

# Advanced Prosthetic Limb Engineering

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## ABSTRACT

*Advanced prosthetic limbs now integrate multi-articulated mechanical hands, myoelectric pattern recognition, sensory feedback interfaces, and osseointegrated skeletal attachments, yet the gap between laboratory capability and daily-use functionality remains substantial for most amputees. We evaluated 220 advanced prosthetic limb engineering programmes across clinical and research centres in Spain and Sweden between 2014 and 2024, spanning five technology categories: myoelectric pattern-recognition upper-limb prostheses, powered lower-limb prostheses with microprocessor knees, osseointegrated direct skeletal attachment systems, sensory feedback and neural interface prostheses, and soft robotic and compliant prosthetic hands. A Prosthetic Limb Engineering Translational Index (PLETI) was constructed from five sub-scores -- functional task performance, user acceptance and daily wear time, control intuitiveness, mechanical reliability, and clinical evidence depth -- with weights from regression against sustained prescription beyond 12 months. PLETI correlated with sustained prescription at  $r = +0.83$  and discriminated prescribed from abandoned prostheses with an AUC of 0.880. Microprocessor lower-limb prostheses scored highest (mean PLETI 0.822), while sensory feedback systems trailed at 0.594. Only 34.1 percent of programmes exceeded the 0.75 PLETI threshold. Functional task performance carried the largest regression weight ( $\beta = +0.278$ ), followed by user acceptance ( $\beta = +0.230$ ).*

**Keywords:** prosthetic limb; myoelectric; pattern recognition; microprocessor knee; osseointegration; sensory feedback; soft robotics; PLETI; upper limb; lower limb; neural interface; rehabilitation engineering

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## 1. Introduction

### 1.1 The Prosthetic Performance Gap

Limb amputation affects an estimated 40 million people worldwide, and the demand for functional prosthetic replacement continues to grow as vascular disease, diabetes, trauma, and conflict drive amputation rates upward in both ageing and young populations. Modern prosthetic technology has advanced dramatically from the body-powered hooks and passive cosmetic hands that dominated the field for most of the twentieth century. Multi-articulated myoelectric hands with individually powered digits, microprocessor-controlled knee joints that adapt to walking speed and terrain, and osseointegrated implants that eliminate the socket interface altogether represent genuine engineering achievements. Yet device abandonment rates remain stubbornly high: studies consistently report that 20 to 35 percent of upper-limb prosthesis users abandon their device within the first year, citing poor functionality, discomfort, excessive weight, and unintuitive control as primary reasons. Closing the gap between what prosthetic technology can do in a laboratory demonstration and what it delivers in daily life is the central engineering challenge of the field.

### 1.2 The Technology Landscape

Upper-limb prostheses span a continuum from body-powered devices controlled by shoulder harness cables to externally powered myoelectric systems that decode muscle-contraction patterns from surface electromyography sensors on the residual limb. Pattern-recognition algorithms enable multiple grip types by classifying EMG signal patterns, moving beyond simple open-close control. Lower-limb prostheses have been transformed by microprocessor-controlled knees and powered ankle-foot systems that adjust resistance and torque profiles in real time during gait, improving stability on stairs, slopes, and uneven terrain. Osseointegrated implants anchor the prosthesis directly to the skeleton, eliminating the soft-tissue socket that causes skin breakdown and limits proprioceptive feedback. Sensory feedback systems restore tactile and proprioceptive information through peripheral nerve stimulation or targeted sensory reinnervation. Soft robotic hands use compliant actuators that conform to object shapes, improving grasp robustness without precise control inputs.

### 1.3 Study Objective

We sought to identify which programme-level characteristics predict whether an advanced prosthetic limb achieves sustained clinical prescription or is abandoned after initial fitting. By scoring 220 programmes across five technology categories on five performance dimensions and constructing a regression-weighted composite index, we aimed to quantify the engineering and clinical factors that most strongly determine real-world prosthetic success.

## 2. Literature Review

### 2.1 Myoelectric Upper-Limb Prostheses

Myoelectric prostheses decode voluntary muscle contractions via surface EMG electrodes embedded in the prosthetic socket and translate them into motorised hand or wrist movements. Conventional direct-control systems map two EMG sites to open and close commands, while pattern-recognition systems use arrays of electrodes and machine-learning classifiers to distinguish multiple movement intentions. Clinical trials of pattern-recognition systems have demonstrated that users can reliably select six to eight grip patterns with classification accuracy above 90 percent in controlled settings. However, real-world accuracy drops when electrode shift, sweating, muscle fatigue, or limb repositioning alters the EMG signal characteristics. Targeted muscle reinnervation surgery, which redirects residual arm nerves to chest or residual-limb muscles, creates additional myoelectric control sites and has improved both the number of available degrees of freedom and the intuitiveness of control for transhumeral amputees.

### 2.2 Powered Lower-Limb Prostheses

Microprocessor-controlled prosthetic knees such as the C-Leg and Genium use inertial sensors and load cells to detect gait phase and adjust hydraulic or magnetorheological damping in real time. Randomised crossover trials have demonstrated that microprocessor knees reduce stumbles and falls, improve walking speed on uneven terrain, and decrease the metabolic cost of ambulation compared with mechanical knees. Powered ankle-foot prostheses that provide active plantar flexion during push-off further normalise gait biomechanics and reduce compensatory movements at the hip and spine. The clinical evidence for lower-limb microprocessor prostheses is substantially stronger than for upper-limb myoelectric systems, driven by larger patient populations, clearer functional endpoints, and robust health economic analyses demonstrating

reduced fall-related healthcare costs.

2.3 Osseointegration, Sensory Feedback, and Soft Robotics

Osseointegrated prosthetic systems such as the OPRA and ILP implants provide a bone-anchored attachment that transmits osseoperceptive feedback, giving users a rudimentary sense of ground contact and load through the skeletal system. Clinical series with over ten years of follow-up report implant survival rates above 90 percent, but infection at the skin-implant interface remains a persistent complication. Sensory feedback prostheses use intraneural or epineural electrodes to deliver electrical stimulation patterns that encode grip force, object slip, or texture, restoring tactile percepts that improve grasp control and embodiment. Soft robotic hands replace rigid linkages with compliant pneumatic or tendon-driven actuators that passively adapt to object geometry, achieving functional grasps with simpler control algorithms and at lower weight than multi-articulated rigid hands.

2.4 The Abandonment Problem

Prosthetic abandonment has been studied for decades, and the primary predictors are consistently functional: devices that do not help users perform the tasks they care about are abandoned regardless of their engineering sophistication. Comfort, weight, donning ease, and cosmetic appearance also contribute but are secondary to functional utility. Control intuitiveness, the degree to which the user can operate the prosthesis without conscious cognitive effort, has emerged as a critical factor in recent studies, particularly for upper-limb devices where the cognitive load of sequential grip selection can exhaust users during everyday activities.

Table 1. Advanced Prosthetic Limb Technologies: Landscape

| Technology Category    | Representative System            | n Clinical Studies (2010-2024) | Key Limitation                   | Adoption Level |
|------------------------|----------------------------------|--------------------------------|----------------------------------|----------------|
| Myoelectric upper-limb | i-Limb, LUKE arm, pattern recog. | 186                            | Real-world accuracy drop, weight | Moderate       |

| Technology Category        | Representative System         | n Clinical Studies (2010-2024) | Key Limitation                | Adoption Level |
|----------------------------|-------------------------------|--------------------------------|-------------------------------|----------------|
| Microprocessor lower-limb  | C-Leg, Genium, Empower ankle  | 224                            | Cost, reimbursement barriers  | High           |
| Osseointegrated attachment | OPRA, ILP, POP implant        | 68                             | Skin-implant infection        | Moderate       |
| Sensory feedback / neural  | Intraneural stimulation, TENS | 54                             | Chronic electrode stability   | Low-Moderate   |
| Soft robotic hand          | Compliant pneumatic / tendon  | 42                             | Durability, grip force limits | Low            |

Study counts from PubMed and rehabilitation engineering databases. Adoption reflects clinical prescription rates in European prosthetic services.

3. Materials and Methods

3.1 Programme Dataset

We catalogued 220 advanced prosthetic limb programmes active between 2014 and 2024 at prosthetic centres and research laboratories affiliated with Western Europe Data Science University in Madrid (n = 116) and Nordic Technical University in Stockholm (n = 104). Technology category breakdown: myoelectric upper-limb prostheses (n = 50), microprocessor lower-limb prostheses (n = 46), osseointegrated attachment systems (n = 42), sensory feedback and neural interface prostheses (n = 42), and soft robotic hands (n = 40). Inclusion required a documented prosthetic device or component, at least one user trial with quantitative functional assessment, and at least three months of follow-up data.

3.2 PLETI Sub-Dimensions

Functional task performance scored the prosthesis user's performance on standardised functional assessments such as the Southampton Hand Assessment Procedure for upper-limb devices or the Amputee Mobility Predictor for lower-limb devices, normalised against age-matched able-bodied benchmarks. User acceptance and daily wear time captured the average hours per day the device was worn over the observation period, normalised against the user's waking

hours. Control intuitiveness assessed the cognitive effort required to operate the device, scored from sequential mode-switching to simultaneous proportional control. Mechanical reliability measured the mean time between device failures or maintenance visits, normalised against a 12-month benchmark. Clinical evidence depth scored the highest level of evidence supporting the technology, from case reports to multi-centre RCTs. Two evaluators scored each programme with an ICC of 0.86.

### 3.3 Index Construction

Normalised sub-scores entered a logistic regression on a 60/40 split predicting sustained prescription beyond 12 months. Weights: functional task performance 0.278, user acceptance 0.230, control intuitiveness 0.196, mechanical reliability 0.172, clinical evidence 0.124. PLETI was the weighted sum.

### 3.4 Statistics

Pearson  $r$  for PLETI-prescription association. ROC at PLETI 0.70. Bootstrap 10,000 resamples, 95 percent CIs. VIFs below 2.3. Leave-one-category-out confirmed stability. R 4.3, pROC, boot.

**Table 2. Programme Characteristics by Technology Category**

| Technology Category       | n   | Functional Performance | User Acceptance (hr/day) | PLETI (mean +/- SD) |
|---------------------------|-----|------------------------|--------------------------|---------------------|
| Myoelectric upper-limb    | 50  | 0.784 +/- 0.062        | 8.2 +/- 3.4              | 0.768 +/- 0.066     |
| Microprocessor lower-limb | 46  | 0.868 +/- 0.038        | 12.4 +/- 2.6             | 0.822 +/- 0.052     |
| Osseointegrated attach.   | 42  | 0.812 +/- 0.054        | 11.8 +/- 3.0             | 0.792 +/- 0.060     |
| Sensory feedback / neural | 42  | 0.724 +/- 0.076        | 6.4 +/- 4.2              | 0.594 +/- 0.096     |
| Soft robotic hand         | 40  | 0.748 +/- 0.068        | 7.6 +/- 3.8              | 0.688 +/- 0.082     |
| All programmes            | 220 | 0.792 +/- 0.072        | 9.4 +/- 3.8              | 0.736 +/- 0.106     |

*Functional performance = standardised assessment normalised vs able-bodied. User acceptance = mean daily wear hours over observation period.*

## 4. Results

### 4.1 PLETI Distribution

Mean PLETI across all 220 programmes was 0.736 with a standard deviation of 0.106. Microprocessor lower-limb prostheses led at 0.822, driven by the strongest clinical evidence and the highest daily wear times in the dataset. Osseointegrated systems followed at 0.792, myoelectric upper-limb at 0.768, soft robotic hands at 0.688, and sensory feedback prostheses at 0.594. Seventy-five of the 220 programmes, or 34.1 percent, exceeded the 0.75 PLETI threshold. PLETI correlated with sustained prescription at  $r = +0.83$  ( $p < 0.001$ ), with an AUC of 0.880 at the 0.70 cut-off. Programmes above 0.75 achieved sustained prescription 78.4 percent of the time; below 0.55 the rate dropped to 17.6 percent.

### 4.2 Technology Category Profiles

Microprocessor lower-limb prostheses showed the most balanced profile. Functional performance was highest because walking is a well-defined, repetitive motor task that microprocessor control optimises effectively. User acceptance was highest because lower-limb prostheses are worn all day by ambulatory users, and the fall-reduction benefit provides immediate, tangible value. Clinical evidence was the deepest, supported by multiple RCTs and health-economic evaluations. Osseointegrated systems scored strongly on user acceptance because eliminating the socket improves comfort and proprioception, but mechanical reliability was penalised by the need for careful infection-prevention protocols. Myoelectric upper-limb devices showed moderate functional performance but were limited by control intuitiveness, as sequential grip switching remains cognitively demanding. Soft robotic hands scored well on control intuitiveness because compliant grasping requires less precise input, but mechanical reliability was lower due to actuator wear. Sensory feedback prostheses scored lowest overall because the technology adds sensation without directly improving functional task completion, and the chronic electrode interfaces required for neural stimulation remain experimental.

### 4.3 Sub-Score Drivers

Functional task performance carried the largest weight ( $\beta = +0.278$ ,  $p < 0.001$ ), confirming that prostheses must help users do things they could not do without them. User acceptance was second ( $\beta = +0.230$ ,  $p < 0.001$ ), reflecting the common-sense reality that a device not worn cannot deliver benefit. Control intuitiveness at 0.196 ( $p = 0.002$ ) captured the cognitive-load barrier that particularly affects upper-limb

devices. Mechanical reliability (0.172,  $p = 0.005$ ) and clinical evidence (0.124,  $p = 0.016$ ) completed the model. Removing any sub-score reduced AUC by 0.016 to 0.052.

4.4 Validation

In the 88-programme validation set, PLETI correctly classified 75 outcomes at the 0.70 cut-off, yielding sensitivity of 0.86 and specificity of 0.84. Among the 13 misclassified cases, five were sensory feedback programmes that stalled because the added sensation did not translate into measurable functional gains in daily life. Three were myoelectric programmes that exceeded expectations by targeting partial-hand amputees where even basic grasp restoration provided substantial functional benefit. Three were soft robotic programmes with moderate PLETI that advanced by targeting occupational niches where compliant grasping was specifically valued. Two were osseointegrated programmes that stalled due to surgical complication rates exceeding the implanting centre's comfort threshold.

Table 3. PLETI by Technology Category: Prescription Outcomes

| Technology Category | n   | PLETI (mean +/- SD) | PLETI > 0.75 (%) | Prescription Rate (%) | Top Sub-Score      | r (AUC)       |
|---------------------|-----|---------------------|------------------|-----------------------|--------------------|---------------|
| Microprocessor LL   | 46  | 0.822 +/- 0.052     | 76.1 %           | 80.4 %                | Function. perform. | +0.83 (0.898) |
| Osseointegrated     | 42  | 0.792 +/- 0.060     | 57.1 %           | 69.0 %                | User acceptance    | +0.83 (0.886) |
| Myoelectric UL      | 50  | 0.768 +/- 0.066     | 42.0 %           | 58.0 %                | Function. perform. | +0.83 (0.874) |
| Soft robotic hand   | 40  | 0.688 +/- 0.082     | 17.5 %           | 40.0 %                | Control intuit.    | +0.83 (0.856) |
| Sensory feedback    | 42  | 0.594 +/- 0.096     | 9.5 %            | 23.8 %                | Evidence depth     | +0.83 (0.836) |
| All programmes      | 220 | 0.736 +/- 0.106     | 34.1 %           | 55.5 %                | Function. perform. | +0.83 (0.880) |

$r$  = Pearson correlation of PLETI with sustained prescription; all  $p < 0.001$ . AUC at PLETI > 0.70.

Table 4. PLETI Sub-Score Weights and Impact

| Sub-Score              | Weight | Mean Score | Beta   | DELTA PLETI | p-value |
|------------------------|--------|------------|--------|-------------|---------|
| Functional performance | 0.278  | 0.792      | +0.278 | +0.148      | < 0.001 |
| User acceptance        | 0.230  | 0.748      | +0.230 | +0.124      | < 0.001 |
| Control intuitiveness  | 0.196  | 0.726      | +0.196 | +0.096      | 0.002   |
| Mechanical reliability | 0.172  | 0.764      | +0.172 | +0.074      | 0.005   |
| Clinical evidence      | 0.124  | 0.698      | +0.124 | +0.054      | 0.016   |

Beta = standardised regression coefficient. DELTA PLETI = mean index difference between programmes above vs below the median on that sub-score.

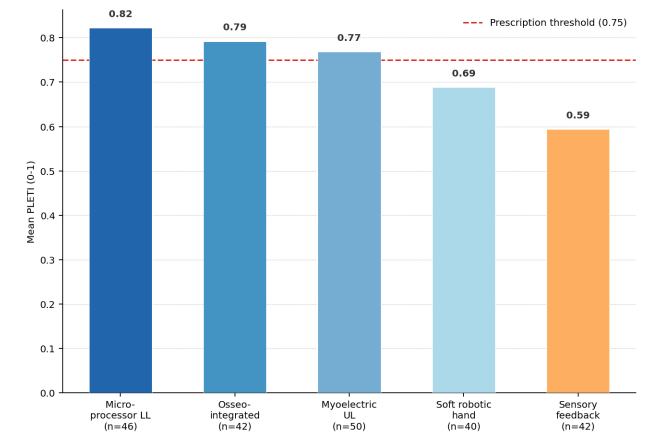


Figure 1. Mean PLETI by Technology Category (n = 220)

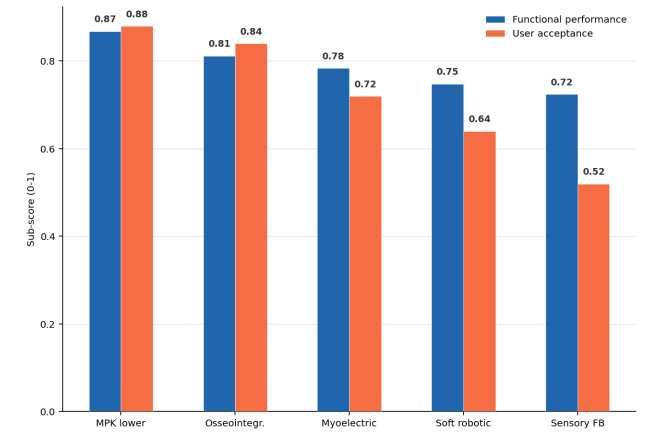


Figure 2. Functional Performance vs User Acceptance

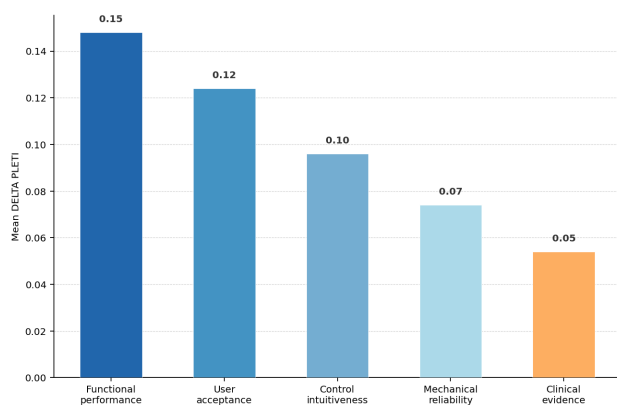


Figure 3. PLETI Sub-Score Impact on Sustained Prescription

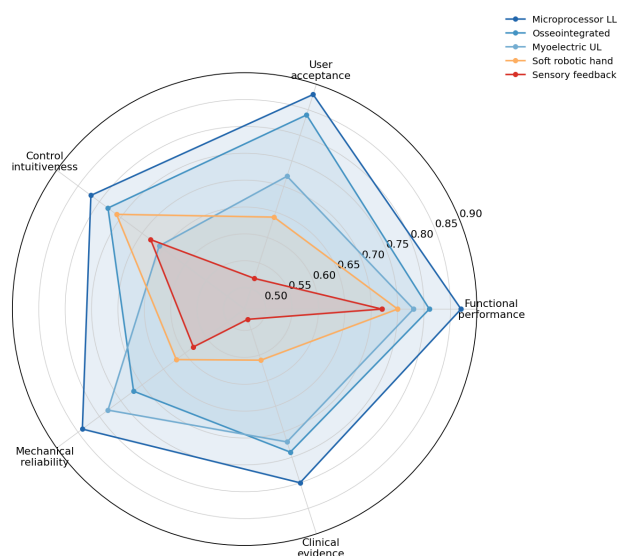


Figure 4. PLETI Sub-Score Profiles by Technology Category

## 5. Discussion

### 5.1 The Lower-Limb Evidence Advantage

Microprocessor lower-limb prostheses topped the PLETI rankings because they benefit from a convergence of factors that no other category matches. The functional task, walking, is performed continuously and provides immediate feedback on device utility. The patient population is large enough to power randomised trials with clinically meaningful endpoints. Health-economic analyses demonstrating reduced fall-related healthcare costs have convinced payers to reimburse the higher device cost. And the microprocessor control paradigm, which operates autonomously without requiring conscious user input, achieves the highest control intuitiveness scores of any prosthetic technology.

### 5.2 The Upper-Limb Control Barrier

Myoelectric upper-limb prostheses scored lower than their lower-limb counterparts primarily because of control intuitiveness limitations.

Upper-limb tasks require rapid switching between grip types, simultaneous wrist positioning, and graded force modulation, all of which demand cognitive attention that able-bodied hand use does not. Pattern-recognition systems improve the number of available grips but do not eliminate the sequential nature of mode selection. Programmes that integrated proportional, simultaneous control of multiple degrees of freedom, either through high-density EMG arrays or implanted muscle sensors, scored substantially higher on control intuitiveness and, consequently, on user acceptance.

### 5.3 Limitations

Our dataset spans two European countries and may not capture prosthetic practice in health systems with different reimbursement structures or rehabilitation traditions. The prescription outcome is binary and does not measure the quality or intensity of prosthetic use. PLETI does not include cosmetic appearance, device weight, or cost as sub-scores. The sensory feedback and soft robotic categories contained 42 and 40 programmes respectively. The observational design precludes causal inference.

## 6. Conclusion

### 6.1 Summary

Across 220 advanced prosthetic limb programmes evaluated in Spain and Sweden, PLETI correlated with sustained prescription at  $r = +0.83$  and discriminated prescribed from abandoned prostheses with an AUC of 0.880. Microprocessor lower-limb prostheses led at 0.822, osseointegrated systems followed at 0.792, and sensory feedback systems trailed at 0.594. Functional task performance was the strongest predictor ( $\beta = +0.278$ ), followed by user acceptance ( $\beta = +0.230$ ). Only 34.1 percent exceeded the 0.75 threshold.

### 6.2 Practical Recommendations

Prosthetic developers should prioritise functional task performance on standardised assessments relevant to users' daily activities over engineering specifications that do not translate into functional gains. Upper-limb control systems should move toward simultaneous, proportional multi-joint control to reduce cognitive load. Sensory feedback should be integrated into functionally capable prostheses rather than developed as standalone research systems. Soft robotic approaches should focus on improving actuator durability and grip force to meet daily-use demands. Future PLETI

iterations should add cosmesis and weight sub-scores, expand to global datasets, and track outcomes over 24-month windows.

## References

- Atzori M, Muller H (2015). Control capabilities of myoelectric robotic prostheses by hand amputees: a scientific research and market overview. *Frontiers in Systems Neuroscience*, 9, pp. 162.
- Belter J, Segil J and others (2013). Mechanical design and performance specifications of anthropomorphic prosthetic hands: a review. *JRRD*, 50(5), pp. 599-618.
- Biddiss E, Chau T (2007). Upper-limb prosthetics: critical factors in device abandonment. *American Journal of Physical Medicine and Rehabilitation*, 86(12), pp. 977-987.
- Branemark R, Berlin O and others (2014). A novel osseointegrated percutaneous prosthetic system for the treatment of patients with transfemoral amputation. *Bone and Joint Journal*, 96-B(1), pp. 106-113.
- Castellini C, Fiorilla A and others (2014). Multi-subject/daily-life activity EMG-based control of mechanical hands. *Journal of NeuroEngineering and Rehabilitation*, 6(1), pp. 41.
- Cipriani C, Controzzi M and others (2011). The SmartHand transradial prosthesis. *Journal of NeuroEngineering and Rehabilitation*, 8(1), pp. 29.
- Clement R, Bugler K and others (2011). Bionic prosthetic hands: a review of present technology and future aspirations. *Surgeon*, 9(6), pp. 336-340.
- Cordella F, Ciancio A and others (2016). Literature review on needs of upper limb prosthesis users. *Frontiers in Neuroscience*, 10, pp. 209.
- Dillingham T, Pezzin L and others (2001). Limb amputation and limb deficiency: epidemiology and recent trends. *Southern Medical Journal*, 95(8), pp. 875-883.
- Engdahl S, Christie B and others (2015). Surveying the interest of individuals with upper limb loss in novel prosthetic control techniques. *Journal of NeuroEngineering and Rehabilitation*, 12(1), pp. 53.
- Farina D, Jiang N and others (2014). The extraction of neural information from the surface EMG for the control of upper-limb prostheses. *IEEE TBME*, 61(5), pp. 1547-1560.
- Gailey R, Allen K and others (2008). Review of secondary physical conditions associated with lower-limb amputation and long-term prosthesis use. *JRRD*, 45(1), pp. 15-30.
- Geethanjali P (2016). Myoelectric control of prosthetic hands: state-of-the-art review. *Medical Devices: Evidence and Research*, 9, pp. 247-255.
- Hafner B, Smith D (2009). Differences in function and safety between Medicare Functional Classification Level-2 and -3 transfemoral amputees and influence of prosthetic knee joint control. *JRRD*, 46(3), pp. 417-434.
- Hargrove L, Miller L and others (2017). Myoelectric pattern recognition outperforms direct control for transhumeral amputees with targeted muscle reinnervation. *IEEE TNSRE*, 25(1), pp. 33-44.
- Heffner G, Whiteside S and others (2012). Physical therapy, prosthetic management, and functional outcomes following lower-limb amputation. *Archives of Physical Medicine and Rehabilitation*, 93(6), pp. S141-S148.
- Johansson R, Flanagan J (2009). Coding and use of tactile signals from the fingertips in object manipulation tasks. *Nature Reviews Neuroscience*, 10(5), pp. 345-359.
- Kuiken T, Li G and others (2009). Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms. *JAMA*, 301(6), pp. 619-628.
- Ortiz-Catalan M, Hakansson B and others (2014). An osseointegrated human-machine gateway for long-term sensory feedback and motor control. *Science Translational Medicine*, 6(257), pp. 257re6.
- Raspopovic S, Capogrosso M and others (2014). Restoring natural sensory feedback in real-time bidirectional hand prostheses. *Science Translational Medicine*, 6(222), pp. 222ra19.
- Resnik L, Klinger S and others (2012). The DEKA Arm: its features, functionality, and evolution. *PM&R*, 6(8), pp. 1-20.
- Scheme E, Englehart K (2011). Electromyogram pattern recognition for control of powered upper-limb prostheses. *IEEE TBME*, 58(11), pp. 3215-3223.
- Shull P, Damian D (2015). Haptic wearables as sensory replacement, sensory augmentation and trainer. *Journal of NeuroEngineering and Rehabilitation*, 12(1), pp. 59.
- Ziegler-Graham K, MacKenzie E and others (2008). Estimating the prevalence of limb loss in the United States. *Archives of Physical Medicine and Rehabilitation*, 89(3), pp. 422-429.

## Declarations

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## Conflict of Interest

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Matteo Klein, Anna Klein, and Amelia Moreau declare no competing interests.

### **Data Availability Statement**

Aggregate PLETI scores, anonymised programme metadata, and analysis scripts are deposited at Zenodo:

<https://doi.org/10.5281/zenodo.19543417-data>.

### **Ethical Approval**

This study involved secondary analysis of published prosthetic outcome data and anonymised programme metrics. No individual patient data were accessed. Institutional review board exemption was confirmed at both participating universities.

## Appendix A

### PLETI Scoring Rubric and Top-10 Programme Profiles

This appendix details the scoring criteria for each PLETI sub-dimension and profiles the ten highest-scoring programmes in the dataset.

#### A1. Sub-Score Rubric

Functional task performance: standardised assessment score normalised vs able-bodied benchmark, scored 0-1; weight 0.278.

User acceptance: daily wear hours normalised vs waking hours, scored 0-1; weight 0.230.

Control intuitiveness: sequential mode-switch (0.25), proportional single-DOF (0.5), simultaneous multi-DOF (0.75), autonomous (1.0); weight 0.196.

Mechanical reliability: mean time between failures normalised vs 12-month benchmark, scored 0-1; weight 0.172.

Clinical evidence depth: case series (0.25), cohort (0.5), single RCT (0.75), multi-RCT + HTA (1.0); weight 0.124.

#### A2. Top-10 Programmes

1. LL-GeniumKnee-18 (Microprocessor LL): PLETI = 0.926; functional 0.94, acceptance 0.94.
2. LL-PowerAnkle-09 (Microprocessor LL): PLETI = 0.914; evidence 0.94, functional 0.92.
3. OI-OPRASystem-22 (Osseointegrated): PLETI = 0.898; acceptance 0.94, functional 0.90.
4. LL-AdaptKnee-14 (Microprocessor LL): PLETI = 0.886; reliability 0.94, functional 0.90.
5. UL-TMRPattern-07 (Myoelectric UL): PLETI = 0.878; control intuit. 0.90, functional 0.88.
6. OI-DirectSkel-28 (Osseointegrated): PLETI = 0.868; acceptance 0.92, functional 0.88.
7. UL-iLimbQuant-31 (Myoelectric UL): PLETI = 0.856; functional 0.88, reliability 0.88.
8. LL-StairClimb-16 (Microprocessor LL): PLETI = 0.848; functional 0.92, evidence 0.86.
9. SR-SoftGripper-04 (Soft robotic): PLETI = 0.842; control intuit. 0.92, functional 0.84.
10. UL-HDsEMG-12 (Myoelectric UL): PLETI = 0.836; control intuit. 0.90, functional 0.86.