between patients. For example, the 50% prediction interval for a 40-year-old man with transtibial amputation notably differs from the 50% prediction interval for a 70-year-old woman with transfemoral amputation (Figure 3). Thus, there is potential for neighbors-based predictions to differentially influence care planning and assist with monitoring treatment response.

The coverage of neighbors-based predictions suggests that prognostic uncertainty was accurately modeled. In other words, the range of potential outcomes for an individual patient's self-reported mobility was accurately displayed, and patient progress over time might be accurately benchmarked against the prediction. For example, if a patient's PLUS-M score at 3 months is observed to fall below what was predicted, the magnitude of the deviation could be accurately quantified. However, interpreting individual predictions remains challenging when considering goals intended for maximizing a new patient's functional potential. Functional outcomes for people with LLA are historically poor; therefore, interpretation should be regarded in light of the data used. Predictions are generated from existing outcomes for people with LLA rather than from function of able-bodied individuals, which would be the optimal reference for functional goal setting.

Although the PLUS-M demonstrates convergent construct validity with performance-based measures,[15] self-reported measures are prone to reporter bias and are suggested to measure different constructs of physical function.[36] Predicting self-reported mobility introduces a method for estimating a patient's perception of how mobility limitations may influence their perceived performance in activities. Overall, this study represents an important step in reporting a neighbors-based prediction model's performance in terms of coverage, for patients with LLA, and has the potential to be implemented using other clinically meaningful measures, such as performance-based measures.

The predictions were well calibrated in both the training and test data sets. In the training data set, the predictions performed accurately in all deciles of the observed data. More importantly, the predictions also performed well in the test data set. Observed medians fell within the predicted medians for all deciles, and accurracy would be expected to improve in future, increased population size sampling. This is notable because predictions were generated from a heterogeneous data set, including multiple clinic locations and care processes. Current clinical prediction tools (eg, the Amputee Mobility Predictor) either have not been evaluated for prediction accuracy or have only been assessed for predictive ability at a single time point (eg, 1 year).[1,7–11,37] For example, existing logistic and linear regression models predict a single outcome (eg, Medicare Functional Classification Level [K-level]) at a single time point, such as 12 months after amputation.[8–11] This study improves on existing work by developing a successful externally validated prediction model using longitudinal data, with the potential to predict a new patient's perceived mobility at any given time point over the first 6 months after providing a new or replacement prosthesis.

Most prosthetists report difficulty in predicting patient outcomes and managing patient expectations for functional mobility with a prosthesis, in part associated with difficulty in interpreting how various factors influence a patient's future function.[3,4] Given that challenge, neighbors-based predictions create a tool for clinicians to focus conversations around goals of care and to inform expectations for future self-reported mobility, specific to the individual. Furthermore, accurate predictions of mobility over time offer potential to support and improve prosthetist's experience-based estimates.

Several features of the prediction methodology may have contributed to the observed results. First, the estimates were based on actual clinical observations, potentially contributing to more realistic estimates of mobility over time than could be achieved with parametric modeling approaches. Second, the neighbors-based approach builds a new prediction model for each patient based on the observed data of similar previous patients matched through select characteristics.[38,39] This may promote external validity of the predictions because any new patient is likely to have a few good matches available in the source data, even if the samples from which patients are drawn are substantially different in the aggregate. Finally, the matches were selected based on the relation of characteristics to the 90-day PLUS-M T-score, thus allowing for the matching characteristics to be weighted according to the strength of their relationship to the PLUS-M outcome. Given the heterogeneity of patients with LLA, the neighbors-based approach is conceptually appealing to patients and clinicians; basing an index patient's prediction on realized data from previous similar patients matched through select characteristics is intuitive and can align with information patients desire to support decisions. For example, a 70-year-old patient with a new transtibial amputation may conceptually relate to a prediction created from existing patients of a similar age and amputation level, rather than interpreting population-level outcomes including younger individuals with transfemoral amputations. The neighbors-based approach offers an opportunity to use clinically collected data to establish realistic recovery expectations, aid in functional goal setting, and inform real-time clinical decisions.

Clinical implications

This neighbor-based approach shows the potential to use existing clinical measures of self-reported mobility to predict a new patient's future estimated mobility, potentially enhancing objectivity around care planning and decisions. Our approach incrementally improves on existing prediction methods by estimating a personalized trajectory of PLUS-M T-scores over 6 months, allowing for interpretation of self-reported mobility at any given time point over the first 6 months after providing a new or replacement prosthesis. Such predictions can inform expectations of future mobility for patients and healthcare providers alike, with potential to support communication around care decisions and goal setting.[6] The approach demonstrates a key foundational step for research in estimating the trajectory of functional mobility after LLA and shows potential for providing high-quality information sourced from clinical data to support estimating outcomes and making clinical decisions, in an area that is currently under-informed by evidence.[1]

Limitations

To the best of our knowledge, this neighbors-based prediction approach is the first attempt to estimate the trajectory of PLUS-M T-scores after amputation. Therefore, there are no alternative approaches against which our results can be compared. Representation of some patient subgroups (e.g., partial foot amputation level, bilateral amputation, certain etiologies, and people early after amputation) was limited in the data set, and people with LLA who did not receive prosthetic care were underrepresented in the data. Predictions may therefore underestimate the possibility of extremely poor outcomes, and future work is needed to expand predictions in these subgroups. In addition, predictions were generated from an existing retrospective clinical data set using data from a subgroup known for generally poor outcomes. For example, walking activity is lower in people with LLA when compared with the average population without LLA, and overall strength, balance, and walking velocity are reduced after LLA.[40–42] Future research using prospective data collection and a comparison of patients with LLA to people without limb loss is warranted, which would improve predictions and allow for recovery monitoring and care planning according to optimal average population outcomes.

Although using time since amputation as a categorized matching characteristic would presumably distinguish people with and without experience using a prosthesis, the prediction model may not be ideal for people who are starting their first proshesis several years after their amputation. In addition, each PLUS-M T-score was evaluated as an independent observation, which could affect the generalizability of the predictions to other data sets. For example, the frequency and timing of PLUS-M data collection can be biased because of clinical practice patterns (such as appointment frequency, timing of administering the PLUS-M over the course of treatment, or within an appointment). To improve clinical application, future research would benefit from comparing the prediction model with predictions based on clinical experience, and prospective testing of the prediction model with new patients.

Finally, the prediction model was limited to the PLUS-M measure of self-reported mobility; future research would benefit from incorporating additional clinical measures (such as performance-based testing) into the prediction model.

Conclusion

Our findings demonstrate the ability to use a neighbors-based prediction approach to predict physical mobility after LLA using a patient's baseline self-reported physical mobility (PLUS-M T-score), age, sex, amputation level, and time since amputation. The predictions performed well when estimating observed PLUS-M T-scores at any point in time during the first 6 months after evaluation for a new or replacement prosthesis. The approach could inform goals and expectations of patients and healthcare providers for self-reported mobility prognosis at the individual level after LLA.

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Box 1.

Summary of the steps for generating a neighbors-based prediction by predictive mean matching

1. Develop a historical databank of relevant patient characteristics and systematically collected outcomes data (PLUS-M scores) for hundreds of patients.
2. Identify matches between historic patients and a new patient by predictive mean matching:
   a. Build a linear model to predict outcomes at a relevant postoperative time point.

      $$\text{(Estimated 90-day PLUS-M score)} = \beta_0 + \beta_1\text{(baseline PLUS-M score)} + \beta_2\text{(age)} + \beta_3\text{(sex)} + \beta_4\text{(level of amputation)} + \beta_5\text{(time since amputation)}$$

   b. For a new patient, obtain a predicted value through the linear model.
   c. Identify the m = 45 historical cases with similar predicted values. These are the matches for the new patient.
3. Use the actual observed recovery data from these matches to build a prognosis for the new patient, using the GAMLSS package (R statistical computing).

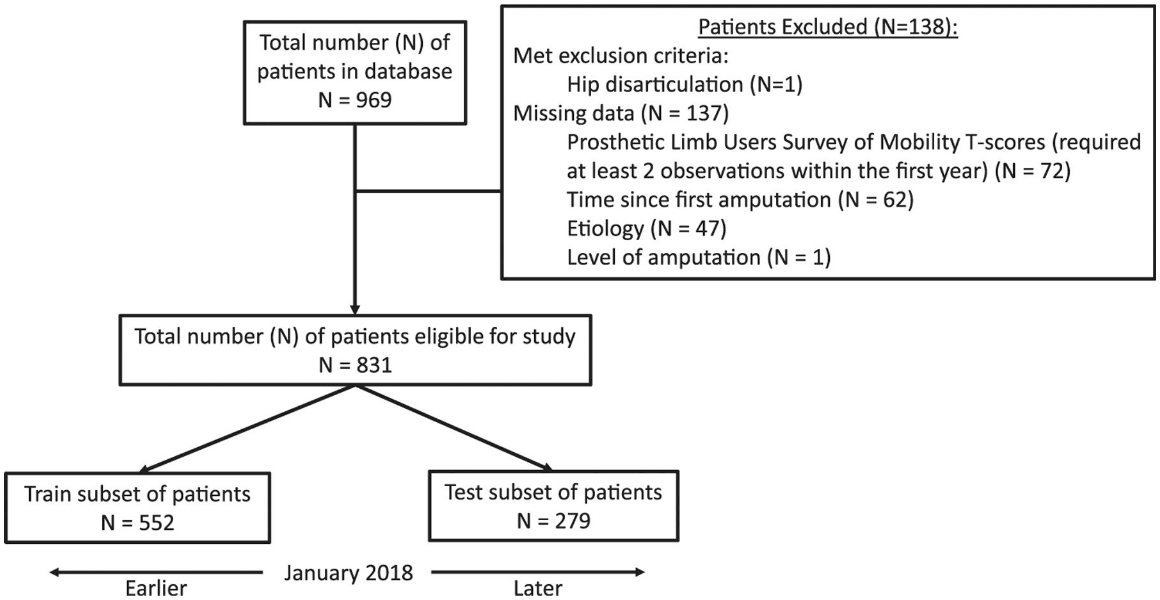

Figure 1.

Flowchart of inclusion/exclusion criteria

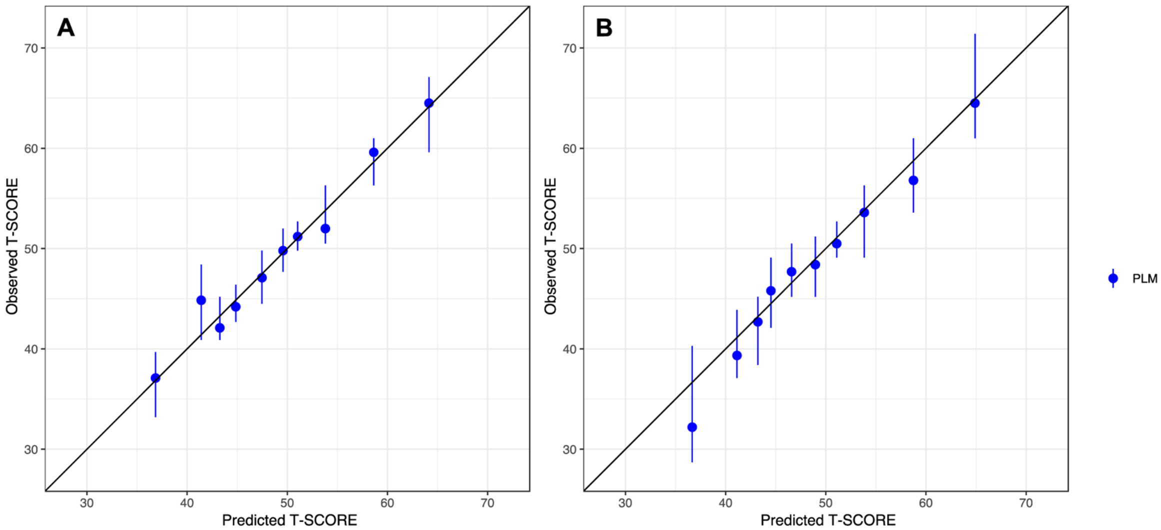

Figure 2.

Calibration plots for neighbors-based predictions in (A) training and (B) test data sets. Training and test data sets were divided into deciles according to the predicted PLUS-M T-scores. For each decile, the median observed PLUS-M T-score is plotted against the prediction median. Error bars indicate the standard error of the median. PLUS-M, Prosthetic Limb Users Survey of Mobility

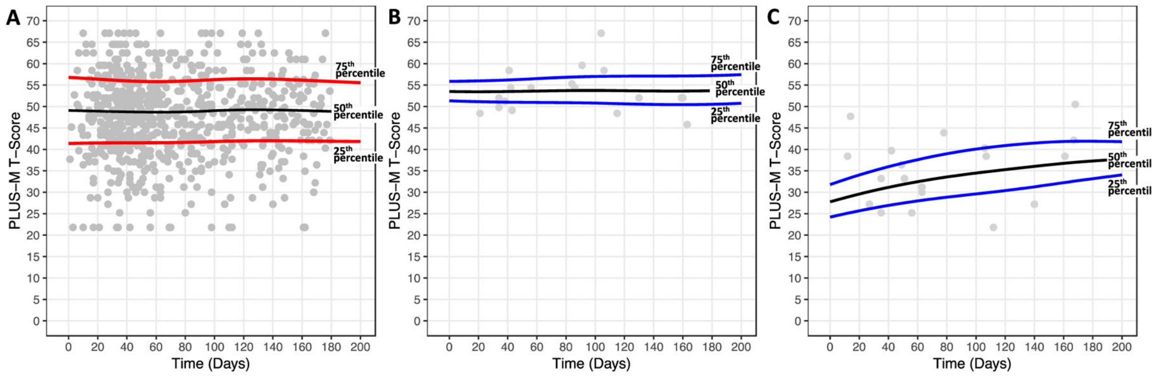

Figure 3.
The 50% prediction interval for the population-level estimate (A) is wider than the 50% prediction interval for the neighbors-based predictions; (B) a 40-year-old man, with below-knee amputation, 6 months after amputation, with a baseline PLUS-M T-score of 50 points; and (C) a 70-year-old woman, with above-knee amputation, 2 years after amputation, with a baseline PLUS-M T-score of 20 points. PLUS-M, Prosthetic Limb Users Survey of Mobility

Table 1.

Study demographics of training and test data sets

Date range	**Train (n = 552)**	**Test (n = 279)**
	April 2016 to January 2018	**January 2018 to March 2018**
	Median (interquartile range)	**Median (interquartile range)**
Age (years)	58.5 (49.4–66.2)	59.1 (48.9–66.6)
Adjusted BMI[a]	30.6 (27.8–33.9)	31.1 (28.0–33.9)
Baseline PLUS-M T-score (points)	40.0 (28.0–50.0)	40.0 (26.5.0–50.0)
Time between PLUS-M T-score data points (days)	103.5 (46–189)	51.0 (34–83)
	N (%)	**N (%)**
Sex, female	144 (26.1%)	83 (29.7%)
Level of amputation		
TTA and ankle disarticulation	403 (73.0%)	215 (77.1%)
TFA and KD	143 (25.9%)	62 (22.2%)
Partial foot	6 (1.1%)	2 (0.7%)
Bilateral amputation	50 (9.1%)	37 (13.3%)
Bilateral TFA	4 (0.7%)	1 (0.4%)
TFA and TTA	2 (0.4%)	5 (1.8%)
Bilateral KD		1 (0.4%)
Bilateral TTA	37 (6.7%)	24 (8.6%)
TTA and symes		1 (0.4%)
TTA and partial foot	7 (1.3%)	3 (1.1%)
Bilateral symes		1 (0.4%)
Symes and partial foot		1 (0.4%)
Etiology		
Vascular/diabetes	271 (49.1%)	134 (48.0%)
Injury/trauma	176 (31.9%)	84 (30.1%)
Other	42 (7.6%)	31 (11.1%)
Infection (no DM)	19 (3.4%)	9 (3.2%)

Date range	Train (n = 552)	Test (n = 279)
	April 2016 to January 2018	**January 2018 to March 2018**
	Median (interquartile range)	**Median (interquartile range)**
Cancer	22 (4.0%)	10 (3.6%)
Congenital	22 (4.0%)	11 (3.9%)
Time since amputation, y		
<1	73 (13.2%)	35 (12.5%)
1–5	209 (37.9%)	96 (34.4%)
>5	270 (48.9%)	148 (53.0%)

Abbreviations: BMI, body mass index; DM, diabetes mellitus; KD, knee disarticulation amputation; PLUS-M, Prosthetic Limb Users Survey of Mobility; TFA, transfemoral amputation; TTA, transtibial amputation.

[a]Adjusted BMI[19] = Weight after amputation/(Height^2 [1 – ΣΔWeight/Weight before amputation]).

Table 2.

Final regression analysis for matching characteristics associated with 90-Day PLUS-M T-score outcome

Characteristic	**Beta**	**SE**	***P***
Intercept	29.32	1.89	<.001
Age	−0.07	0.02	.02
Sex (male)	1.84	0.65	.002
Amputation level (relative to transtibial/symes)			
Transfemoral/knee disarticulation	−1.48	0.65	.023
Partial foot	5.53	2.68	.040
Time since amputation (relative to <1 y)			
1–5 y	−2.43	0.89	.006
>5 y	−0.34	0.88	.70
Baseline PLUS-M T-score	0.51	0.02	<.001

Abbreviations: PLUS-M, Prosthetic Limb Users Survey of Mobility; SE, standard error.