



Mobility Analysis of Amputees (MAAT 4): Classification tree analysis for probability of lower limb prosthesis user functional potential

Shane R. Wurdeman, Phillip M. Stevens & James H. Campbell

To cite this article: Shane R. Wurdeman, Phillip M. Stevens & James H. Campbell (2019): Mobility Analysis of Amputees (MAAT 4): Classification tree analysis for probability of lower limb prosthesis user functional potential, Disability and Rehabilitation: Assistive Technology

To link to this article: <https://doi.org/10.1080/17483107.2018.1555290>



© 2019 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group



Published online: 11 Feb 2019.



Submit your article to this journal [↗](#)



View Crossmark data [↗](#)

Mobility Analysis of Amputees (MAAT 4): Classification tree analysis for probability of lower limb prosthesis user functional potential

Shane R. Wurdeman^{a,b}, Phillip M. Stevens^{a,c} and James H. Campbell^a

^aDepartment of Clinical and Scientific Affairs, Hanger Clinic, Austin, TX, USA; ^bDepartment of Biomechanics, University of Nebraska at Omaha, Omaha, NE, USA; ^cSchool of Medicine, University of Utah, Salt Lake City, UT, USA

ABSTRACT

Purpose: To develop a predictive model to inform the probability of lower limb prosthesis users' functional potential for ambulation.

Materials and Methods: A retrospective analysis of a database of outcomes for 2770 lower limb prosthesis users was used to inform a classification and regression tree analysis. Gender, age, height, weight, body mass index adjusted for amputation, amputation level, cause of amputation, comorbid health status and functional mobility score [Prosthetic Limb Users Survey of Mobility (PLUS-MTM)] were entered as potential predictive variables. Patient K-Level was used to assign dependent variable status as unlimited community ambulator (i.e., K3 or K4) or limited community/household ambulator (i.e., K1 or K2). The classification tree was initially trained from 20% of the sample and subsequently tested with the remaining sample.

Results: A classification tree was successfully developed, able to accurately classify 87.4% of individuals within the model's training group (standard error 1.4%), and 81.6% within the model's testing group (standard error 0.82%). Age, PLUS-MTM T-score, cause of amputation and body weight were retained within the tree logic.

Conclusions: The resultant classification tree has the ability to provide members of the clinical care team with predictive probabilities of a patient's functional potential to help assist care decisions.

ARTICLE HISTORY

Received 10 July 2018
Accepted 29 November 2018

KEYWORDS

Mobility; outcomes;
K-level; ambulator

► IMPLICATIONS FOR REHABILITATION

- Classification and regression tree analysis is a simple analytical tool that can be used to provide simple predictive models for patients with a lower limb prosthesis.
- The resultant classification tree had an 81.6% (standard error 0.82%) accuracy predicting functional potential as an unlimited community ambulator (i.e., K3 or K4) or limited community/household ambulator (i.e., K1 or K2) in an unknown group of 2770 lower limb prosthesis users.
- The resultant classification tree can assist with the rehabilitation team's care planning providing probabilities of functional potential for the lower limb prosthesis user.



Introduction

Lower limb prosthetic rehabilitation within the United States currently relies on the Medicare Functional Classification Level system to provide reimbursement eligibility guidelines for prostheses [1]. Although the Medicare Functional Classification Level, or commonly referred to K-level classification, was originally introduced by the United States Health Care Financing Administration in 1995 to provide coverage guidelines for Medicare beneficiaries with lower limb amputation, it has since been widely adopted by private payers [2,3]. Subsequently, a patient's K-level assignment often has a large impact on the patient's prosthesis prescription [2,4,5], with some commentary going so far as to note "K-level designation is important because it is the driving factor in the decision on what prosthetic device to provide" [6].

The K-levels consist of five classifications of ambulatory function for individuals with a lower limb amputation with a primary

division occurring between K2 and K3. Patients that are K3 and above are classified as unlimited community ambulators with a plan of care that aligns with a more active individual. In order to meet the demands of the unlimited community ambulator, these patients have increased access to advanced technologies such as hydraulic/pneumatic knee joints, microprocessor controlled components, and feet with higher elastic energy return due to materials such as carbon fibre [1,2,6].

Within the United States, the overseeing physician determines the status or potential for a patient to be an unlimited community ambulator or a limited community ambulator. The K-level is a determination from the prescribing physician utilizing their clinical judgment. As part of that clinical judgment, the prescribing physician often depends on members of the rehabilitation team such as therapists and prosthetists for increased clinical insight [5]. In working through the determination process, clinicians may use various factors such as age, cause and level of amputation, body

CONTACT Shane R. Wurdeman  swurdeman@hanger.com  Department of Clinical and Scientific Affairs, Hanger Clinic, 10910 Domain Dr., Ste. 300, Austin, TX 78758, USA

© 2019 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group

This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives License (<http://creativecommons.org/licenses/by-nc-nd/4.0/>), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited, and is not altered, transformed, or built upon in any way.

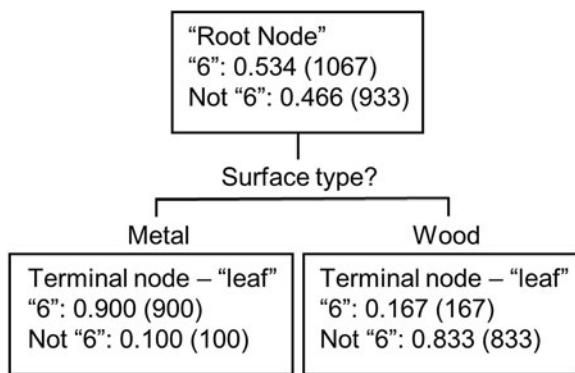


Figure 1. Example classification tree providing probability of rolling a “6” with a magnetic “funny die” based on 2000 rolls. Without any further information, the probability of rolling a “6” is 53.4% which was the result of 1067/2000 rolls showing a “6”. Since the “funny die” is magnetic, in the fictional example rolling on either a metal or wood surface then alters the occurrences of a “6” appearing such that knowledge of surface type dramatically improves probability of expecting either a “6” or not to appear. Similarly, a classification tree can be used to guide clinical decision making by providing probabilities based on patient characteristics.

mass index and comorbid health as well as assessment and outcome instruments such as the Amputee Mobility Predictor [2,3,5,7]. With respect to K-levels, there is limited evidence to match such factors with care planning [2,3]. Increased guidance could better assist the design of care plans based on the expectations that a given individual will realize unlimited community ambulation or limited community/household ambulation.

In other arenas of healthcare, improved clinical decision-making processes are becoming possible through the use of “big” data. The increase in computing power and statistical insights has provided the ability to synthesize “big” data into complex predictive models to inform evidence-based decision trees. Despite increased utility and growing use of decision trees across healthcare, such predictive models have not been implemented within prosthetic rehabilitation. This is likely due to the inherent need for large datasets and the limited availability of such data within prosthetic care. The lack of implementation of such predictive models in prosthetic rehabilitation hinders evidence-based decision making. Without studies developing and testing predictive models, it is unclear if such decision trees could effectively determine proper care pathways more effectively than random decision selection.

Thus, the purpose of this study was to develop a classification-based decision tree for patients with a lower limb prosthesis as a means to examine the applicability for future applications of predictive decision trees in the field of prosthetic rehabilitation. The specific goal was the development of a model that effectively informs the care pathway by providing the probability of a patient being a limited community or household ambulator (i.e., K2 or below within the K-level classification) or an unlimited community ambulator (i.e., K3 or above), henceforth labelled as the patient’s functional potential. It was hypothesized that the ending nodes within the decision tree would provide probabilities for functional potential determination greater than random determination.

Methods

Study design

We performed an analysis based on review of a database containing patient information and outcomes from April 2016 through

March 2018. Outcomes and patient information within the database were collected from multiple clinics across the United States spanning regions including Northwest, Southwest, Rocky Mountains, Midwest, Southeast, Northeast and East. Cases were excluded from the model if there were any missing predictor variables.

This database review was approved and deemed exempt from patient consent by Western Investigational Review Board (Protocol #20170059).

Classification and regression tree analysis

While traditional predictive models such as logistic and linear regression are feasible, these models can have issues with their implementation and ultimately interpretation by healthcare providers with perceived “black box” results [8,9]. Classification and regression tree analysis (CART) is a technique that is gaining popularity within healthcare due to its ease of interpretation and implementation [8,10–15]. Common examples can be noted for guidelines on paediatric head trauma [16–18] and paediatric abdominal injuries [19–21]. Specifically, CART analysis starts with a large group of individuals, and then makes a series of binary node splits based on some criterion that improves group purity in order to effectively classify individuals. The end result is an easily interpretable logic tree with a series of splits (i.e., branches) leading to end nodes (i.e., leaves) represented in an illustrated figure format. Each branch, and in turn, each leaf, yields a classification probability which ultimately drives the end decision. Due to the sequential binary splitting process, in order to allow for multiple branches and leaves, the initial starting sample must be substantial enough to allow multiple splits.

In order to illustrate CART analysis, consider a classic probability example. A six-sided die holds the probability of 1/6, or 16.67%, of rolling a “6”. If one were to roll the die 100 times, a “6” would likely come up 16 times (16%), but might only come up 11 times, or 11%, due to some associated error. This error would decrease with increased sampling. If, however, one was to roll the die enough times and continue to note that a “6” appears 90% of the time, then it would be possible to conclude that it is a trick die causing the probability of a “6” to be much higher. Consider though if the characteristic that made it a trick die was an embedded magnet causing a magnetic force that flipped the die to a “6”. If the person were to roll the die 1000 times on a wood board and 1000 times on a metal surface, a “6” would then appear 1067 times (167 plus 900 on wood and metal surfaces respectfully). Looking at the output, the conclusion would be a probability of 0.5335 for a “6” to appear. Thus, the individual would be left to believe the chances of rolling a “6” is practically equivalent to a coin toss. But, if more information on the magnetic die was provided, very quickly the probability of a “6” can be adjusted by assessing the surface on which the die will be rolled.

This is a basic example of a narrative classification tree where the dependent variable was rolling a “6” or not. This can be illustrated in a CART classification tree (Figure 1). Note the top grouping consists of all outcomes of the 2000 rolls (i.e., group members). The top grouping, or node, is labelled as the root node, representing the start of the classification tree. The root node subsequently undergoes a split based on information that provides greater clarity, or purity within the subsequent nodes. In the example, the criterion is surface type on which the magnetic die is rolled. There are no further characteristics that can improve the purity of the sample and thereby improve the probabilities,

and thus the classification tree is complete with two terminal nodes, or leaves. Had additional characteristics been identified, it may have been possible to further split the second layer nodes. In that case, the nodes that split would be labelled as branches and the third layer nodes would become the leaves.

It is possible that there may have been other characteristics or factors that were also recorded that would not provide any improved predictive ability, such as which hand was used to roll the die or eyes open/closed when rolling the die. A CART analysis should assess all recorded factors at each node to identify those that best improve dependent variable prediction. Since the analysis is reperformed on the groups at each node, each node becomes increasingly pure. This instills CART with an additional benefit over traditional regression analysis by reducing error and being able to explain higher variance at each node [8,22].

Importantly, during the CART analysis at each node, the model must determine whether a factor is important through the use of some sort of purity criterion. While there are several methods, the most common for classification trees is the Gini impurity index [8,11,12,16,19,22]. The Gini impurity index determines the optimal means for splitting the members of a node by maximizing the decrease in impurity. Splitting the membership into two groups makes it possible to then look at the “purity” on each side of the split. In our example with the die, choosing the factor of surface on which the die is rolled resulted in a split of 1000 and 1000 rolls. On the metal surface, the “purity” is:

$$P_M = \sum_i^C \frac{x_i}{C} \left(1 - \frac{x_i}{C}\right) = \frac{900}{1000} \left(1 - \frac{900}{1000}\right) + \frac{100}{1000} \left(1 - \frac{100}{1000}\right) = 0.18 \quad (1)$$

and the wood surface is:

$$P_W = \sum_i^C \frac{x_i}{C} \left(1 - \frac{x_i}{C}\right) = \frac{167}{1000} \left(1 - \frac{167}{1000}\right) + \frac{833}{1000} \left(1 - \frac{833}{1000}\right) = 0.28 \quad (2)$$

The average then is 0.23. If the same calculation were applied to another factor such as rolling the die with right or left hand, now the Gini purity calculations are (assuming there was no impact and this factor yielded a 0.5 probability):

$$P_{\text{Right}} = \sum_i^C \frac{x_i}{C} \left(1 - \frac{x_i}{C}\right) = \frac{500}{1000} \left(1 - \frac{500}{1000}\right) + \frac{500}{1000} \left(1 - \frac{500}{1000}\right) = 0.5 \quad (3)$$

$$P_{\text{Left}} = \sum_i^C \frac{x_i}{C} \left(1 - \frac{x_i}{C}\right) = \frac{500}{1000} \left(1 - \frac{500}{1000}\right) + \frac{500}{1000} \left(1 - \frac{500}{1000}\right) = 0.5 \quad (4)$$

The average for this factor is 0.5, which is a higher impurity. Thus, the factor for surface type would be a better choice to maximize the decrease in impurity. If the independent factors were continuous or interval rather than dichotomous variables, the same process is implemented but more “cut points” are tested going through the entire scale.

Importantly, it is possible to split members of nodes continuously until there is only a single member within each terminal node. This, however, comes with the trade-off of increased classification error when implementing the model to predict classification on an unknown sample. As a result, limits must be put on the minimum number of members in a node before it can be allowed to split into subsequent nodes, and minimum number of members allowed in a leaf should also be set.

Lastly, a classification tree should be tested for repeatability. This process is done by partitioning the dataset into multiple datasets so that a large dataset can be used to “train” the classification tree, or build the model, and smaller datasets can be used to test the accuracy of predicting the correct classification of an unknown group. For the die example, perhaps the 2000 rolls used to develop the classification tree were part of a larger set of 5000 rolls. Then one might take three additional datasets of 1000 rolls to confirm classification accuracy for the model. Based on the results, factors such as node limits can be adjusted to yield the highest classification accuracy for the targeted category. Importantly, the improved classification accuracy of one category will sacrifice the accuracy of the other category so it is critical that the analysis yield to clinical oversight.

Predictor variables

Variables included within the CART analysis model for individuals with lower limb amputation included gender, height, weight, cause of amputation, history of smoking, body mass index (adjusted for limb loss [23,24]), comorbid health status and age. Additionally, three variables from patient-reported outcome measures were included, the satisfaction and quality of life measures from the Prosthesis Evaluation Questionnaire Well-Being subsection [25,26] and the Prosthetic Limb Users Survey of Mobility T-Score (PLUS-MTM) [27–29]. For comorbid health, the Functional Comorbidity Index [30] was entered as an interval variable. Level of amputation was entered as a categorical variable separating into primary levels of amputation between hip disarticulation and partial foot amputation. Bilateral amputations were grouped and coded as a single group.

The demographic variables are reviewed with patients as routine standard of care. The PLUS-MTM is a patient-reported outcomes questionnaire, administered via the 12 question format [31]. The PLUS-MTM is a validated, reliable instrument for assessing functional mobility in individuals with a lower limb prosthesis [28]. As it is not valid for those who have not received a prosthesis, individuals that had assessments for their initial prosthesis were thus excluded. The Prosthesis Evaluation Questionnaire is also a patient-reported outcomes questionnaire [25]. In its entirety, it is an exhaustive review of multiple constructs with regards to the use of an external prosthesis with each of its multiple subsections also valid for administering separately. For the purposes of the participating clinics, only the Well-Being subsection is administered, comprising of questions that ask individuals to report their health satisfaction and quality of life. Although originally administered as a continuous visual analogue scale, it has since been administered in the form of a discrete interval scale such as is currently the case utilizing a 1–10 response scale to improve clinical feasibility [26,32].

Data reduction and analysis

Data was examined prior to analysis to remove multiple entries using only the most recent records and to eliminate records

Table 1. Subject demographics according to group.

| | Training Group (n = 554) | Testing Group (n = 2216) |
|--------------------------------------|--------------------------|--------------------------|
| Gender | 149 F | 576 F |
| Age (years) | 57.0 (14.7) | 57.2 (14.5) |
| Height (cm) | 174.4 (11.4) | 174.6 (11.2) |
| Mass (kg) | 89.2 (23.5) | 89.9 (23.1) |
| Body Mass Index (kg/m ²) | 31.5 (7.1) | 31.7 (7.2) |
| Amputation Level | | |
| Below-knee | 355 | 1454 |
| Above-knee | 144 | 512 |
| Bilateral | 55 | 250 |
| Cause of Amputation | | |
| PVD/ diabetes | 228 | 1098 |
| Trauma | 174 | 616 |
| Infection (without diabetes) | 59 | 186 |
| Cancer/Tumour | 26 | 90 |
| Congenital | 25 | 66 |
| Other | 42 | 160 |
| Functional Comorbidity Index | 2.51 (2.16) | 2.33 (1.96) |
| PLUS-M TM T-Score | 47.1 (12.2) | 46.9 (11.7) |
| Unlimited Community Ambulators | 431 | 1756 |

Mean (SD). PVD: peripheral vascular disease; PLUS-MTM: Prosthetic Limb Users Survey of MobilityTM.

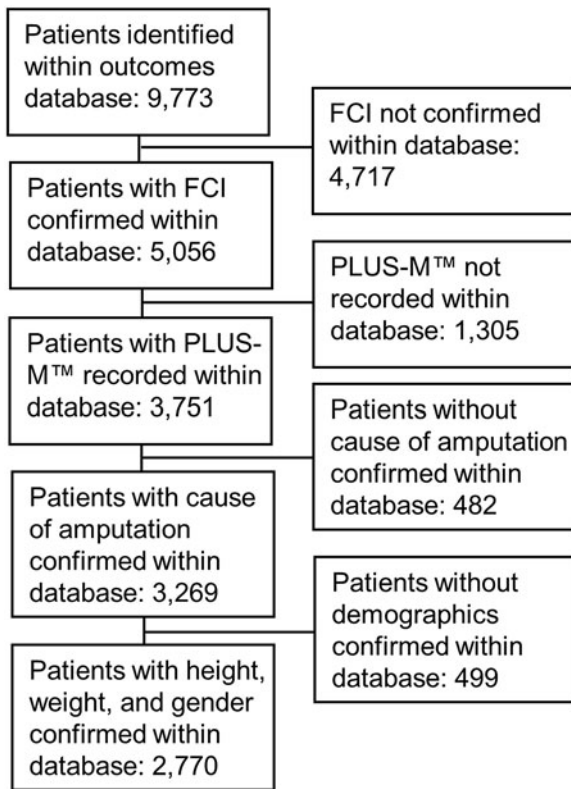


Figure 2. Eligibility flow chart, from 9773 outcomes entries, 2770 met inclusion criteria and were utilized for building and testing the classification and regression tree analysis model. FCI: Functional Comorbidity Index; PLUS-MTM: Prosthetic Limb Users Survey of MobilityTM.

where data had not been completed yet. Categorical variables were coded. Cause of amputation was reduced to diabetes/vascular disease, trauma, infection without diabetes, cancer, congenital and other. The dependent variable of functional potential was coded based on the patient's assigned K-level, with K1 and K2 categorized as limited community/household ambulators, and K3 and K4 individuals categorized as unlimited community ambulators. The decision was made to design a model to inform these broad classifications (rather than K-levels) for three reasons: 1) such a model will have more universal application extending beyond the United States payer system, 2) CART methodology

lends itself better to binary dependent variables and 3) such a model is better suited to inform rehabilitation potential rather than payer classification but can simultaneously serve to assist with K-level determination.

A CART analysis was implemented through the Matlab[®] function 'fitctree' with modifications to allow optimization of the tree. Gini impurity is the most commonly used method for node splitting in CART analysis and was used for the current analysis [22]. A robust sample size of 20% of the dataset was utilized to train the model. The remaining dataset was used to test the model. Testing the model allows for risk assessment (or misclassification analysis) and standard error assessment of the model. The branch and leaf size were run through an optimization procedure that yielded greatest mean classification of patients with lowest associated testing accuracy for those that were limited community/household ambulators. The decision was made to optimize for limited community/household ambulators *a priori* due to noted imbalance of subjects classified as limited community/household ambulators which made it more difficult to accurately classify such individuals.

Statistical analysis

To test the hypothesis and examine the ability of each node within the model to inform the functional potential determination of a patient beyond random selection, each branch and leaf node was subsequently tested utilizing a one-sided non-parametric rank order test. Essentially, each node of the classification tree provided an associated probability for the classifications of functional potential. Using the premise that any significant classification should provide a better probability than random selection, for each of the test cases, 19 random assignments of functional potential were generated through Matlab[®] random number generator. This yielded 20 total assignments (19 random plus the CART results). The subsequent classification error was determined for these 19 random assignments and compared to the classification error from the assigned node within the CART analysis. The rank order of the classification error associated with each node was then used to determine significance at $p \leq 0.05$, noting that a ranking of 1 or 20 is consistent with the top or bottom 5% [33].

Results

The initial data extraction returned 9773 cases, which yielded 2770 cases with full data sets to be included (Table 1; flowchart Figure 2).

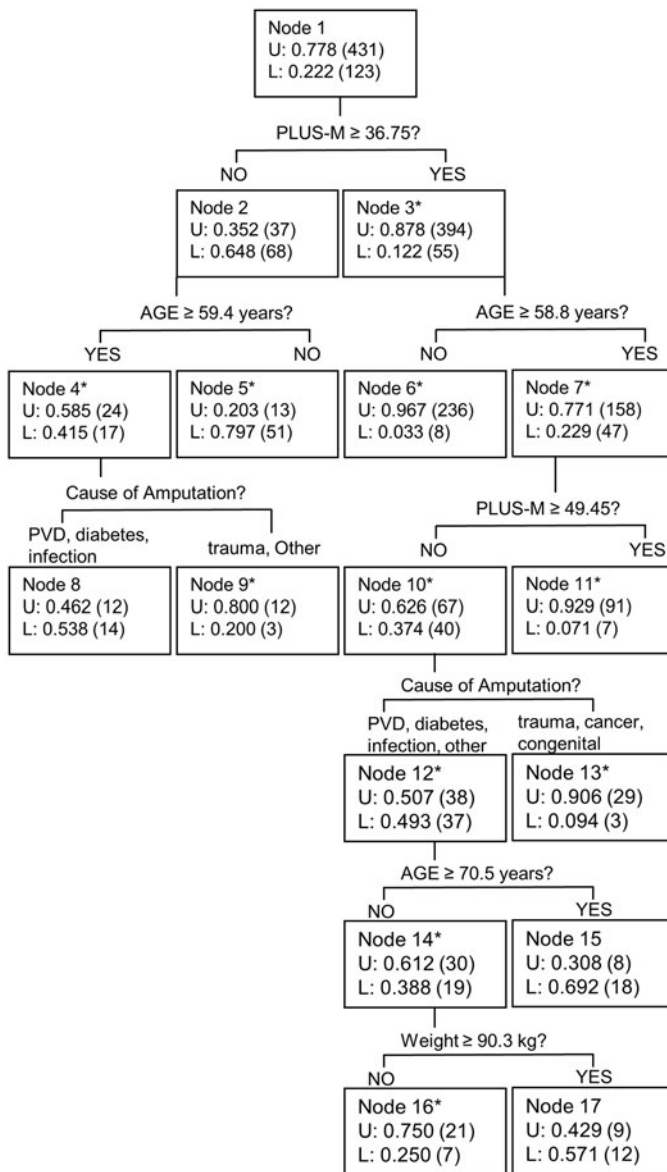


Figure 3. Classification tree developed and tested based on data from 2770 patients. The overall correct classification rate was 87.4%, with a risk of 12.6% and standard error 1.4% when training the model. Correct classification for limited community/household ambulators was 77.2% and 90.3% for unlimited community ambulators. Each node displays class probability and membership in parentheses for training sample. U: unlimited community ambulator, in Medicare Functional Classification System would be K3 or K4; L: limited community/household ambulator, in Medicare Functional Classification System would be K2 or K1. *node classification significantly different than random assignment process, clinicians should obtain more information for patients *not* ending in these nodes when making functional potential determination.

This resulted in a training sample size of 554 patients, and test sample size of 2216. The low return of full data sets was not unexpected given the inclusion criteria for complete data and certain factors (e.g., comorbid health) are only reviewed at evaluation type appointments and not necessarily at follow-ups or adjustments.

Classification tree

The classification tree ultimately ended with 7 branches and 9 leaves (Figure 3). Among the 16 branch and leaf nodes, 12 tested significant compared to the random class assignment (Figure 3). The four non-significant nodes included three terminal leaves, all

Table 2. Classification table for training and testing groups.

| Group | Observed | Predicted | | Percent correct |
|----------|--------------------|-----------|-------|-----------------|
| | | L | U | |
| Training | L | 95 | 28 | 77.2% |
| | U | 42 | 389 | 90.3% |
| | Overall Percentage | 24.7% | 75.3% | 87.4% |
| Testing | L | 316 | 144 | 68.7% |
| | U | 263 | 2493 | 85.0% |
| | Overall Percentage | 26.1% | 73.9% | 81.6% |

L: limited community/household ambulator; U: unlimited community ambulator.

of which however had branch nodes that were significant at $p \leq 0.05$.

The optimal size for each leaf and branch was 13 and 30. The PLUS-M™ T-Score, age, cause of amputation and weight were ultimately included as decision factors within the classification tree. Overall correct classification of the tree for the original training sample was 87.4%, with a risk of 12.6% and standard error 1.4% (Table 2). Among the training sample, the correct classification for limited community/household ambulators was 77.2% and 90.3% for unlimited community ambulators. For the testing samples, the overall correct classification was 81.6% (risk 18.4%, standard error 0.82%). Among the training sample, the correct classification for limited community/household ambulators for the testing samples was 68.7% and 85.0% for unlimited community ambulators (Table 2).

Discussion

The goal of this study was to effectively develop a classification tree that could provide probabilities associated with identifying individuals with a lower limb prosthesis as either limited community/household ambulators or unlimited community ambulators to help inform prosthetic rehabilitation plans of care. The goal was successfully accomplished, developing a classification tree that was able to correctly classify 87.4% of individuals in the training sample and then 81.6% of the subsequent testing samples. It was hypothesized that the nodes within the classification tree would inform the functional potential determination with greater probability than random selection. This hypothesis was largely supported with 12 out of 16 nodes ultimately providing the ability to determine appropriate functional potential beyond random selection.

Model strengths

The use of a CART analysis and subsequent production of a classification tree for the care of individuals with lower limb prostheses is unique. There is growing popularity and use of classification trees across healthcare (e.g., see references [8,10–15]). The classification tree developed in this analysis provides probability for determining a patient’s functional potential. In the United States payer system, this has the benefit of assisting with determination of a patient as either K2 or below (i.e., limited community/household ambulator), or K3 and above (unlimited community ambulator). For example, if a clinician has a patient who reports a PLUS-M™ T-Score of 49.5, and is aged 75, and amputation due to diabetes, the patient has a 92.9% probability of being an unlimited community ambulator (Figure 3, Node 13). Additionally, the clinician can put together a plan of care to maintain the patient’s mobility level knowing that if the patient’s mobility drops down below 49.5 the probability of being an unlimited community

ambulator drops as well, thus informing proactive physical therapy or prosthetic componentry that can drive improved mobility.

Model weaknesses

As with any model, the strength of the model is predicated on the data used to inform the model. In this case, while the training sample size was adequate, far exceeding those used in many predictive models, the model's accuracy could likely be improved with a richer and more diverse dataset. Specifically, the model did not include any physical performance measures despite the use of these in some clinical practices to help inform functional potential [2,3,5,7]. The Amputee Mobility Predictor, in particular, is a physical performance measure that was designed to inform functional potential and would thus be expected to improve the model's accuracy and predictive ability, and indeed has been to an extent tried to be utilized within predictive modelling [2,3]. Similar to our results, Dillon et al. were able to predict K2 and K3 functional potential at approximately 80% accuracy. However, the clinical implementation of physical performance measures is more challenging with time and space constraints and subsequently, the current study's classification tree arguably has greater clinical utility. In light of Dillon et al.'s findings, it would seem the addition of physical performance measures in conjunction with patient report outcomes for future predictive models warrants further investigation.

In clinical applications, it is also important to understand the importance of non-significant nodes. In particular, if a patient falls on a non-significant node (i.e., nodes 8, 15 or 17), then it would serve prudent to gather more information in support of functional potential determination such as perhaps an Amputee Mobility Predictor. Additionally, it is always important to recognize decision trees as population-based guidance and there may be specific cases that physicians and other healthcare providers feel do not align with the decision tree and in such instances, further information should be collected to support reasoning individual should be considered an exception.

Study limitations

A limitation of the study is that the model was built retrospectively which resulted in limited ability to implement specific measures for the purpose of building the classification model. A retrospective approach is also limiting as it prevents inputting data such as the Amputee Mobility Predictor. This is due to the fact that the Amputee Mobility Predictor provides functional potential decision guidance thus creating bias if the same individual administers the test and makes functional potential determination. The PLUS-M™ is a new instrument that has not been implemented or advertised for guidance of functional potential which allows it to be applied within this study in the retrospective manner.

Additionally, it should be noted that the results from CART analysis do not imply factors that impact a patient's mobility or functional potential. Specifically, the results are descriptors that carried the most information within the analysis towards classification. However, there are factors that impact a patient's functional potential more directly on the principle of a cause and effect. The simplest example would be a patient's desire to ambulate. The probability of a patient achieving unlimited community ambulator status if the patient does not wish to leave their home is probably 100%. It is also important to recognize that some variables may have never reached significance to be used as a splitting criterion

due to lack of representation within the population, or inability to provide the highest level of information at any single node. In other words, consider Functional Comorbidity Index where it has been reported that individuals with increased Functional Comorbidity Index had reduced mobility [34], yet this failed to be a factor within the current model. Functional Comorbidity Index may have just provided the second most information and thus was not utilized within the current decision tree.

Clinical application

Despite the limitations and weaknesses, the classification tree represents a start to working towards better informed decision making for the care team. There will be certain patient demographics that will require further information and justification to help guide functional potential decision making. For example, if a patient scores a 50.0 on the PLUS-M, is age 70, weighs 100 kg, and cause of amputation is diabetes, then the care team is aware that the patient's probability of being an unlimited community ambulator is 92.9% (Figure 3, node 11). Furthermore, the team can plan ahead knowing that if the patient's mobility on the PLUS-M drops, the patient's probability of being an unlimited community ambulator drops to possibly less than 50% (Figure 3, node 17). Additionally, as the patient ages, the probability would further decline (Figure 3, node 15). In both cases, the team would want to do further assessments to fully inform the functional potential. Although the classification tree provides a probability of 57.1% that the person will be a limited community/household ambulator (Figure 3, node 17), without significance from a random assignment, it should not be considered enough to make a clinical decision and further information and testing is warranted. Intuitively, a probability of 57.1% is not much better than a coin toss, indicating that the factors used in this analysis are not enough to inform functional potential for this individual. However, despite that, knowing how probabilities change with dynamic factors such as age, mobility and weight, the care team is now able to better plan necessary steps to provide optimal care as these factors change.

Conclusion

Decision trees are commonly used in data mining to create a model that predicts the value of a target (or dependent variable) based on the values of several inputs (or independent variables). The current study had the intention of developing a classification-based decision tree through CART analysis, to present the basic characteristics of decision trees and to examine the applicability and possible future applications in the field of prosthetic rehabilitation.

A large lower limb prosthetic users database ($n = 9773$) containing patient information and outcomes was utilized to inform the classification tree with the goal of providing the probability of a patient's status as an unlimited community ambulator (i.e., K3 or K4) or a limited community/household ambulator (i.e., K1 or K2). It was hypothesized that the decision tree could inform the functional potential determination beyond random selection. Results overall supported the hypothesis with 12/16 decision nodes resulting in significance. Ultimately, the classification tree was able to accurately classify 87.4% of individuals within the model's training group (standard error 1.4%), and 81.6% within the model's testing group (standard error 0.82%). The resultant classification tree should be viewed as effectively having the ability to provide members of the clinical care team with probabilities

of a patient's functional potential and subsequent ability to help guide care decisions.

Disclosure statement

The authors report no conflicts of interest.

Funding

Support for this work was partially provided by a Small Grant Award [EB-043016] from the American Orthotics and Prosthetics Association.

References

- [1] LCD: Lower Limb Prostheses [Internet]: Noridian Medicare; c2013 [cited 2013 Aug 9; accessed 2015 Jul 15]. Available from: https://www.noridianmedicare.com/dme/coverage/docs/lcds/current_lcds/lower_limb_prostheses.htm
- [2] Dillon MP, Major MJ, Kaluf B, et al. Predict the medicare functional classification level (K-level) using the amputee mobility predictor in people with unilateral transfemoral and transtibial amputation: A pilot study. *Prosthet Orthot Int*. 2018;42:191–197.
- [3] Gailey RS, Roach KE, Applegate EB, et al. The amputee mobility predictor: an instrument to assess determinants of the lower-limb amputee's ability to ambulate. *Arch Phys Med Rehabil*. 2002;83:613–627.
- [4] Hafner BJ, Smith DG. Differences in function and safety between Medicare functional classification level-2 and -3 transfemoral amputees and influence of prosthetic knee joint control. *J Rehabil Res Dev* 2009;46: 417–433.
- [5] Borrenpohl D, Kaluf B, Major MJ. Survey of U.S. practitioners on the validity of the Medicare Functional Classification Level system and utility of clinical outcome measures for aiding K-level assignment. *Arch Phys Med Rehabil*. 2016;97:1053–1063.
- [6] Amputee Coalition of America. Do you know your K-level? *In Motion* 2013;23(5):24–27.
- [7] Sansam K, Neumann V, O'Connor R, et al. Predicting walking ability following lower limb amputation: a systematic review of the literature. *J Rehabil Med*. 2009;41: 593–603.
- [8] Henrard S, Speybroeck N, Hermans C. Classification and regression tree analysis vs. multivariable linear and logistic regression methods as statistical tools for studying haemophilia. *Haemophilia*. 2015;21:715–722.
- [9] Harrell FE, Jr, Lee KL, Mark DB. Multivariable prognostic models: issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. *Statist Med*. 1996;15:361–387.
- [10] Crowe M, O'Sullivan M, Cassetti O, et al. Weight status and dental problems in early childhood: classification tree analysis of a national cohort. *Dent J (Basel)*. 2017; 5(3):25.
- [11] Phakhounthong K, Chaovalit P, Jittamala P, et al. Predicting the severity of dengue fever in children on admission based on clinical features and laboratory indicators: application of classification tree analysis. *BMC Pediatr*. 2018;18: 109.
- [12] Wang Y, Liu Z, Chen S, et al. Identifying at-risk subgroups for acute postsurgical pain: a classification tree analysis. *Pain Med*. 2018;19(11):2283–2295.
- [13] Linden A, Yarnold PR. Estimating causal effects for survival (time-to-event) outcomes by combining classification tree analysis and propensity score weighting. *J Eval Clin Pract*. 2018;24:380–387.
- [14] Linden A, Yarnold PR. Identifying causal mechanisms in health care interventions using classification tree analysis. *J Eval Clin Pract*. 2018;24:353–361.
- [15] Facchinello Y, Richard-Denis A, Beausejour M, et al. The use of classification tree analysis to assess the influence of surgical timing on neurological recovery following severe cervical traumatic spinal cord injury. *Spinal Cord*. 2018 ;56: 687–694.
- [16] Kuppermann N, Holmes JF, Dayan PS, et al.; Pediatric Emergency Care Applied Research Network (PECARN). Identification of children at very low risk of clinically-important brain injuries after head trauma: a prospective cohort study. *Lancet*. 2009;374:1160–1170.
- [17] Kuppermann N, Holmes JF, Dayan PS. Head injury decision rules in children. *Lancet*. 2017;390:1487–1488.
- [18] Nishijima DK, Yang Z, Urbich M, et al. Cost-effectiveness of the PECARN rules in children with minor head trauma. *Ann Emerg Med*. 2015;65:72–80.e6.
- [19] Holmes JF, Lillis K, Monroe D, et al; Pediatric Emergency Care Applied Research Network (PECARN). Identifying children at very low risk of clinically important blunt abdominal injuries. *Ann Emerg Med*. 2013;62: 107–116.e2.
- [20] Halaweish I, Riebe-Rodgers J, Randall A, et al. Compliance with evidence-based guidelines for computed tomography of children with head and abdominal trauma. *J Pediatr Surg*. 2018;53:748–751.
- [21] Nishijima DK, Yang Z, Clark JA, et al. A cost-effectiveness analysis comparing a clinical decision rule versus usual care to risk stratify children for intraabdominal injury after blunt torso trauma. *Acad Emerg Med*. 2013;20:1131–1138.
- [22] Breiman L, Friedman J, Olshen R, et al. Classification and regression trees. New York (NY): Chapman and Hall; 1994.
- [23] Tzamaloukas AH, Patron A, Malhotra D. Body mass index in amputees. *JPEN J Parenter Enteral Nutr*. 1994;18: 355–358.
- [24] Tzamaloukas AH, Leger A, Hill J, et al. Body mass index in patients with amputations on peritoneal dialysis: error of uncorrected estimates and proposed correction. *Adv Perit Dial*. 2000;16:138–142.
- [25] Legro MW, Reiber GD, Smith DG, et al. Prosthesis evaluation questionnaire for persons with lower limb amputations: assessing prosthesis-related quality of life. *Arch Phys Med Rehabil*. 1998;79:931–938.
- [26] Wurdeman SR, Stevens PM, Campbell JH. Mobility analysis of AmpuTees (MAAT I): quality of life and satisfaction are strongly related to mobility for patients with a lower limb prosthesis. *Prosthet Orthot Int*. 2018;42:498–503.
- [27] Hafner BJ, Morgan SJ, Abrahamson DC, et al. Characterizing mobility from the prosthetic limb user's perspective: use of focus groups to guide development of the prosthetic limb users survey of mobility. *Prosthet Orthot Int*. 2016;40: 582–590.
- [28] Hafner BJ, Gaunaud IA, Morgan SJ, et al. Construct validity of the Prosthetic Limb Users Survey of Mobility (PLUS-M) in

- adults with lower limb amputation. *Arch Phys Med Rehabil.* 2017;98:277–285.
- [29] Hafner BJ, Morgan SJ, Askew RL, et al. Psychometric evaluation of self-report outcome measures for prosthetic applications. *J Rehabil Res Dev.* 2016;53:797–812.
- [30] Groll D, To T, Bombardier C, et al. The development of a comorbidity index with physical function as the outcome. *J Clin Epidemiol.* 2005;58:595–602.
- [31] Prosthetic Limb User Survey [Internet]; c2013 [cited 2016 Dec]. Available from: www.plus-m.org
- [32] Franchignoni F, Giordano A, Ferriero G, et al. Measuring mobility in people with lower limb amputation: Rasch analysis of the mobility section of the Prosthesis Evaluation Questionnaire. *Acta Derm Venereol.* 2007;39:138–144.
- [33] Wurdeman SR, Myers SA, Stergiou N. Amputation effects on the underlying complexity within transtibial amputee ankle motion. *Chaos.* 2014;24:013140.
- [34] Wurdeman SR, Stevens PM, Campbell JH. Mobility analysis of Amputees II: comorbidities and mobility in lower limb prosthesis users. *Am J Phys Med Rehabil.* 2018;97:782–788.