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REVIEW

Evaluation of Natural Hand Movements and Grasp Force in Prosthetic Hands: A Systematic Review

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Abstract: Traditional myoelectric prostheses remain limited to only one or two functional grip patterns and are prohibitively expensive, rendering them inaccessible to most amputees in developing countries. The biggest challenge for prosthetic engineers remains how to make an artificial hand move naturally and squeeze with exactly the right force for whatever object is in front of it. This systematic review searched five major databases (*Medline, PubMed, Embase, Scopus, Cochrane*) from 2010 to 2025 and included 47 studies that met predefined criteria. We examined how modern prosthetic hands read user intent from residual-muscle surface electromyography, translate it into smooth proportional grip strength—often aided by embedded pressure sensors—and how far we have really come toward natural control. Deep learning approaches, particularly convolutional neural networks, generally outperform traditional machine learning methods in motion classification and force estimation among able-bodied subjects, although performance remains substantially lower in amputees and traditional algorithms can achieve higher peak accuracy in specific settings. In actual amputees, however, performance drops sharply because residual signals are weak, noisy, and highly individual. Adding recurrent layers (Long Short-Term Memory), cheap inertial sensors (inertial measurement units), or vision dramatically narrows that gap and improves robustness. Overall, this systematic review shows that deep learning plus multimodal sensing is finally pushing prosthetic hands toward intuitive daily-life use, although major challenges in signal quality, training burden, and cost still stand in the way of truly seamless embodiment.

Keywords: humanoid prosthetic hand, sEMG, CNN, LSTM, hybrid frameworks

1. Introduction

Loss of the upper limb is one of the major challenges for upper-limb amputees in leading their daily lives. They become functionally dependent for typical activities of daily living (ADL) such as bathing, dressing, grooming, and mobility. Inability to perform these basic tasks independently affects not only their physical health but also their mental well-being. This leads to a decline in the overall quality of life (QoL) [1]. Prosthetic hands serve the need by restoring their functional movements, regaining their confidence to lead their daily lives [2]. From the designer's perspective, prosthetic hands can be classified into two types: gripper-based and humanoid. Gripper-based prosthetic hands primarily focus on handling objects, that is, for pick-and-place applications, rather than esthetic appearance, whereas the humanoid prosthetic hands focus on multiple aspects, such as natural hand movements, object handling with optimal forces, and esthetic appearance. Though there are design and functional complexities in humanoid hands compared to gripper-based ones, the former mimic natural hand movements, which helps address the functional needs of the amputees in their ADL effectively [3]. In this review, "natural hand movement" refers to multi-degree-of-freedom (DoF) wrist and finger coordination that approximates able-bodied kinematics (e.g., 5–10 grasp patterns with smooth, proportional force modulation) as measured by clinical tests (SHAP, ACMC) and quantitative metrics (joint angle correlation, grasp success rate, and low-latency real-time control. From the patients' perspective, that is, based on the type of amputation, they may be classified into three types: transcarpal humanoid prosthetic hand for amputations below the wrist, transradial humanoid prosthetic hand for amputations below the elbow, and transhumeral humanoid prosthetic hand for amputations below the shoulder [3]. Based on the mechanism, they are classified into two types: active and passive. Passive ones are body-powered, which work based on the biomechanical movements of the upper limb, such as the shoulder and elbow, depending on the type of amputation. In contrast, the active ones operate based on the biological signals from the brain or muscles. A feedback-based prosthetic hand that alters the course of action based on the environment in which it is put is one of the major challenges in prosthetic hand system design. Passive hands do not provide any electrical feedback to the user to perform course correction, whereas active ones do [4, 5]. The movement feedback is fed to the system to exert optimal movements and grasp forces to reach, pick, and place objects [6].

Some of the common limitations in conventional prosthetic hand control are their poor dexterity, slow response, and high

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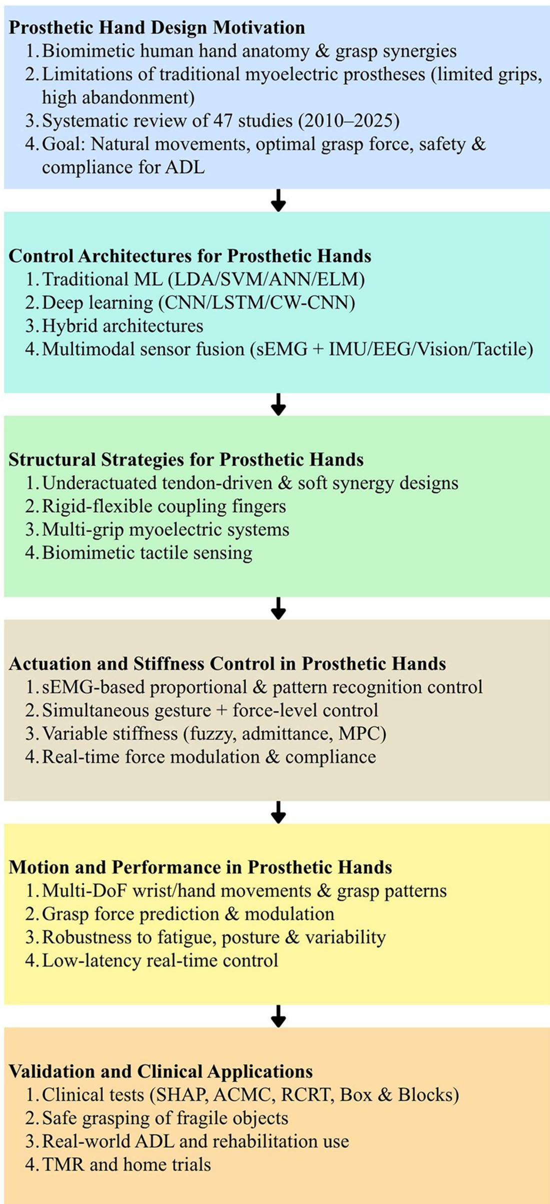
abandonment rates [1]. Surface electromyography (sEMG) signal acquisition and processing are one of the most common methods followed to drive prosthetic hands. They are used to accurately track and record the neuromuscular activity of the lower and upper arm movements. However, the versatility and robustness of the traditional electromyography (EMG) acquisition methods have been limited by noise, signal variability, and nonlinearity [3]. Various machine learning (ML) algorithms, such as linear discriminant analysis (LDA), support vector machine (SVM), artificial neural network (ANN), and regression models, have been used for classification and feature extraction of sEMG signals for the smooth operation of prosthetic hands. There were challenges in inter-subject variability and real-time adaptability, despite the improved motion accuracy of the algorithms [3, 7]. To overcome that, deep learning (DL) approaches such as convolutional neural network (CNN), Long Short-Term Memory (LSTM), and Channel-Wise Convolutional Neural Network (CW-CNN) were employed for automatic feature extraction and complex linear relations. The outcomes of gesture recognition, natural hand movements replication, and grasp force estimation were superior when these models were employed for signal processing compared to ML models [8–10]. Studies that employed hybrid architectures such as Autoencoder and CNN, LSTM, and CW-CNN led to better results in offering noise robustness and spatiotemporal precision [9]. Grasp force estimation is one of the key parameters that decides the functional performance of a prosthetic hand. It is especially used for the safe manipulation of objects of various sizes and shapes. Exercising high grip forces on fragile objects might damage them, while forces lower than the required threshold cause object slippage. To solve this, several studies have employed EMG-based grasp force prediction algorithms using ML models and fuzzy logic models for adaptive control [11, 12]. Combining sEMG signals with tactile or electroencephalography (EEG) sensors improves stability and classification accuracy, compensating for the effects of muscle fatigue and electrode displacement [4, 5, 13]. Incorporating sEMG with force or haptic feedback systems improves grasp precision and user embodiment [14]. Validating the algorithms on amputees is limited but crucial for improving the functional performance of prosthetic hands. SHapley Additive exPlanations (SHAP) is a post hoc explainability technique that generates explainers furnishing both local and global explanations of ML models. Local explanations dissect individual predictions using feature-based plots, while global explanations elucidate model predictions across features [15]. Clothespin Relocation Task (CRT) and Assessment of Capacity for Myoelectric Control (ACMC) are two standard clinical tests to measure the functional performance of an individual wearing a prosthetic hand [16].

The main aim of the systematic review is to systematically investigate the evolution of humanoid prosthetic hands from being manually operated devices to artificially intelligent ones capable of mimicking the natural hand movements, especially optimal grasp forces on objects. The study examines the performance of prosthetic hands that utilize various neural network algorithms, spanning traditional ML models to hybrid and customized neural architectures. In addition, the effectiveness of multimodal sensor integration and feedback systems encompassing invasive and noninvasive EMG acquisition systems and multimodal fusion strategies of prosthetic hands in terms of speed and accuracy was also investigated. Furthermore, the review investigated the grip force estimation to learn the optimal forces exerted on objects of various sizes and shapes, which helps understand the significance of adaptive grasping and feedback learning. The practical challenges in implementing an application-level prosthetic hand in a real-world scenario were also examined via the literature. Conclusively, the review aims to map the technological evolution and identify the most optimal methods for enhancing the natural hand function in prosthetic users. Figure 1 visually maps the full spectrum of sEMG-based prosthetic control classifications, tracing pathways from signal decoding to ML, modeling, integration, and validation, with highlighted metrics like CNN accuracies (94.75%/78.3%) and overarching issues like noise across 47 studies.

Figure 1
Flowchart encompassing all classifications of sEMG-based prosthetic hand control strategies, including machine learning, grasp force modeling, multimodal integration, and application validation, with key outcomes like CNN accuracies (94.75% healthy, 78.3% amputee) and feedback improvements (69–83% R^2)



2. Methodology

2.1. Search strategy

The search was conducted in *Medline, PubMed, Embase, Scopus*, and *Cochrane* from 2010 to 2025. The following Boolean search strings were used: ("prosthetic hand" OR "myoelectric prosthesis" OR "upper limb prosthesis") AND ("sEMG" OR "surface electromyography" OR "EMG") AND ("machine learning" OR "deep learning" OR "neural network" OR "CNN" OR "LSTM" OR "force estimation" OR "grasp force" OR "multimodal"). Limits: English language, human subjects, peer-reviewed journal articles. Searches were performed on February 25, 2026, and updated on April 15, 2026. Two independent reviewers screened titles, abstracts, and full texts. Disagreements were resolved by consensus.

2.2. Search outcomes

A total of 2673 records were identified through the database search (*Medline, PubMed, Embase, Scopus*, and *Cochrane*). All records were imported into EndNote reference management software. Duplicates were removed using the software's automated duplicate identification algorithm, followed by manual verification by two independent reviewers. No duplicate records were identified (n = 0). This result is attributable to the highly specific and focused search strategy, the use of database-specific search strings tailored to each platform, and careful export settings that minimized overlap between the five databases.

Following title screening, 375 articles proceeded to abstract screening. After abstract review, 328 articles were excluded, leaving 47 unique articles for full-text assessment. Upon detailed full-text evaluation against the pre-specified inclusion and exclusion criteria, all 47 articles fully met the eligibility requirements and were included in the systematic review. No articles were excluded at the full-text stage (n = 0). This high retention rate reflects the narrow and precisely defined scope of the eligibility criteria, which were designed to capture only studies directly addressing sEMG-based neural network control, grasp force modulation, and multimodal integration in humanoid prosthetic hands.

2.3. Inclusion and exclusion criteria

Studies that focused on prosthetic hands that mimicked the working of natural hand movements and followed the force control strategies were included. Studies investigating force estimation, object manipulation, and grasping using sEMG, intramuscular electromyography (iEMG), force myography (FMG), inertial measurement units (IMUs), tactile sensors, and EEG integrated with EMG for driving upper-limb prosthetic hands were included. Studies that conducted experimental validation with simulation-based control trials, human participants, and prosthetic systems were included. Studies that applied ML control algorithms such as CNN, SVM, LDA, extreme learning machines (ELM), recurrent neural networks, gene expression programming (GEP), backpropagation neural networks (BPNN), fuzzy logic controllers, autoencoders, and neural network regressors for effective functioning of the prosthetic hands were included. Studies that discussed grasp force modulation, tendon-driven actuation, and motor control for driving the upper-limb prosthetic hands were included. Studies that implemented electrotactile, haptic, vibrotactile, and visual feedback systems were included. Studies that performed experimental validation using the acquired data from human subjects, prosthetic control simulation, real-time grasping experiments, and force tracking tasks were included. Studies that demonstrated the prosthetic hand's performance using quantitative metrics such as accuracy, task completion, grip force error, or usability were included. Studies that examined learning curves, training paradigms, mimic/mirror tasks, or long-term signal stability for enhanced upper-limb prosthetic hand control were included.

Studies that focused on the characterization of the materials chosen for the sensor embedded or retrofitted to the prosthetic hands were excluded. Studies that focused on flexible electronics or soft robotic materials used for driving prosthetic hands without practical applications were excluded. Studies based on lower limb prosthetics, gait training devices, and hand exoskeletons not designed for fine and gross hand control were excluded. Studies based on rehabilitation robots that are not relevant to upper-limb prosthetic limbs were excluded. Studies that lacked experimental validation of the acquired biosignals or those without simulation trials or quantitative outcomes were excluded. Studies centered on sensors and signal transmission systems without any prosthetic applications were excluded. Literature reviews, systematic reviews, and meta-analyses on upper-limb prosthetic hands and related articles were excluded. Studies that lacked adequate details on sensor configurations, control methodologies, actuation mechanisms, force-feedback mechanisms, and performance metrics were excluded.

2.4. Classification of articles

The articles were classified into four major categories with subclassifications under them. They were machine learning–based grasp force estimation and control, whose subclassification includes traditional ML and statistical models, DL models, hybrid and custom neural network architectures; multimodal sensor integration and feedback systems, whose subclassifications were surface and implanted EMG systems, and multimodal fusion strategies; grasp force modeling and adaptive grasping mechanisms, whose subclassifications are grip force estimation and control models and adaptive grasping and feedback learning; and application-level validation and user performance studies.

2.5. Risk of bias

Though the studies selected for review provide insights into the evaluation of the outcomes, to ensure methodological rigor and transparency, multiple bias categories were identified and assessed. The studies that reported positive or substantial functional outcomes of upper-limb prostheses showed publication bias. Selection bias was observed due to the exclusion of inaccessible full-text or non-English studies. The experimental protocols used different types of sensors, variation in electrode placements, and setting different sampling frequencies that differed among studies, demonstrating heterogeneity in the methodology. There is non-uniformity in sample sizes compared; that is, the number of amputees (non-healthy participants) differs from the number of healthy individuals (Control subjects). There was a lack of randomization and blinding in the validation studies. The sample sizes in each study were small, leading to a reduction in statistical power and an increase in variance. Direct comparisons of prosthetic hand performance and overall functional outcomes of the patients were hindered by inconsistent performance metrics across the selected studies. The algorithms or hardware designed by independent research groups were meekly replicated by others for their studies. The architecture of control algorithms chosen for the studies was either reported with limitations, that is, no detailed descriptions about the validation procedures or the algorithm itself. There were potential data processing biases that resulted from feature selection methods or due to unreported processing methods. Figure 2 shows the PRISMA-compliant study selection, from 2673 records across five databases and narrowing to 47 through, ensuring a focused review on sEMG-based prosthetic advancements from 2010 to 2025.

To ensure methodological rigor and transparency, the risk of bias was systematically assessed across the 47 included studies using key domains adapted from the Cochrane and ROBINS-I tools. Results are summarized in Table 1.

Figure 2
PRISMA flow diagram detailing screening from 2673 database records to 47 included studies, with zero duplicates and 2298 title exclusions

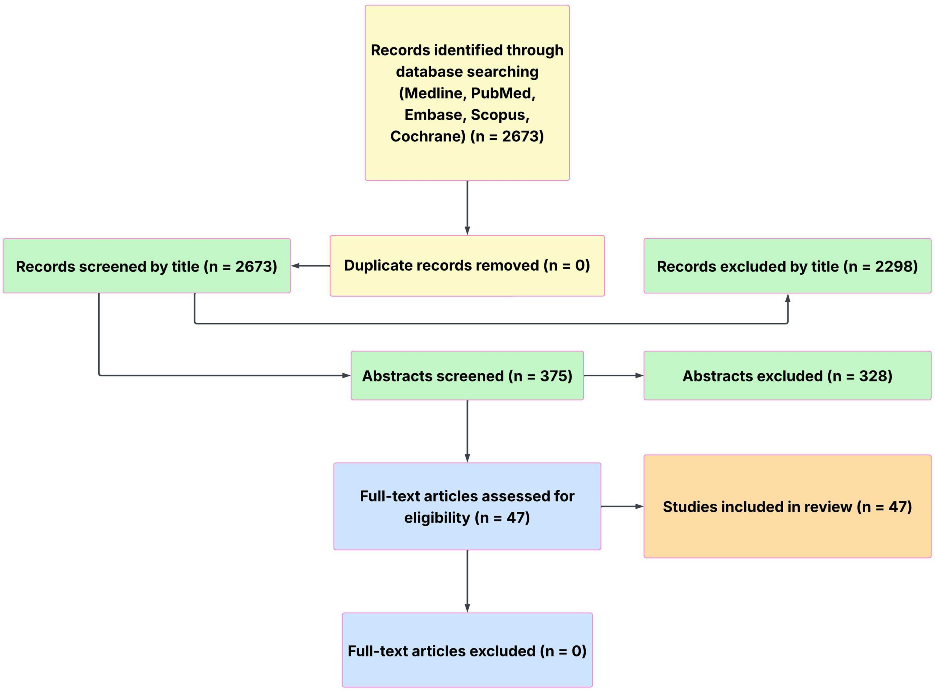


Table 1
Risk of bias assessment of included studies (n = 47)

Bias domain	Low risk	Moderate risk	High risk	Key concerns
Selection bias (participant selection and sampling)	12 (26%)	28 (60%)	7 (15%)	Small sample sizes; heavy reliance on healthy volunteers; limited amputee inclusion
Performance bias (blinding of participants/personnel)	0 (0%)	5 (11%)	42 (89%)	Blinding not feasible in prosthetic control experiments
Detection bias (blinding of outcome assessment)	8 (17%)	15 (32%)	24 (51%)	Lack of independent assessors in most validation studies
Attrition bias (incomplete outcome data)	35 (74%)	10 (21%)	2 (4%)	Most studies reported complete datasets
Reporting bias (selective outcome reporting)	31 (66%)	12 (26%)	4 (9%)	Some studies omitted negative results or detailed limitations
Other bias (small sample, heterogeneity, lack of standardization)	10 (21%)	22 (47%)	15 (32%)	High inter-study heterogeneity in sensors, metrics, and protocols; few long-term studies

Table 2
Synthesis of techniques in sEMG-based intention decoding and grasp force modulation for prosthetic hands

Representative studies	Main category	Subcategory	Techniques/algorithms	Outcomes	Challenges and limitations
Li et al. [17], Sidek et al. [18], Engeberg [19], Cao et al. [20], Liu et al. [21], Maimeri et al. [22], Prakash et al. [23], Lee et al. [24], Joshi et al. [25], Mora et al. [26], Wang et al. [27], Leone et al. [28], Yuan et al. [29]	Machine learning–based grasp force estimation and control	Traditional machine learning and statistical models	LDA, ANN, ELM, SVM, BPNN, WWPE, fuzzy logic, XGBoost, MLP, LightGBM, logistic regression	Classification accuracy 79–100% in healthy subjects, lower (~54–79%) in amputees; real-time control feasible with fewer channels; FMG low-cost alternative; intuitive biomimetic control	Lower performance in amputees; limited initial multi-grasp capability; effects of wrist angle, muscle fatigue, electrode shift
Atzori et al. [30], Li et al. [31], Fang et al. [32], Qin et al. [33], Tully et al. [34], Fratti et al. [8], Shin et al. [9], Martínez et al. [11], Dunai et al. [35], Wu et al. [36]	Machine learning–based grasp force estimation and control	Deep learning models	CNN, DNN, CW-CNN, temporal CNN, multitask CNN, multi-scale CNN, time-varying feature enhancement	60–94% gesture accuracy; up to 94% gesture + 86% force in healthy; superior automatic feature extraction; robust to noise offline	Sharp performance drop in amputees; high computational demand; overfitting risk; better offline than real time
Wu et al. [37], Xu et al. [38], Won et al. [39], Luo et al. [40], Meselmani et al. [41]	Machine learning–based grasp force estimation and control	Hybrid and custom neural network architectures	CNN–autoencoder, NARX, CNN–LSTM hybrids, synergistic myoelectric decoding	95%+ novelty rejection; reduced latency; improved spatiotemporal precision and robustness to interference	Transient phase issues; requires real-time optimization; complex training
Mastinu et al. [42], Dewald et al. [43]	Multimodal sensor integration and feedback systems	Surface and implanted EMG systems	Intramuscular EMG (iEMG), synergistic sEMG, KNN regression	iEMG stable >12 weeks; 100% posture matching; higher SNR and coordination than sEMG	Invasive surgery required; limited long-term clinical data
Krasoulis et al. [44], Li et al. [45], Kasuya et al. [46], Zhang et al. [47], Wang et al. [48], Zandigohar et al. [49], Li et al. [45]	Multimodal sensor integration and feedback systems	Multimodal fusion strategies	sEMG + IMU, sEMG + EEG, sEMG + muscle stiffness, sEMG + tactile sensors, sEMG + vision, sEMG + hardness/roughness perception	Accuracy 82–95%; fewer sensors needed; earlier/predictive grasp detection; improved stability and embodiment	Calibration complexity; increased power consumption; vision occlusion; fusion latency
Xu et al. [50], Esposito et al. [51], Wen et al. [52], Ma et al. [53], Ameri et al. [12]	Grasp force modeling and adaptive grasping mechanisms	Grip force estimation and control models	Huxley model + fuzzy logic, neural regression, GEP, BPNN, admittance control, Support Vector Regression (SVR)	RMSE <10%; R^2 up to 0.95; compliant grasping of fragile/deformable objects; energy-efficient actuation	Poor cross-user generalization; requires object property estimation (texture, stiffness, weight)

(*Continued*)

Table 2
(*Continued*)

Representative studies	Main category	Subcategory	Techniques/algorithms	Outcomes	Challenges and limitations
Kim and Colgate [54], Gailey et al. [55], Barontini et al. [56], Schweisfurth et al. [57], Zahabi et al. [58], Wang et al. [59]	Grasp force modeling and adaptive grasping mechanisms	Adaptive grasping and feedback learning	Soft synergy control, vibrotactile/haptic/electrotactile feedback, multisensor hardness/roughness, force-guided sEMG	Improved force modulation and precision; higher task success; reduced slippage/breakage; better embodiment with feedback	Feedback efficacy varies by user training/experience; sensory substitution challenges
Kerver et al. [60], Capsi-Morales et al. [61], Mukaiyama et al. [62], Simon et al. [63]	Application-level validation and user performance studies	Application-level validation and user performance studies	Clinical tests (SHAP, ACMC, RCRT, BBT, Cybathlon), real-world ADL tasks, targeted muscle reinnervation, cognitive modeling	Multi-grip hands show no clear functional advantage over standard; post-reinnervation improvements; real-world robustness gaps highlighted	High abandonment rates; cost–benefit mismatch; inconsistent metrics; limited translation to daily life

3. Results

Table 2 synthesizes sEMG techniques across categories, from Li et al.'s [17] ML foundations to Valle et al.'s [64] sensory feedback, highlighting CNN outperformance but challenges like high abandonment and cost mismatches in application validation.

3.1. Machine learning–based grasp force estimation and control

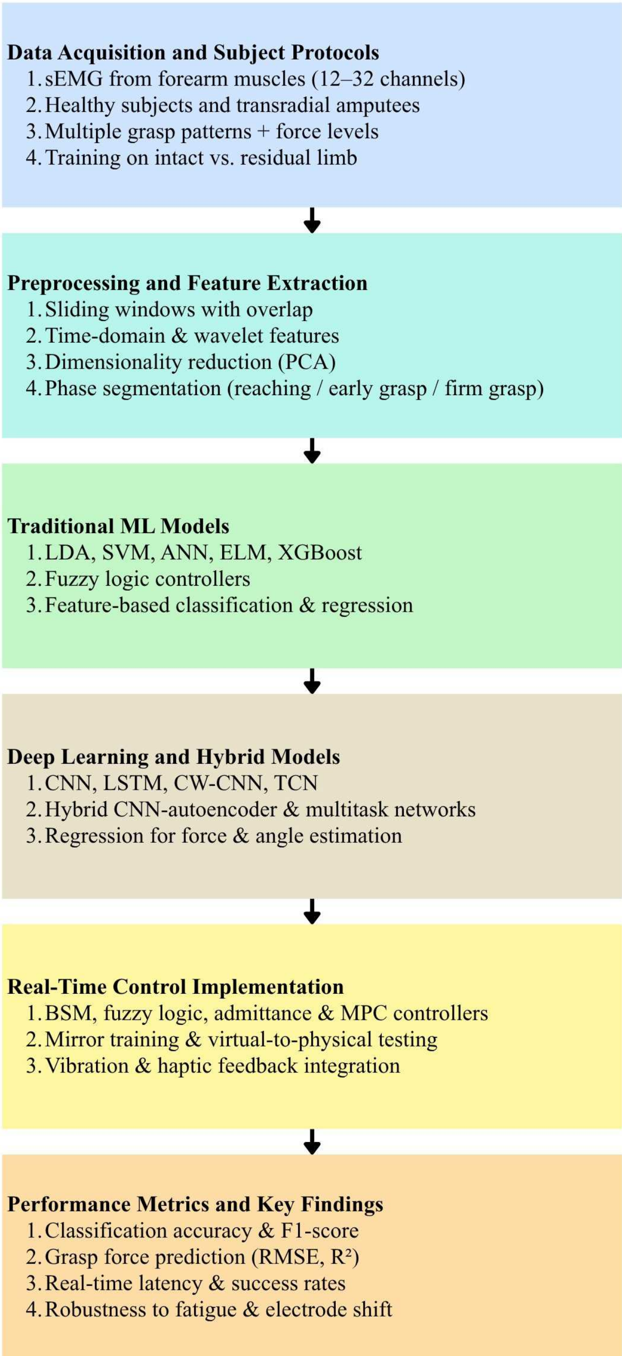
Figure 3 diagrams the workflow of ML grasp force methods, illustrating sEMG processing through traditional (LDA 79–100%), deep (CNN 94.75%/78.3%), and hybrid (95% rejection, R^2 0.93) branches, including real-time rates (57–75%) and hurdles like fatigue from 28 studies.

3.1.1. Traditional machine learning and statistical models

Li et al. [17] explored real-time myoelectric pattern recognition (MPR) control of multifunctional transradial prostheses using motion classification accuracy and control performance in virtual prosthetic manipulation. Switch-based control methods are typical of conventional myoelectric prosthetic control and can be slow and nonintuitive. The current study sought to establish whether transradial amputees could gain stable, accurate real-time control of EMG pattern recognition (PR), an improvement in the usability of a prosthesis. There were five unilateral transradial amputees participating in the study between the ages of 28 and 77, with a variation in duration of amputation ranging from 3 months to 21 years. Three utilized myoelectric prostheses, one employed a body-powered prosthesis, and the other had yet to receive one. All participants performed three trials: training on the amputated arm, training on the intact arm to compare performance, and one last test on the amputated arm to check learning effects. Twelve bipolar EMG electrodes were inserted around the proximal forearm to capture sEMG activity. Volunteers executed 10 motion classes, including flexion/extension of the wrist, pronation/supination of the wrist, hand opening, and five hand-grasping patterns (chuck grip, key grip, power grip, fine pinch, and tool grip). An LDA classifier was trained using 150 ms analysis windows with 50 ms overlap, providing a new classification decision every 100 ms. Participants then controlled a virtual prosthesis to test real-time performance using motion selection time, motion completion time (CT), and motion completion rate (CR) as key metrics. The accuracy of classification was significantly lower for the amputated arm compared to the intact arm (79% vs 94%). Wrist movements were better classified than hand grasps, with nearly 100% completion of motion for wrist actions but much lower for hand grasps (54% for amputated arms vs 71% for intact arms, $p < 0.05$). The mean time to choose a motion was around 0.2 s, and all motions took less than 1.25 s. Decreasing the number of EMG electrodes from 12 to 6 best placed channels minimally impacted accuracy, rendering the system more convenient for practical application. The study demonstrated that residual forearm muscles are adequate for real-time wrist control through EMG information but are not effective in the beginning for multiple hand grasps. Table 3 shows LDA application in transradial amputees, comparing 94% intact arm accuracy to 79% residual, with wrist actions at ~100% success but grasps at 54–71%, suggesting electrode reduction for affordable devices despite signal noise issues.

Sidek et al. [18] investigated the interaction between forearm EMG signals, hand grip force, and wrist angles for better control of cybernetic prosthetic hands. When compared to other research that compared EMG and grip force at a constant wrist position, this study attempted to define a dynamic relationship between these factors to improve more natural and intuitive control of prostheses. They designed a myoelectric interface comprising an EMG signal conditioning circuit as well as recording and processing data software. There were five healthy male subjects taking part in the study, all of whom had a range of maximum voluntary contraction (MVC) grip forces between 48N and 62N. All of them performed grip force tasks ranging between 2% and 30% MVC and with wrist angles of 60°, 90°, and 120°. The EMG

Figure 3
Flowchart of machine learning–based grasp force estimation and control strategies, detailing traditional ML (e.g., LDA/SVM with 79–100% healthy accuracy), deep learning (e.g., CNN multitask at 94.75%/78.3% healthy/amputee), and hybrid architectures (e.g., 95% novelty rejection), highlighting amputee performance drops (15–25%)



signals were obtained from three prominent forearm muscles: flexor digitorum superficialis (FDS), flexor carpi radialis (FCR), and extensor digitorum communis (EDC). The grip force was tested with a hand dynamometer (Vernier HD-BTA), and EMG signals were recorded with a sampling rate of 1000 Hz using a National Instruments USB 6008 data acquisition device. The results showed a positive correlation between EMG signal power and grip force, with FDS and FCR having higher activity during wrist flexion and EDC during wrist extension. For grip forces above 30% MVC, the EMG signals were unable to differentiate between wrist extension and flexion movements. For the estimation of grip force and wrist angle from EMG signals, a three-layer feedforward ANN was trained that accurately predicted both parameters with low mean squared error (MSE) values in all subjects. The study concluded that the inclusion of information about wrist angle in EMG-based prosthetic control would improve grip force estimation and overall prosthetic functioning.

Engeberg [19] conducted a study to enhance prosthetic hand control through the comparison of the use of a conventional proportional-derivative (PD) force controller to that of a new biomimetic sliding mode (BSM) controller that translates electromyogram (EMG) signals to motor commands in a physiologically natural manner. The study involved 10 subjects, one of whom was a transradial amputee with a 10-year history of utilizing a dual-site myoelectric prosthetic hand and nine non-amputee subjects, who all wore a CyberGlove to compare their natural hand motion with the motion of the prosthetic hand. Three primary experiments were conducted: force tracking, in which subjects tried to reproduce a time-varying force signal, illustrating that the BSM controller minimized force error by 9% over the PD controller; posture replication, illustrating that the BSM controller better replicated human hand motion with a position error of 0.38 versus 0.65 for the PD controller; and a two-object lifting task, in which subjects lifted objects with both hands at the same time, with an 89% success rate using the BSM controller, versus complete failure with the PD controller. Subjective assessments verified that the BSM controller was scored much closer to natural hand control in both force and position tasks. The study concluded that BSM control provides a more intuitive, accurate, and effective means of prosthetic hand control, with high potential for practical use in commercial prostheses.

Precise and fast prediction of handgrip force is crucial for real-time control of myoelectric prostheses. Cao et al. [20] examined the use of the ELM algorithm for the prediction of handgrip force from forearm muscle sEMG signals. ELM with SVM and Multiple Nonlinear Regression (MNLR) were compared to assess performance in accuracy and speed of processing. The study involved 10 subjects (age = 24 ± 3 years, weight = 61.6 ± 8.0 kg) who gripped a custom dynamometer using their dominant right hands while six forearm muscles' sEMG data were recorded. The root mean square (RMS) of sEMG signals was taken as input features. Results indicated that SVM was the most accurate, but ELM was balanced between processing time and prediction accuracy. The mean root mean squared error (RMSE) on the test set was 1.165 kfg for ELM, 0.806 kfg for SVM, and 3.369 kfg for MNLR, respectively, indicating that SVM outperformed the other models in prediction accuracy. The study concluded that ELM is a valid and computationally effective approach to handgrip force estimation and recommended further work to improve its accuracy for real-time prosthetic control.

Standard time-domain and frequency-domain-based feature extraction schemes tend to overlook the intricate, nonlinear nature of sEMG signals, hindering classification efficiency. Liu et al. [21] designed a wavelet-weighted permutation entropy (WWPE) approach to extract features from sEMG signals to enhance hand movement recognition accuracy in the control of myoelectric prosthesis. This study aimed to incorporate wavelet decomposition with weighted permutation entropy (WPE) analysis to improve motion classification accuracy. The investigation consisted of four healthy volunteers, two males and two females, aged 24–26 years,

Table 3
Traditional machine learning for sEMG pattern recognition in transradial amputees

Aspect	Details
Study reference	Li et al. [17] —focused on how well LDA works for real prosthetic control in people with below-elbow amputations
Participants	Five people with one-sided transradial amputation; they compared signals from the healthy arm and the amputated side
System/sensors	Twelve bipolar sEMG electrodes positioned carefully on whatever muscles were left in the forearm stump
Method/algorithm	Straightforward linear discriminant analysis (LDA) to sort out different movement intentions, using basic time-domain features
Task/experiment	Ten different hand and wrist actions tested in a virtual setup—things like wrist turns and various grips—checking how often motions were completed right, how accurate the system was, and how long each action took; also tried cutting down the number of electrodes
Key findings	On the healthy arm, accuracy hit 94%; on the amputated side, it dropped to 79%. Wrist actions were almost perfect (~100% success), but grasps only managed 54–71%. Motions took under 1.25 s on average. Cutting electrodes didn't hurt performance much
Implications	LDA is still practical and doesn't need heavy computing, good for cheaper devices, but the drop in grasp success shows we really need better ways to handle weak or messy signals from stumps

with a height range of 160–180 cm and weights from 48 to 70 kg. Seven typical hand actions were performed by volunteers: Open, Close, Point, Yeah, Ok, Tripod, and Grip. sEMG signals were captured with Trigno™ Wireless EMG sensors (Delsys Inc.), positioned across four forearm muscles: FCR, FDS, Flexor Pollicis Longus (FPL), and ED. The sensors relayed data wirelessly through Bluetooth at 1000 Hz, and every movement was performed 30 times for each participant to provide a total of 120 trials for every motion. The suggested approach used the wavelet transform (WT) to decompose sEMG signals into five subbands—a4, d1, d2, d3, and d4—and then WPE analysis was performed to extract local structural features of time-series data. The WWPE feature set was classified by SVM and BPNN models. The results indicated that WWPE performed better than conventional time-domain feature sets (RMS, mean absolute value, waveform length, zero crossings, and slope sign changes), with 100% accuracy using SVM and 98% accuracy using BPNN. The d3 sub-band had the highest recognition accuracy, validating that wavelet decomposition preserves key sEMG features. The study concluded that wavelet-based entropy analysis greatly improves sEMG feature extraction, enhancing PR accuracy for myoelectric prosthetic control.

Maimeri et al. [22] examined the control strategies for multichannel sEMG-controlled prostheses and supernumerary limbs, dealing with the difficulty of extracting and mapping independent electromyographic signals for natural prosthetic control. Conventional myoelectric control techniques demand double the number of independent sEMG signals needed to be controlled by actuators, constraining usability. Six new control maps were proposed, three based purely on sEMG signals and three combining sEMG signals with postural information, to enable proportional and parallel control of artificial limbs. The work involved 12 healthy participants (six males, six females, 23–31 years of age), who demonstrated the algorithms using a virtual setup by controlling a cursor using sEMG signals. The performance of the proposed maps was also compared to a benchmark algorithm that utilized twice as many sEMG inputs. The results indicated that the proposed maps performed comparably to the benchmark, even with fewer independent sEMG signals. Eight healthy participants were also tested on the maps on a physical robotic prosthesis, a soft robotic hand with an actuated wrist, and performed effective grasping and object manipulation. Additionally, two individuals with limb loss tested exploratory trials, controlling the prosthesis with two independent EMG signals. Subject 1 was a 37-year-old female who suffered from a congenital transradial malformation and used cosmetic and myoelectric prostheses sporadically. Subject 2 was a 41-year-old male with a transradial amputation who lost his limb eight years ago and was experienced in the use of body-powered and myoelectric prostheses. Both participants effectively controlled the prosthetic hand, showing that the suggested maps can enhance prosthetic usability even in people with a small number of available muscle signals. The study concluded that the control maps make prosthetic control more usable and efficient through optimal utilization of limited sEMG signals, which makes them a viable candidate for real-world prosthetic applications.

Prakash et al. [23] designed a low-cost FMG-controlled hand prosthesis for transradial amputees to overcome the drawbacks of EMG-based prostheses, including susceptibility to sweat, motion artifacts, electrode shift, and signal instability. A new FMG sensor was built to record the muscle contractions from the residual forearm, and two control techniques were adopted: proportional control (Prototype 1) and fuzzy logic-based classification control (Prototype 2). The study involved 13 participants, consisting of five transradial amputees (four males and one female) ranging from age 12 to 50 years, as well as eight able-bodied persons of the same age group. The amputees had lost their limbs as a result of accidents, and the amputation periods varied from 2 to 20 years. Prototype 1 was tried on all five amputees so that they could grasp different objects without training. Prototype 2 was tried on all 13 subjects, with a grasping success rate of over 95% in real-time trials. The system proved to be capable of recognizing six grip patterns: fine pinch, tripod grip, spherical grip, finger flexion, cylindrical grip, and power grip, with offline classification accuracy of 97.75%. The prosthesis based on FMG was able to offer similar functionality as commercial myoelectric hands at a much lower price, with Prototype 1 being capable of fast, intuitive control and Prototype 2 being able to provide multi-grip capability. The study concluded that FMG-based control offers a practical, stable, and cost-effective solution for upper-limb prosthetic users.

Lee et al. [24] examined the isometric force control skills of users of upper-limb prosthetics to assess their functional abilities compared to healthy subjects. The study involved the Upper Limb End-effector type Force control test device (ULEF), which utilized a 6-axis force/torque sensor and a visual cue system to quantify force modulation during controlled movements. The study was designed to fill the gap in the standardized measures for assessing force control in prosthetic users. The experiment was conducted on four prosthetic users of the upper limb and six right-handed male subjects, except one who was left-handed. The prosthetic users used the Bebionic hand (Ottobock, Germany) with a well-fitting socket. Three of them were transradial amputees, and the remaining one was a wrist disarticulation amputee. One subject (S1) had a background in using a myoelectric prosthesis (10 years), and the rest were novice subjects who were not exposed to myoelectric prosthetic control beforehand. The research did not involve female subjects to eliminate any neuromuscular variation that could result from sex hormones. Isometric force tasks were performed in four directions (medial, lateral, anterior, and posterior) with their dominant hand (prosthetic or intact). The assessment was based on the Degree of Translation, control instability, force response rate (FRR), and FRR variability. The Southampton Hand Assessment Procedure (SHAP) tests were also conducted to evaluate the functional ability for everyday activities. The outcome showed that prosthetic users demonstrated significantly reduced force control capabilities compared to healthy individuals, especially in the production of lateral force. The prosthetic user group showed greater anterior direction control instability for lateral tasks ($p < 0.05$) and higher force generation rate variability in all directions ($p < 0.05$). EMG analysis indicated significantly lower biceps activation in prosthetic users during posterior and anterior tasks ($p < 0.05$), implying changed muscle recruitment patterns. SHAP scores reflected significantly poor functional performance by prosthetic users compared to the healthy cohort ($p < 0.01$). Specifically, S1, the advanced prosthetic user, was a better performer compared to novice individuals but still performed with compromised force control relative to healthy participants. The research concluded that measuring isometric force control capacities can provide important information useful for prosthetic design enhancement, control algorithm adaptation, and training rehabilitation. It highlighted the importance of improved feedback mechanisms, optimized socket design, and adaptive control strategies to enhance prosthetic user performance. Longitudinal training effects, advanced control algorithms, and real-world functional integration of prosthetic hands are areas that need to be investigated in future research.

Joshi et al. [25] explored the viability of EMG signal-based accurate force control for prosthetic hands, utilizing anthropometric variables like muscle mass, body fat percentage, and subcutaneous fat. Conventional EMG-controlled prosthetics rely heavily on gesture detection, and in this research, the potential of EMG for the modulation of grip force was investigated through the examination of how the quality of EMG signals and force output are affected by physiological and demographic variables. In total, 37 participants, comprising 25 men and 12 women between the ages of 21 and 50, were involved. The heterogeneous database enabled an analysis of how diverse body compositions impact EMG signal reliability. Subjects' grip strength and EMG signals were tested at 100%, 50%, and 25% of their MVC. Muscle and fat content were measured using bioelectrical impedance analysis, and their impact on EMG variability was determined. An extreme gradient boosting (XGBoost) algorithm was used to model the correlation between EMG amplitude and grip force, which indicated robust linear relationships with r^2 values of up to 0.93 and 0.83 in most instances. The results showed a strong positive correlation (0.57) between muscle mass and EMG signal strength and a strong negative correlation (−0.40) between fat content and EMG values. The results indicate that body composition has a significant influence on EMG-based force estimation, and the incorporation of anthropometric measures into EMG prediction models can enhance the accuracy and responsiveness of prosthetic force control.

Mora et al. [26] designed a novel approach for ML-based, real-time posture grasping recognition based on sEMG signals to enhance the control of low-cost prosthetic and robotic hands. Most prosthetic hands that are widely available are lacking in dexterity, are costly, and suffer from high rates of abandonment, thus making them unaffordable. This research aimed to create a lightweight, real-time, and efficient hand control system that would be able to run on low-cost platforms with high classification accuracy. The research used 20 healthy subjects, whose data were collected from the NinaPro DS5 dataset (10 subjects) and experiments in the lab (10 subjects, 5 males and 5 females, aged 18–60 years). The subjects executed nine grasping postures, covering 90% of ADL. The tests that were conducted included pulp pinch, lateral pinch, diagonal volar grip, cylindrical grip, extension grip, tripod pinch, spherical grip, hook grasp, and rest posture. sEMG data were collected with an eight-electrode Myo armband sampling at 200 Hz on the forearm to identify muscle activity. The data were analyzed with two important features, mean absolute value and skewness, and classified with a low-memory, high-speed, optimized multi-layer perceptron (MLP) neural network. The results indicated that the MLP classifier attained a global accuracy of 73% and exhibited sound resistance to electrode shifts and changing muscle activation levels. The model was effective enough to be used for real-time control with a latency not exceeding 600 ms, which is tolerable for low-cost embedded devices such as Raspberry Pi or Arduino. It is concluded from the study that the system presented offered an effective solution to controlling prosthetic and robotic hands.

Wang et al. [27] investigated phase-based grasp classification for myoelectric prosthetic hand control using sEMG with the aim of reducing control delay observed in conventional grasp recognition methods. Previous approaches primarily depended on sEMG signals acquired during the firm grasping phase due to signal stability and high accuracy, which introduced latency because this phase occurred at the end of the reach-to-grasp action. To address this limitation, the study examined how grasp classification accuracy changed across the entire reaching and grasping sequence to identify an earlier prediction window. An open-source sEMG dataset from 30 healthy subjects was used with 12 forearm sensors recording muscle activity during ten functional grasp gestures. The grasping process was segmented into reaching, early grasping, and firm grasping phases using synchronized video recordings. Overlapping sliding windows of 200 ms with a 50 ms step size were applied, and eight time-domain features were selected after performance evaluation. Classification was performed using the Light Gradient Boosting Machine due to its efficiency with high-dimensional data, and the model validation was conducted using leave-one-repetition-out cross-validation. Results from the first experiment showed that classification accuracy increased during reaching and stabilized at the start of early grasping and remained high during firm grasping. A "sweet period" between 1100 ms and 1400 ms after movement onset was identified within the early grasping phase, where high accuracy was achieved with a 300 ms window providing the best balance between speed and accuracy, before stable grasp formation. The second experiment demonstrated that the highest classification accuracy of 85.50%

was achieved when the model was trained using data from all grasp phases and tested within an early prediction window of 300 milliseconds. In contrast, limiting the training to specific phases resulted in decreased performance. The findings confirmed that early grasping sEMG signals contain enough discriminative information. Additionally, training the model with data from all phases while focusing on early prediction effectively reduces control delay while maintaining high accuracy for real-time prosthetic control.

Leone et al. [28] proposed a hierarchical sEMG-based PR control strategy, which is designed to enable simultaneous classification of hand and wrist gestures with grasp force levels in transradial amputees. Existing myoelectric control systems typically addressed gesture or force recognition independently, which limited intuitive real-time control when both parameters were required. The proposed control strategy was able to recognize seven distinct hand and wrist gestures, along with three discrete force levels during grasping tasks. Fifteen transradial amputees participated in the study. In order to measure sEMG signals and grasp forces using a custom data acquisition system, the participants were made to wear a hand dynamometer and 12 commercial sEMG sensors. The participants performed seven predefined motion classes and executed grasping actions at low, medium, and high perceived force levels. The experimental protocol included force threshold calibration followed by training and online validation, where force thresholds were defined based on user perception to enhance repeatability and natural control. Following preprocessing, the sEMG signals were subjected to a feature extraction stage in which five time-domain features were derived using a sliding-window approach. The extracted features were incorporated within a hierarchical control structure for simultaneous gesture and force-level classification using logistic regression, nonlinear logistic regression, and LDA. The control structure assessment reported strong offline performance, reaching a high accuracy with mean F1 scores exceeding 90% for gesture classification and 95% for force-level recognition, while misclassification rates were below 10%. Further, the control strategy was validated in real time using a prosthetic hand and wrist module, enabling evaluation under realistic operational conditions. This testing confirmed the feasibility of the system, achieving response times of approximately 100 ms and consistently maintaining online accuracy above 90% across all algorithms. The real-time testing among classifiers showed no significant performance difference. The results demonstrated that hierarchical sEMG-based classification supported reliable low latency and intuitive control of both gestures and force levels and highlighted its potential to improve functional prosthetic use during daily activities.

Yuan et al. [29] proposed an sEMG-based hand motion recognition method intended to improve classification accuracy for rehabilitation and prosthetic control applications by addressing the difficulty of extracting informative components from noisy and redundant sEMG signals. The study introduced a hybrid framework that combined variational mode decomposition with the ReliefF feature selection algorithm to enhance motion intention representation. sEMG signals were decomposed into multiple variational mode functions, which enabled the extraction of stable narrow-band components while reducing noise and modal aliasing. From these components, mean absolute value, median frequency, mean frequency, and permutation entropy features were extracted to construct an initial high-dimensional feature set. ReliefF was then applied to remove redundant and weakly relevant features, which resulted in a compact and discriminative low-dimensional feature space. The method was evaluated using the UCI sEMG dataset for basic hand movements collected from five healthy subjects who performed six grasp types under controlled conditions. Signal preprocessing involved band-pass and notch filtering, followed by sliding window segmentation. Classification was performed using LDA, SVM, and bagging algorithms, and performance was evaluated through 10-fold cross-validation using accuracy, precision, recall, and F1 score metrics. Results showed that selecting 10 variational mode functions produced optimal performance, and a 42-dimensional feature space achieved the best balance between accuracy and computational efficiency. Among the classifiers, the SVM achieved the highest recognition accuracy of 99.14% across all hand movements. The findings demonstrated that the proposed framework achieved superior accuracy and robustness compared to existing approaches and showed strong potential for real-time hand motion recognition, prosthetic control, and rehabilitation training. Table 4 summarizes 14 traditional ML studies, from Li et al.'s [17] LDA (94%/79% accuracy) to Yuan et al.'s [29] SVM (99.14%), noting wrist control strengths but sharp multi-grasp drops in amputees and healthy-only limitations.

Table 4
In-depth exploration of traditional ML approaches to prosthetic grasp force, revealing wrist precision strengths amid real-world amputee variability and implementation hurdles

Study (author et al., year)	Participants (H/A)	Algorithm	Gesture Acc (H/A)	Force metric	Real time?	Physical prosthesis?	Key outcome	Main limitation
Li et al. (2010) [17]	0/5	LDA	94%/79%	—	Yes (virtual)	No	Good wrist control, fewer electrodes feasible	Sharp drop in multi-grasp for amputees
Sidek et al. (2012) [18]	5/0	ANN	—	Low MSE for grip + wrist angle	No	No	Wrist angle improves force estimation	Limited to <30% MVC

(*Continued*)

Table 4
(*Continued*)

Study (author et al., year)	Participants (H/A)	Algorithm	Gesture Acc (H/A)	Force metric	Real time?	Physical prosthesis?	Key outcome	Main limitation
Engeberg (2013) [19]	9/1	Biomimetic sliding mode	—	9% lower force error	Yes	Yes	Superior to PD controller	Very small amputee sample
Cao et al. (2017) [20]	10/0	ELM	—	RMSE 1.165 kgf	Potential	No	Fast processing for real time	Lower accuracy than SVM
Liu et al. (2020) [21]	4/0	WWPE + SVM/ BPNN	100%/98%	—	No	No	Wavelet entropy improves feature extraction	Healthy only
Maimeri et al. (2019) [22]	12/2	New control maps	Comparable to benchmark	—	Yes	Yes	Effective with fewer signals	—
Prakash et al. (2020) [23]	8/5	FMG + fuzzy logic	97.75% offline	—	Yes	Yes	Low-cost alternative to myoelectric	—
Lee et al. [24] (2021)	6/4	Isometric force control test	—	Reduced control in prosthetics	No	Yes	Prosthetic users have poorer force control	No female subjects
Joshi et al. [25] (2024)	37/0	XGBoost	—	r^2 up to 0.93	No	No	Body composition affects EMG-force relationship	Healthy only
Mora et al. [26] (2024)	20/0	MLP	73%	—	Yes	Potential	Low-cost real-time control	Healthy only
Meselmani et al. [41] (2016)	1/0	SVM	100%	—	Yes	Yes	Low-cost 3D-printed arm	Single participant
Wang et al. [27] (2022)	30/0	LightGBM (phase-based)	85.5%	—	Potential	No	Early prediction reduces delay	Healthy only
Leone et al. [28] (2023)	0/15	Hierarchical logistic regression	—	95% force level	Yes	Yes	Simultaneous gesture + force in amputees	—
Yuan et al. [29] (2024)	5/0	VMD + ReliefF + SVM	99.14%	—	Potential	No	High accuracy with feature selection	Healthy only

3.1.2. Deep learning models

Atzori et al. [30] examined the use of DL, that is, CNNs, for hand movement classification using EMG signals to enhance prosthetic hand control. sEMG and PR have been reportedly promising in the control of myoelectric prostheses, but real-world resilience is still problematic. An investigation was conducted to determine if CNNs could improve accuracy and reliability in classification by capitalizing on large-scale EMG datasets. 78 participants with 67 non-disabled subjects and 11 transradial amputees across three NinaPro database datasets. Dataset 1 comprised 27 non-disabled subjects executing 52 hand movements, Dataset 2 had 40 non-disabled participants executing 50 movements using two types of EMG sensors, and Dataset 3 was a group of 11 transradial amputees who were asked to perform 50 movements based on residual forearm EMG signals. The muscle activity, hand kinematics, and the forces applied were recorded using sEMG electrodes, motion capture gloves, and force sensors, respectively. Multi-layer CNN models with convolutional and pooling layers were trained based on data augmentation and hyperparameter optimization to improve performance. The study found that CNNs outperformed traditional classification methods, with 66.59%, 60.27%, and 38.09% accuracies for Datasets 1, 2, and 3, respectively. Nonetheless, SVMs and Random Forests (RFs) exhibited higher maximum accuracy (75.32%) in certain instances, demonstrating that traditional ML models are still useful in some cases. CNNs performed well for non-amputee feature extraction but were inefficient when used with amputee data due to high inter-subject variability and poor residual muscle activity. The study reports CNNs to be a potential option for sEMG-based prosthetic control; robust real-world prosthetic applications necessitate network design development, real-time adaptation, and dataset expansion.

Li et al. [31] aimed to enhance the stability and precision of prosthetic hand-grasping control using a biosignal-driven approach. The objective was to develop a reliable method for predicting grip force through sEMG signals and to implement this in a control framework for prosthetic hands. The study utilized a MYO gesture control armband to collect sEMG signals from the upper limbs of 15 able-bodied participants (8 males and 7 females). The raw sEMG signals were segmented, and relevant features were extracted from each segment for further analysis. To reduce the feature dimensionality, principal component analysis (PCA) was applied, reducing 32 features to 8. These reduced features were fed to a deep neural network (DNN) designed to perform sEMG-force regression for grip force prediction. The predicted force values were then passed through a fuzzy logic controller to achieve fine control over the prosthetic arm. To enhance sensory feedback and improve user interaction, a vibration feedback device was incorporated. The method demonstrated strong stability and robustness, as evidenced by a standard deviation (SD) in the range of 3.58% to 1.25%. The system achieved a high classification accuracy, with an average recognition rate exceeding 95%, validating its effectiveness in real-time prosthetic control.

Fang et al. [32] aimed to enhance the control of prosthetic hands by simultaneously recognizing hand gestures and force levels using sEMG signals. The objective was to improve recognition accuracy and processing efficiency through a multitask classification approach based on a CNN. The study compared the CNN model's performance with LSTM, SVM, and a hybrid CNN + LSTM model. sEMG data were collected from four healthy individuals and three amputee subjects, all aged around 25 years. Healthy subjects used six wireless sEMG sensors, while amputee subjects used three, placed over their FDS, FCR, and extensor carpi radialis. Each subject performed 9 distinct motions (a combination of 3 gestures and 3 force levels), with 20 trials per motion. The CNN model achieved the highest average accuracy, 94.75% for gesture recognition and 86.5% for force level recognition in healthy subjects, and 78.3% and 76.3%, respectively, in amputee subjects. The results demonstrated the CNN model's effectiveness in improving real-time prosthetic hand interaction by accurately identifying both gesture and force levels. Table 5 examines a multitask CNN, achieving 94.75% gesture/86.5% force in healthy subjects but 78.3%/76.3% in amputees, with three-sensor viability, advancing natural prosthetics but stressing amputee data gaps.

Table 5
Deep learning multitask model for simultaneous gesture classification and grasp force estimation detailing study reference, participants, sensors, algorithm, task/experiment, key findings, and implications

Study (author et al., year)	Participants (H/A)	Algorithm	Gesture Acc (H/A)	Force metric	Real time?	Physical prosthesis?	Key outcome	Main limitation
Atzori et al. (2016) [30]	67/11	CNN	66.59%/38.09%	—	No	No	CNN outperforms traditional in healthy	Very low in amputees
Li et al. (2018) [31]	15/0	DNN + PCA	>95%	SD 1.25–3.58%	Yes	Potential	Stable grip force prediction	Healthy only
Fang et al. (2022) [32]	4/3	Multitask CNN	94.75%/78.3%	86.5%/ 76.3%	Yes	Yes	Simultaneous gesture + force	Amputee drop
Qin et al. (2022) [33]	8/0	CW-CNN regression	CC >0.85	Good regression	Yes	Virtual	Low-latency 3-DoF control	No amputee testing
Tully et al. (2024) [34]	13/4	CNN (mirror training)	RMSE 0.16	—	Yes	Yes	Mirror training better than mimic	—

(*Continued*)

Table 5
(*Continued*)

Study (author et al., year)	Participants (H/A)	Algorithm	Gesture Acc (H/A)	Force metric	Real time?	Physical prosthesis?	Key outcome	Main limitation
Dunai et al. (2025) [35]	6/0	ANN (Keras)	98%	—	Yes	Potential	Low-cost anatomical design	Healthy only
Wu et al. (2025) [36]	5/0	Temporal CNN	14.66% RMSE	R^2 ~0.7	Yes	Yes	Adaptive grasping for flexible objects	Healthy only

Current sEMG-based control systems are limited because of high variation, motion artifacts, and delays in real-time processing. Qin et al. [33] created a real-time control system for virtual hand movement via a CW-CNN regression model to enhance accuracy and natural movement in control of myoelectric prosthetics. The main aim was to design a DL-based regression method for multi-joint angle estimation to facilitate more natural, precise, and effective control of prosthetic hands. Eight healthy participants completed three experimental sessions over two different days at the Tokyo Institute of Technology. Participants were equipped with bipolar multi-array electrodes (32-channel sEMG sleeve) for data recording with 500 Hz sampling. The control system approximated three DoFs: wrist flexion/extension, wrist pronation/supination, and hand grip/relaxation. Joint angles were captured with a Perception Neuron Motion Capture System at 120 Hz. A 10-fold cross-validation technique was used to train the CW-CNN regression model, and an adaptive Kalman filter (AF) was used to suppress signal oscillation and ensure real-time stability. A Target Achievement Control (TAC) test was used to assess real-time regression accuracy in virtual hand control. The results showed that the CW-CNN model performed with high regression accuracy, with correlation coefficients (CC) of over 0.85 for all DoFs. System latency was consistent at a mean of 74–75 ms ($p > 0.5$), within real-time requirements (<300 ms). All TAC test tasks were completed by participants, validating accurate and controllable joint movement in three DoFs. The study concluded that the CW-CNN regression-based control system presents a promising real-time solution for the control of natural prosthetic hands.

Tully et al. [34] compared the accuracy and efficacy of two training paradigms, mimic training and mirror training, for acquiring training data in myoelectric prosthetic control. The main aim of the study was to identify which method better represented hand kinematics, resulting in enhanced machine learning performance and real-time prosthetic control. Conventional mimic training involves reproducing preprogrammed prosthetic movements, whereas mirror training entails mimicking their intact contralateral hand and hence may yield more natural movement data. Four transradial amputees (mean age 56 ± 2.55 years, 75% male) and 13 healthy subjects (18–65 years old) participated in the study. The healthy subjects performed 18 distinct movements, such as finger flexion/extension, wrist pronation/supination, and power grasps, captured with Leap Motion infrared motion capture. Muscle activity was recorded with 32-channel sEMG electrodes, and analysis was performed using a KF and an eight-layer CNN. The amputee subjects executed the Clothespin Relocation Task (CRT) with a LUKE Arm prosthesis to assess real-time performance under each of the training paradigms. The outcomes demonstrated that mirror training enhanced the accuracy and precision of motion data and decreased the magnitude and timing error compared to mimic training ($p < 0.005$). In machine learning model training, mirror training provided greater CNN accuracy when the dataset size was larger, at an RMSE of 0.16 compared to 0.19 for mimic training. With real-time prosthetic use, mirror training resulted in a considerably shorter task duration (6.95 ± 1.60s vs 8.50 ± 6.67s, $p < 0.05$) with equivalent cognitive workload and success rates. The study showed that the training yielded more precise training data, better myoelectric control performance, and enhanced execution of real-time tasks.

Dunai et al. [35] explored the development of an sEMG-controlled prosthetic hand inspired by human anatomy. The prosthetic hand was controlled using ANNs to improve reliability, reduce complexity, and lower the costs of myoelectric systems without compromising computational efficiency. The sEMG signals were acquired from six healthy individuals using OYMotion and MyoWare sensors. Each participant performed several repetitions of wrist flexion, wrist extension, fist clenching, and functional gestures, such as holding a bottle and pointing with an index finger. Further, the signals were amplified, filtered, sampled, and segmented using adjacent non-overlapping windows before feature extraction. After preprocessing, gesture classification was performed using an ANN implemented in Keras and trained with the Adam optimizer, which showed rapid convergence during repeated training sessions. The performance evaluation demonstrated a high recognition ability, with an overall accuracy of nearly 98% and a weighted F1 score of 0.98. Class-wise results indicated that wrist extension yielded the best performance, while wrist flexion had slightly lower recall due to muscle overlap. The system's robustness was tested with different users under various operating conditions using MyoWare sensors and Oymotion sensors. Although the MyoWare sensors produced weaker signal quality compared to the OYMotion sensors, the model still maintained an accuracy of nearly 90%. In practical real-world operation, the system demonstrated about 95% reliability while maintaining low processing time and minimal use of computational resources. This makes the system suitable for use on embedded platforms. Furthermore, the double-trigger control mechanism improved the system's overall functionality. The results demonstrated that, when combined with appropriate signal processing and anatomical design, an ANN and affordable sEMG sensors could provide accurate and efficient control of prosthetic hands. According to the study, further testing with amputee people may improve its clinical applicability.

Wu et al. [36] introduced an adaptive multi-DoF prosthetic hand, validated through experiments, to enhance grasping of flexible objects through integrated mechanical design and advanced control. Addressing shortcomings in prior prosthetic hands, like imprecise force regulation with deformable objects of varying stiffness, they introduced a rigid-flexible coupling finger mechanism featuring 10 active and 4 passive DoFs. This design enabled adaptive distal joint motion without increasing the number of actuators, which enhanced contact area grasp stability and human-like kinematics. For intuitive operation, the author developed an enhanced temporal convolutional network that decodes eight-channel sEMG signals into intended grasping forces, which then feed into a linear iterative approximator and model predictive control system to predict actuator displacements and ensure accurate force tracking during manipulation of flexible objects. Five healthy individuals aged between 25 and 35 years participated in the study. Experimental validation was conducted using a functional prototype with EMG-force calibration, real-time grasping trials, and benchmarks against admittance and Proportional–Integral–Derivative controller (PID) controls. The results showed that the improved temporal convolutional network yielded superior performance with approximately 14.66% RMSE and a higher correlation with an R-squared of approximately 0.7. The hybrid linear iterative approximator and model predictive control approach significantly outperformed conventional controllers during constant- and variable-force grasps of sponge blocks, cotton dolls, and soft containers. The hybrid approach reported a reduction in tracking errors and enhanced stability. The results showed that this synergy of rigid-flexible mechanics, DL-based EMG estimation, and predictive control enabled effective adaptive grasping performance. Table 6 details studies (e.g., Atzori et al. [30]: CNN, 66.59%/38.09% accuracy), metrics (e.g., 86.5% force), real-time validation, physical implementation, outcomes (e.g., simultaneous gesture + force), and limitations (e.g., low amputee performance).

3.1.3. Hybrid and custom neural network architectures

Standard MPR systems recognize a learned set of motion patterns, yet unlearned motions are mistaken and result in false activations and control errors. Wu et al. [37] constructed a hybrid neural network method for enhancing MPR to eliminate new motion interferences, which tend to undermine prosthetic control performance. To tackle this, the research incorporated CNNs for spatiotemporal feature extraction and autoencoder networks for rejection of new motion in high-density sEMG (HD-sEMG) signals. Nine healthy subjects (six males, three females, aged 22–27 years) with no neuromuscular disease participated in the study. Participants executed seven target motion tasks, namely, wrist pronation, wrist supination, wrist extension, wrist flexion, hand opening, hand closing, and shooting. Furthermore, six new motion tasks were added as interference tasks, consisting of pinch, radial deviation, ulnar deviation, manipulation of a mouse, writing, and typing on a keyboard. HD-sEMG signals were captured with two 8 × 6 electrode arrays positioned over the flexors and extensors of the forearm and acquired 96-channel sEMG at a sampling rate of 1 kHz. The results showed that the novel CNN–autoencoder framework accurately increased novelty rejection accuracy, achieving over 95% novel motion task rejection accuracy. Receiver operating characteristic curve analysis indicated that the new method was superior to traditional LDA-MD (Linear Discriminant Analysis with Mahalanobis Distance) methods ($p < 0.05$). While LDA-MD had an Area Under the Curve (AUC) of 0.91, the hybrid neural network-based method raised the AUC to 0.93 while lowering false positives to 3% while still having an 85% true positive rate. Misclassifications during transient phases of motion were found to be prevalent in the study, and further tuning in real-time control contexts was recommended. The study concluded that hybrid CNN–autoencoder networks give a strong solution for rejecting novel motions in myoelectric prosthetic control to improve real-world usability. Table 7 shows a summary of hybrid CNN–autoencoder approaches for rejecting interference motions in prosthetic/Brain-Computer Interface (BCI) control.

Xu et al. [38] focused on improving prosthesis control accuracy by analyzing and estimating the force exerted during natural movements. This study was carried out on five able-bodied subjects (aged 22–26, right-handed) and primarily focused on classifying four different types of natural hand movements and the force that was expected during those movements. For this purpose, the study devised a platform where subjects performed four common natural grasping movements termed as pinch, palmar, twist, and plug grasp. Delsys Inc. EMG acquisition system was used for the experiment with eight wireless channels and a sampling frequency of 2000 Hz. These channels were linked to eight electrodes

Table 6
In-depth quantitative synthesis of machine learning–based grasp force estimation and control—deep learning subset (seven studies)

Study (author et al., year)	Participants (H/A)	Algorithm	Gesture Acc (H/A)	Force metric	Real time?	Physical prosthesis?	Key outcome	Main limitation
Wu et al. (2022) [37]	9/0	CNN + autoencoder	95% novelty rejection	—	Potential	No	Excellent interference rejection	Transient phase errors
Xu et al. (2022) [38]	5/0	Natural grasp CNN	91–97%	R^2 up to 0.908	No	No	Good natural force estimation	No amputee testing
Won et al. (2024) [39]	1/0	NARX + ZPETC-PID	Reduced delay	—	Yes	Yes	Highly responsive control	Healthy only
Luo et al. (2019) [40]	5/0	Synergistic sEMG	>96%	—	No	No	Robust to electrode shift	Healthy only

Table 7
Hybrid CNN–autoencoder architecture for rejecting interference motions including study reference, participants, sensors, method/algorithm, task/experiment, key findings, and implications

Aspect	Details
Study reference	Wu et al. [37]—tackled the problem of accidental activations when the arm moves in ways not meant to control the hand
Participants	Nine healthy volunteers doing both intended actions and random interfering movements
System/sensors	A dense grid of 96 sEMG channels to capture detailed muscle patterns across the forearm
Method/algorithm	Combined a CNN for pulling out features with an autoencoder trained to spot and block anything that wasn't a trained motion
Task/experiment	Seven proper target motions mixed with six kinds of distractions; tested how well the system ignored the junk
Key findings	Blocked unwanted motions over 95% of the time; AUC score of 0.93 (better than old LDA methods at 0.91); false triggers down to about 3%
Implications	In everyday life, this could stop the hand from twitching or grabbing when you don't want it to—a huge step for making prosthetics less frustrating

placed on specific muscles corresponding to channels C1, C2, C3, C4, C5, C6, C7, and C8. The EMG signals were filtered using a sixth-order Butterworth filter within the 10–500 Hz region and a notch filter at 50 Hz. The findings suggested that average accuracy analysis during natural grasping movements ranges from 91.43% to 97.33% with differing force levels of 20%, 50%, and 80%. The plug grasp shows the most accurate regression performance, where the average R-squared stood at 0.9082. In addition, the study showed that the speed of force application had a significant impact on the regression results.

Won and Iwase [39] investigated the effects of response delay in myoelectric prosthetic hand control and aimed to reduce performance degradation caused by electromechanical delays between EMG generation and actual movement exceeding 300 ms. The study aimed to enhance both responsiveness and accuracy by shifting from earlier wrist-based systems, which were limited by four-channel wired sensors and single-input models, to a more scalable framework suitable for complex, multi-DoF control. To enhance user comfort and facilitate future multi-joint prosthetic control, the study employed an eight-channel wireless Myo armband instead of a conventional wired setup. Meanwhile, wrist motion was evaluated using a hand-shaped robotic platform. EMG data were collected from a healthy subject performing wrist palmar flexion and dorsiflexion. Concurrently, wrist angles were measured using a high-resolution electronic goniometer. To examine the nonlinear, time-varying association between EMG signals and wrist movement, a multi-input, single-output Nonlinear Autoregressive with Exogenous Input (NARX) model was utilized. The model order was determined using the Akaike information criterion, and ridge regression was used to mitigate overfitting caused by inter-channel correlation. Control was achieved by using zero-phase-error tracking control (ZPETC) as a feedforward strategy, combined with PID feedback, to compensate for the servo motor phase delay using the available electromechanical delay. The results demonstrated that the latency of wireless communication was negligible compared to the electromechanical delay, which facilitated effective predictive control in the wireless configuration. The eight-channel model substantially reduced wrist angle estimation error relative to the four-channel baseline, and the integrated ZPETC–PID controller cut motor response delay from 0.428 s down to 0.188 s. Overall, the study demonstrated that combining multi-channel wireless EMG sensing with electromechanical delay-aware modeling and control significantly improves prosthetic responsiveness and lays the groundwork for more sophisticated hand and finger-level prosthetic control schemes.

3.1.4. Amputee-specific challenges

Amputee performance was consistently lower than that of able-bodied (e.g., 15–25% drop in classification accuracy) due to weak residual muscle signals, high inter-subject variability, muscle atrophy, and electrode shift. These factors were partially mitigated by multimodal fusion and mirror training but remain a major barrier to clinical translation.

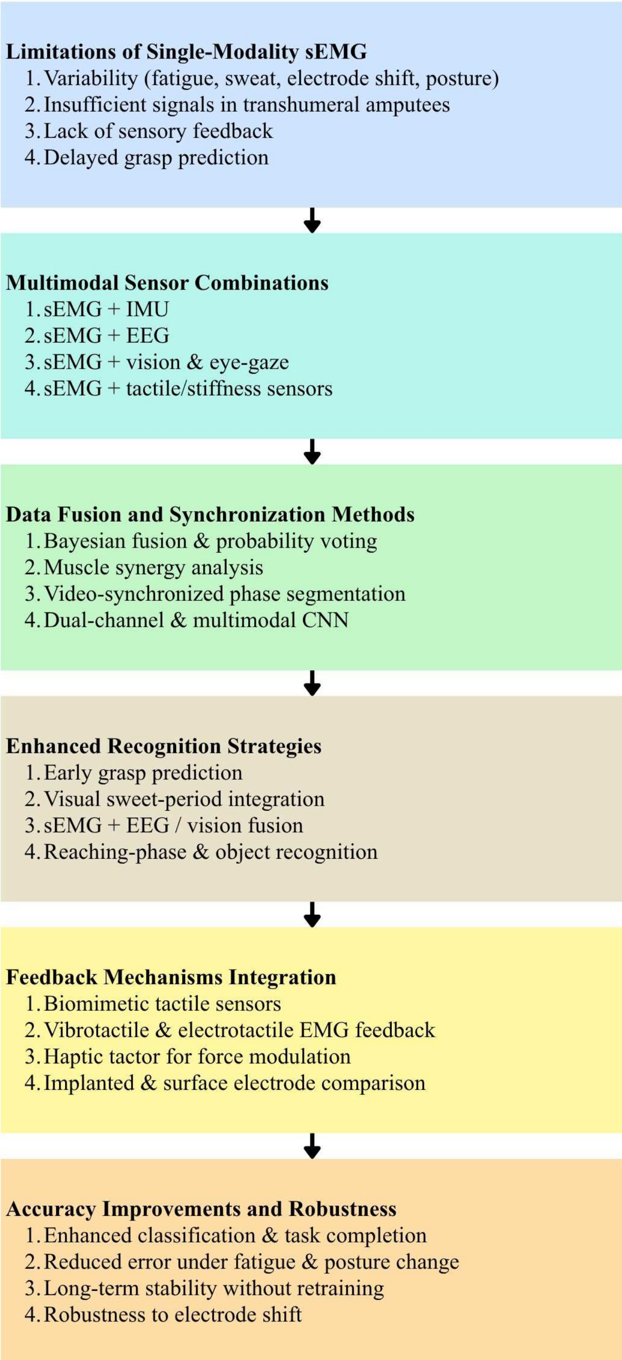
3.2. Multimodal sensor integration and feedback systems

Figure 4 sketches multimodal sensor systems, showing sEMG drawbacks evolving into fusion (IMU gains 14.7–37.1% to 77.8–91.7%) and implanted setups (SNR stability >12 weeks), with feedback reductions (12–32%) and real-time emphasis (80–86%) from 10 studies.

3.2.1. Surface and implanted EMG systems

Conventional gesture recognition systems are based on direct sEMG feature extraction, but they tend to be plagued by signal instability because of muscle fatigue and electrode displacement. Luo et al. [40] examined synergistic myoelectrical activities of forearm muscles to enhance hand gesture recognition robustness based on sEMG. This research aimed to investigate whether muscle synergy patterns could increase classification accuracy and robustness in multi-fingered gesture recognition. Five healthy subjects (mean age: 24.2 ± 1.2 years; height: 175.1 ± 9.8 cm; weight: 65.62 ± 8.1 kg), all right-hand dominant and free from musculoskeletal or neurological diseases, participated in the study. Five everyday life hand movements, namely, pinch, fist, open hand, grip, and extension, were executed by the participants. sEMG signals were registered with a six-channel sEMG system (ME6000, Mega Electronics Ltd.) placed on six muscles of the forearm: flexor digitorum sublimis (FDS), palmaris longus, brachioradialis (MB), extensor indicis proprius, extensor digitorum (ED), and extensor pollicis brevis. A single gesture was repeated 40 times by each participant, consisting of four seconds of muscle activation and five seconds of relaxation in order to avoid fatigue. The Nonnegative Matrix Factorization algorithm was employed to retrieve

Figure 4
Flowchart of multimodal sensor integration and feedback systems, covering fusion techniques (e.g., sEMG + IMU with + 22.6–37.1% accuracy gains to 77.8–91.7%), surface/implanted electrodes (e.g., higher SNR for stable grips >12 weeks), and feedback mechanisms (e.g., electrotactile reducing variability 12–32%), addressing electrode shifts and fatigue



muscle synergy patterns, and SVM was utilized as a classifier for gesture recognition. The results indicated that the classification accuracy of gestures was consistently over 96% and exhibited good robustness in the presence of electrode shifts and muscle variations. The feature set based on synergies outperformed standard time- and frequency-domain features in classification. Doubling the number of participants did not significantly impact recognition accuracy, indicating a robust and generalizable classification method. The study concluded that muscle synergy-based gesture recognition improves robustness and accuracy in sEMG-based prosthetic control systems.

Traditional myoelectric prosthetic control often relies on limited DoFs and expensive hardware, restricting accessibility, particularly in developing countries. Meselmani et al. [41] developed a PR-based myoelectric control system to operate a 3D-printed robotic arm. The study aimed to provide an affordable and efficient alternative to commercial prostheses. To address these limitations, a low-cost robotic arm with adaptive EMG control using SVM classification was designed. The study involved a single participant, a 21-year-old male of normal weight, who was tested using sEMG electrodes placed on the forearm. The system acquired sEMG signals from the FCR or FDS muscles, processed them through a custom-built circuit with high-pass (20 Hz) and low-pass (500 Hz) filtering, and fed the extracted features into an SVM classifier for binary classification of muscle contractions. The robotic arm was 3D-printed and actuated using five servo motors, each corresponding to one finger. Data processing and classification were implemented in LabVIEW and RapidMiner, with extracted features including RMS, standard deviation, variance, arithmetic mean, kurtosis, median, mode, summation, and skewness. The results showed that the SVM classifier achieved 100% classification accuracy, distinguishing between muscle contractions and relaxations. The robotic arm effectively responded to EMG commands, confirming the fidelity of the signal acquisition system and classification model. However, the study acknowledged that the small sample size limited statistical validation.

Mastinu et al. [42] compared the efficacy of epimysially implanted electrodes to standard sEMG electrodes for controlling an osseointegrated prosthetic hand. The study aimed to evaluate grip force control and motor coordination in transhumeral amputees using the e-OPRA Implant System, which combines skeletal attachment with neuromuscular interfaces for bidirectional control. Three e-OPRA implant transhumeral amputees were studied, with two of the subjects having also received targeted muscle reinnervation (TMR) for enhanced myoelectric control. Two functional tasks were tested: the Virtual Eggs Test (VET), to assess the subject's ability to control grip force when manipulating delicate objects, and the Pick and Lift Test (PLT), to test motor coordination by comparing grip and load force synchronization. Subjects completed these tasks with both epimysial and sEMG electrodes. The findings showed that epimysial electrodes improved grip force control significantly, preventing excessive force exertion and ensuring more stable grasping. With the VET, subjects damaged fewer delicate objects (p = 0.003) when using epimysial electrodes compared to sEMG, proving higher accuracy. Likewise, during the PLT, grip force was preserved after lift-off, with lower involuntary increases in force ($p < 0.001$). But motor coordination was surprisingly poorer with epimysial electrodes since grip and load forces were less synchronized and seemed to depend on visual feedback instead of natural tactile perception. The study concluded that implanted electrodes provide better control reliability but fail to restore natural motor coordination in the absence of sensory feedback integration.

sEMG prosthetic control has traditionally been compromised by variations in skin impedance, electrode positioning, and motion artifacts, necessitating frequent retraining. Dewald et al. [43] investigated the application of chronically implanted bipolar intramuscular electrodes to facilitate three DoFs myoelectric prosthetic control for transradial amputees. In this study, the authors tried to overcome such drawbacks by utilizing intramuscular electrodes that ensure greater signal stability, less crosstalk, and better long-term performance without retraining. The research involved a male subject aged 37 years with a left transradial amputation who had prior experience using a myoelectric prosthetic hook. The subject underwent surgical implantation of eight bipolar intramuscular electrodes aimed at major wrist and finger muscles. For 12 weeks, a K-Nearest Neighbor (KNN) regression velocity controller was learned from a single session of EMG data collection, enabling the participant to manipulate a virtual prosthetic hand during a three-DoF posture-matching task. The performance of the controller was tested over time and in six different arm postures compared to a position-based controller controlled by the participant's intact hand. The findings indicated that intramuscular EMG (iEMG) signals had considerably reduced crosstalk and a greater signal-to-noise ratio (SNR) compared to sEMG signals. The KNN controller based on iEMG performed stably for 12 weeks without retraining with a 100% posture-matching success rate in all sessions and arm positions. Compared with the intact hand-based controller, the controller was a bit slower but offered accurate and reliable multi-DoF control. The study concluded that chronically implanted intramuscular electrodes provide a stable, promising platform for advanced myoelectric prosthetic control, decreasing the frequency of training and enhancing long-term use. Table 8 details studies (implanted EMG, higher SNR), accuracy gains, real time/physical, outcomes (e.g., stable >12 weeks), and limitations (e.g., invasive).

3.2.2. Multimodal fusion strategies

Krasoulis et al. [44] studied the improvement of myoelectric control of prosthetic hands through the use of sEMG and inertial measurements (IMs). Conventional sEMG-controlled prosthetics tend to suffer from classification errors, instability resulting from electrode movement, and the need for numerous sensors. In this research, a multimodal approach was suggested to combine sEMG with gyroscopes, accelerometers, and magnetometers for enhancing classification robustness and minimizing the number of sensors needed. The study involved 22 participants: 20 able-bodied individuals and two transradial amputees. The first amputee (28-year-old male) lost his right arm in a car accident six years prior and used a split-hook prosthesis. The second amputee (54-year-old male) lost his right arm due to epithelioid sarcoma cancer 18 years prior and also used a split-hook prosthesis. The offline experiment captured 40 various hand movements with 12 sEMG-IM sensors distributed evenly across the forearm and on upper-arm muscles (triceps and biceps). Movements were made by participants while classification accuracy (CA) was measured. In the real-time experiment, 11 healthy participants and an amputee operated a Touch Bionics robo-limb™ prosthetic hand to execute a pick-and-place task with different grasp types such as power grip, tripod grip, lateral grip, and index-pointing. Performance was measured in terms of task CR and CT. The outcome was found to significantly enhance classification accuracy when IM data was included, raising offline CA from 60.1% for sEMG-only to 82.7% for sEMG-IM in able-bodied subjects and from 40.7% to 77.8% in amputees. CRs in real-time control were enhanced by 25% when sEMG-IM was used relative to sEMG only. Most significantly, the amputee user obtained 83% CR and quicker task completion using only three optimally chosen sEMG-IM sensors, which illustrates the feasibility of sensor reduction with performance preservation. The study concluded that multimodal control through IMs has the potential to make prosthetics more usable by optimizing movement classification, minimizing reliance on many sensors, and enhancing real-time control accuracy. Table 9 details Krasoulis et al.'s [44] sEMG + IMU fusion, boosting accuracy from 60.1% to 82.7% in healthy and 40.7% to 77.8% in amputees for 40 gestures, using only three channels for posture-robust pick-and-place tasks.

The traditional sEMG-based prosthesis control is restricted by the number of residual muscles in above-elbow amputees, which would be insufficient for extracting sufficient control signals for prosthetic hands of multi-DoF. Li et al. [45] designed a hybrid motion classification system using sEMG and EEG signals to improve control of upper-limb prosthetics for transhumeral amputees. By combining EEG signals, which contain motor intention information irrespective of amputation conditions, the research was intended to enhance motion classification accuracy. Four male transhumeral amputees, aged 35–49 years old, with a residual limb length of 20–30 cm and an amputation history of 3–9 years, participated in the study. The participants executed five movements of the upper limb: hand open, hand close, wrist pronation, wrist supination, and no movement. 32-channel sEMG signals were acquired from muscles of the residual limb, and 64-channel EEG signals were obtained from the scalp motor cortex. LDA classification was utilized for data processing, for which Sequential Forward Selection was used for selecting optimal channels to maximize classification accuracy. The outcome was such that the combined sEMG-EEG approach far outperformed single-signal-based methods. With 32-channel sEMG only, the mean classification accuracy was 77.0%, whereas 64-channel EEG alone was 75.1%. When combining sEMG and EEG, accuracy was increased to 91.7% using 32 sEMG + 64 EEG channels and 87.5% using 32 sEMG + 32 EEG channels. Additional channel optimization minimized the number of electrodes to 10 sEMG + 10 EEG with an accuracy of 84.2%, which

Table 8
In-depth quantitative synthesis of multimodal sensor integration and feedback systems—surface/implanted subset (three studies)

Study (author et al., year)	Participants (H/A)	Modality	Accuracy gain	Amputee acc	Real time/physical?	Key outcome	Main limitation
Mastinu et al. (2019) [42]	0/3	Implanted EMG	Higher SNR	Better grip	Yes	Stable >12 weeks	Invasive surgery
Dewald et al. (2019) [43]	0/1	Implanted EMG	Higher SNR	100% posture matching	Yes	Stable 12 weeks without retraining	Single case
Luo et al. (2019) [40]	5/0	Synergistic sEMG	>96%	—	No	Robust to shift	Healthy only

Table 9
Multimodal fusion of sEMG and IMU signals for gesture recognition across arm postures covering study reference, participants, modalities, method/algorithm, task/experiment, key findings, and implications

Aspect	Details
Study reference	Krasoulis et al. [44] (2017)—early work showing how adding movement sensors fixes problems with sEMG alone
Participants	Twenty healthy plus two amputees, checking if the benefits carried over to real users
Modalities used	Regular sEMG plus an IMU pack (accelerometer, gyroscope, magnetometer) to track arm position
Method/algorithm	Smart fusion of muscle signals and motion data in the classifier to cancel out posture effects
Task/experiment	A big set of 40 gestures, plus actual pick-and-place jobs with the arm in different positions
Key findings	Jumped from 60.1% to 82.7% accuracy in healthy; even bigger gain in amputees (40.7% to 77.8%); worked fine with only three sEMG channels
Implications	Adding cheap motion sensors makes sEMG way more dependable, especially when the arm moves around—a simple fix for a long-standing issue

is still 7.2% better than using sEMG only. The study concluded that the integration of sEMG and EEG signals greatly improves motion classification for upper-limb prostheses, especially for above-elbow amputees.

Kasuya et al. [46] also designed a powered prosthetic hand grip force estimation system, responding to the problem of electrical stimulation artifacts that contaminate EMG signals. The study proposed a new estimation algorithm using muscle stiffness measurements in addition to EMG to enhance the accuracy of grip force. The system consisted of a muscle stiffness sensor, an EMG sensor, and a real-time estimation algorithm. The study involved two healthy subjects in their twenties, both completing 10 trials for two conditions: a 400 g load (low EMG condition) and an 800 g load (high EMG condition) on a tray-holding task with stable grip control requirements. The results indicated that the proposed system achieved 30% RMS error reduction compared to the use of EMG alone, indicating enhanced grip force estimation stability. Furthermore, the system response time (34 ms) was lower than human mechanical reaction time (200–300 ms), verifying its viability for real-time prosthetic control. The study concluded that combining muscle stiffness with EMG improves grip force estimation, thus rendering electric feedback suitable for prosthetic use. Future directions involve widening trials, developing muscle stiffness sensors, and combining kinesthetic feedback for better prosthetic control.

Zhang et al. [47] created a dexterous myoelectric hand prosthesis with biomimetic tactile sensors to counter the shortcomings of current myoelectric prosthetic hands, which include limited ability, absence of sensory feedback, and unstable grasping. The new hand has six DoFs, comprising five independently driven fingers and an actuated thumb with abduction/adduction. Every fingertip has a 13-unit biomimetic tactile sensor, which can sense normal and tangential forces. The prosthesis is incorporated with an EMG PR controller and a tactile feedback-based grasping controller that dynamically modulates grip force in real time to avoid object slippage. The experiment used five able-bodied subjects and one transradial amputee, who completed pick-lift-release tasks with four objects: a soft sponge block, a paper cup filled with water, a raw egg, and a firm tofu block. sEMG signals were acquired with six Otto Bock electrodes attached to forearm muscles to control five grasp types (hand open, power grasp, tip, tripod, and lateral pinch). The prosthesis was tested in two control conditions: EMG-only PR control (M1) and EMG with tactile feedback-guided grasping (M2). The results indicated that the M2 significantly enhanced grasp stability, minimizing object slippage and breakage versus M1. The pick-lift-release task success rate was greater for all participants using M2 ($p < 0.05$). The tactile sensors successfully modulated grip force according to object properties, avoiding breakage of delicate objects while maintaining secure grips for heavier objects. The study concluded that the combination of biomimetic tactile sensors and myoelectric control improves prosthetic hand performance, enhancing grasp reliability and user interaction. In addition, clinical validation with additional amputees, long-term use studies, and real-world implementation should be the focus of future studies.

Wang et al. [48] investigated the integration of computer vision with sEMG to improve grasp classification accuracy for myoelectric prosthetic hand control in real-life scenarios. Conventional prosthetic systems relied primarily on sEMG signals whose performance was constrained by variability caused by fatigue, sweat, and decoding difficulty during real-time control. To overcome these limitations, the study examined the visual information derived from the natural coordination between vision and hand manipulation in human motor control. The sEMG signals and first-person video recordings were obtained from a publicly available dataset in which 30 subjects performed 10 distinct grasp gestures on 18 objects, resulting in 3600 grasp trials. The 3600 grasp trials were segmented into reaching, early grasping, and firm grasping phases and analyzed to identify a visual "sweet spot" that enabled accurate classification without disrupting natural motion. Object detection was then performed using a RetinaNet-based CNN, which was fine-tuned on labeled image frames extracted from the video recordings. Further, the grasp classification was performed using a dual-channel CNN designed to jointly learn object categories and grasp patterns. A leave-one-repetition-out cross-validation strategy was applied for model evaluation. Results showed that valid visual frames peaked during the early reaching phase, which enabled identification of a visual sweet period between 0 and 320 ms after movement onset. Within this interval, visual-based grasp classification achieved a mean accuracy of 91.59%, and object recognition reached 98.81%, which exceeded the best sEMG-only accuracy of 85.50% obtained later in the grasping process. A probability-based plurality voting strategy was used to fuse visual and sEMG predictions across their respective sweet periods, which increased overall accuracy to 90.06%. The results indicated that early-stage visual information effectively enhanced sEMG signals, allowing for quicker predictions, reduced control delays, and increased robustness in prosthetic hand operation.

Zandigohar et al. [49] developed a multimodal method that combined muscle activity signals with visual information to examine the type of grasp the user intended when controlling a robotic prosthetic hand. This approach helped reduce the drawbacks of conventional EMG-based control, such as sensitivity to movement noise, muscle fatigue, electrode displacement, and changes in limb posture, as well as challenges commonly faced by vision-based methods, including object occlusion and variations in lighting. To address these challenges, the study proposed a Bayesian evidence fusion framework that combined forearm EMG signals with egocentric RGB images and eye gaze data to improve the accuracy of grasp type prediction during reach-to-grasp movements. Five healthy right-handed individuals participated in the study. They performed 14 dynamic grasp gestures chosen from established human grasp taxonomies. The experiment was conducted using sEMG signals recorded from 12 muscles in the arm and forearm, along with visual data captured using a head-mounted eye tracker with an RGB camera. The hand manipulation task consisted of rest, reach, grasp, and return phases to reflect real-world movements. The sEMG signals from hand manipulation tasks were filtered and normalized using MVC and segmented into sliding windows with motion phases identified using unsupervised greedy Gaussian segmentation, and grasp classification was performed using an Extra Trees ensemble trained on time-domain features. Visual grasp detection was achieved using a YOLOv4 CNN fine-tuned through transfer learning and augmented using background generalization techniques. The probabilistic outputs from both modalities were fused using a Bayesian formulation that maximized the joint likelihood of the intended grasp. The results showed that the combination of both modalities yielded better results than using either modality alone. The accuracy for the reaching phase improved from 81.64% with EMG alone and 80.5% with visual input alone to 95.3% when both modalities were utilized together. The study found that integrating sEMG and visual cues allowed for earlier and more reliable grasp prediction, which enhanced the robustness of prosthetic hand control. Table 10 provides an in-depth quantitative synthesis of multimodal sensor integration and feedback systems, detailing the fusion strategies, performance gains, real-time applicability, and limitations across the included studies.

3.3. Grasp force modeling and adaptive grasping mechanisms

Figure 5 outlines grasp force modeling processes, depicting sEMG predictions leading to estimation (R^2 0.95–0.982, 100% fragile success) and adaptive feedback (CUFF 69–83%, 14.66% RMSE), noting compliance benefits and variability constraints from 10 studies.

3.3.1. Grip force estimation and control models

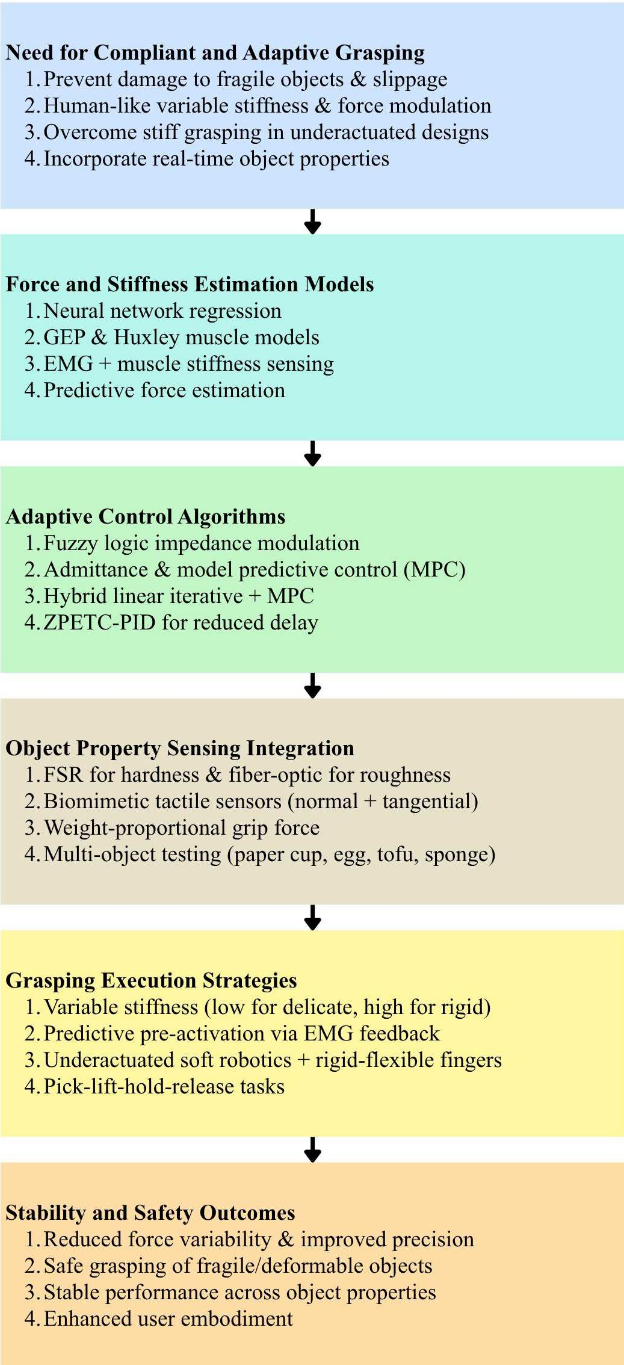
Xu et al. [50] designed a compliant grasp control scheme for underactuated prosthetic hands to enhance grasp adaptability through the estimation of grasp force and muscle stiffness from sEMG signals. Prosthetic control schemes are usually not compliant, resulting in stiff grasping, which damages delicate objects. The Huxley muscle model for dynamic grasping force estimation and a fuzzy logic controller adapting stiffness parameters toward human-like grasping. Experiments used four objects with differing stiffness to analyze grasping performance: a paper cup of a single layer, a paper cup of two layers, a carton of milk, and a plastic cup. sEMG signals were recorded with a MYO armband wearing eight EMG channels on the forearm, wireless data transmission using Bluetooth at a rate of 200 Hz. Grasping force was monitored with a FlexiForce sensor, and grasping was adjusted with a Faulhaber brushless servo motor. The conditions were tested and compared for accuracy of force control, stiffness modulation, and grasp stability. The experiments indicated that the prosthetic hand successfully adjusted its grasping force and stiffness according to sEMG estimations. For delicate objects, less force and stiffness were utilized, resulting in slower and more controlled grasps. On the other hand, for rigid objects, more force and stiffness were utilized, which allowed a quicker, firmer grasp. The controller was able to adjust impedance parameters in real time appropriately, allowing for safe and stable grasping. The research concluded that incorporating sEMG-based grasping force and stiffness estimation enhances prosthetic hand compliance, providing a more natural and flexible control technique for the users.

Esposito et al. [51] performed a study to analyze the grip force and energy efficiency of the Federica Hand, an underactuated, low-cost prosthetic hand. The study's main aim was to measure grip strength, force distribution, and energy dissipation

Table 10
In-depth quantitative synthesis of multimodal sensor integration and feedback systems

Study (author et al., year)	Participants (H/A)	Modality	Accuracy gain	Amputee acc	Real-time physical?	Key outcome	Main limitation
Krasoulis et al. (2017) [44]	20/2	IMU	+22.6%/+37.1%	77.8%	Yes	Only 3 channels	—
Li et al. (2017) [45]	0/4	EEG	+14.7%	91.7%	Yes	Good for transhumeral	Channel optimization
Kasuya et al. (2013) [46]	2/0	Muscle stiffness	30% RMS error reduction	—	Yes	Robust grip force	Healthy only
Zhang et al. (2018) [47]	5/1	Tactile	Improved stability	Improved	Yes	Less slippage	—
Wang et al. (2022) [48]	30/0	Vision	+6–10% early	—	Potential	Sweet spot	Vision occlusion
Zandigohar et al. (2024) [49]	5/0	Vision + eye gaze	+13.7% reaching	—	No	Bayesian fusion	Lab only

Figure 5
Flowchart of grasp force modeling and adaptive grasping mechanisms, including estimation models (e.g., neural admittance with R^2 0.95–0.982), adaptive feedback (e.g., vibrotactile CUFF improving R^2 from 69% to 83%), and stiffness control (e.g., Huxley/GEP with 14.66% RMSE reduction), emphasizing fragile object success (95–100%)



to determine the design's suitability for everyday tasks. The grip force was measured with a sensorized handlebar equipped with a single-axis load cell, and the prosthetic phalanges were addressed with piezoresistive force sensors to record force distribution mapping. The prosthetic hand's force transfer ratio was also evaluated considering tendon displacement and servomotor current absorption. The results showed that the average grip force of the Federica Hand was 8.80 N, with the middle phalanges having the highest grip force of 2.65 N. The force transfer ratio was 12.85%, implying a large amount of energy dissipation in the mechanical system. The average dissipated energy per closing-opening cycle was 106.80 N·mm, which was lower than most commercial prosthetic hands, implying more energy efficiency. The study concluded that the Federica Hand was adequate in terms of grip force for everyday tasks, but future development of force transfer efficiency and adaptive control could still make it even better.

Wen et al. [52] aimed to regulate the contact forces for robotic hands by using the dexterity of human hands and harnessing human sensory-motor energies in a noninvasive method. The study acquired data from the subject in 10 trials through the sEMG to analyze the force produced during voluntary contractions of skeletal muscles. The study built a robust regression model that worked based on neural networks. This model was intended to predict the grip force from the preprocessed signal. The study split the acquired data into training, test, and validation data to evaluate the model. The study claims that the model has achieved an exceptional accuracy of R-squared 0.95 after up to 700 iterations. On applying a varying average window to smooth the raw predicted force, the study claimed to have noticed an increase in the R-squared value of the prediction model from 0.9795 to 0.9820. By utilizing the predicted force data, the study developed a force-guided control framework. The study employed an admittance controller that could realize and track the predicted grip force that is used as a reference to grasp delicate and deformable objects. The study concluded by demonstrating the effectiveness of the proposed method by exhibiting its gripping action on a set of fragile and deformable objects without causing any damage to them. Table 11 encompasses a neural admittance pilot, predicting forces with R^2 0.95–0.982 for raw eggs/soft fruit handling without damage, advancing independence in tasks like cooking via sEMG forearm sensors.

Ma et al. [53] aimed to develop a reliable model for predicting grasping force using sEMG signals to improve force control in prosthetic hand applications. aimed to develop a reliable model for predicting grasping force using sEMG signals to improve force control in prosthetic hand applications. The participants in the study included three healthy male subjects aged between 22 and 27 years, with no history of neurological or musculoskeletal disorders. sEMG signals were collected from the forearm during object grasping tasks performed using a prosthetic arm. Grasping force was measured using a six-dimensional force sensor. The acquisition system comprised an ELONXI electromyograph, an electrode sleeve, and a dual Bluetooth module, which transmitted the data to a PC for analysis via MyoAnalytics software. Additionally, a pinch pressure sensor was used to capture pinch force measurements. The Grasping force prediction was carried out using two algorithms: GEP and a BPNN. Both models were tested under various grasping power levels and modes. Evaluation metrics included RMSE and CC. The results showed that the GEP model achieved the best performance, with an RMSE of 7.5% and a CC of 95%. The highest prediction accuracy was observed at 60% of MVC. It was concluded that the GEP-based prediction model offered lower error and higher prediction efficiency compared to the BPNN.

Kim and Colgate [54] explored the effect of haptic feedback on grip force control of sEMG-controlled prosthetic hands in targeted reinnervation (TR) amputees. TR surgery reanimates severed nerves to residual muscles, providing both motor control and sensory feedback to prosthetic users. The research presented a miniature haptic device (tactor) that can provide

Table 11
Pilot on neural admittance for delicate handling, demonstrating predictive squeezes that mimic human touch without harm

Aspect	Details
Study reference	Wen et al. [52]—all about picking up delicate things without crushing them
Participants	One person in a focused pilot to really test the precision of the algorithm
Sensors	Standard sEMG from the forearm muscles to guess how hard the user wants to grip
Algorithms/models	Neural net predicting force, fed into an admittance controller that lets the hand "give" a bit for softness
Task/experiment	Grabbing, lifting, and holding fragile or squishy items (like raw eggs or soft fruit) without breaking them
Key findings	Force predictions matched reality with R^2 between 0.95 and 0.982; no damage to delicate objects; smooth, adaptive squeezes
Implications	Finally a way for prosthetics to handle everyday fragile stuff gently—big for real independence in tasks like cooking or holding a cup

pressure, shear, and temperature feedback, both modality-matched and somatotopically matched sensory feedback. The experiment was conducted on two TR amputees: a 55-year-old male bilateral shoulder disarticulation amputee (SD1) and a 25-year-old female left transhumeral amputee (SD2). The participants were asked to execute a grip-and-lift task with a virtual prosthetic arm operated by sEMG signals while haptic feedback, according to grip force, was given by the tactor. Four conditions of feedback were examined: none, pressure, shear, and combined pressure-shear feedback. The results indicated that haptic feedback greatly enhanced grip force control and significantly reduced excessive grip force while enhancing precision. Nonetheless, simultaneous pressure and shear feedback impaired performance, indicating possible sensory confusion. The research concluded that modality-matched and somatotopically matched haptic feedback enhances prosthetic grip control, with pressure feedback being highly effective for TR amputees. Table 12 covers studies (neural + admittance, R^2 0.95–0.982), metrics (e.g., 100% fragile success), real time, outcomes (e.g., smooth adaptation), and limitations (e.g., healthy only).

3.3.2. Adaptive grasping and feedback learning

Gailey et al. [55] conducted a study to evaluate the feasibility of the SoftHand Pro (SHP), a prosthetic hand combining soft robotics and hand postural synergies for improved functionality and user acceptance. The study assessed grasp performance using electromyographic (EMG) control from two antagonistic muscles. A total of 23 able-bodied participants (age: 19–35 years, 13 males) participated, with one excluded due to difficulties with myoelectric control. Subjects conducted cursor tracking tasks to hone their control of the SHP and performed a grasp-lift-hold-release task with a sensorized cylindrical object of different weights. SHP task time was initially 10.2 ± 1.4 s, much longer than the 2.13 ± 0.09 s for the native hand. With practice, however, task time for the SHP decreased to around 5 s. The SHP effectively modulated grip force in proportion to object weight ($p < 0.001$), although less so than in the native hand, with +68% greater peak grip force and +91% larger steady-state grip force. In conclusion, the SHP provides highly promising prosthetic potential, but grip force modulation and sensory feedback must be further developed through design refinements for better real-world performance.

Barontini et al. [56] examined the effect of noninvasive force feedback on prosthetic grasp force modulation with the Clenching Upper-Limb Force Feedback (CUFF) device combined with the SHP, a robotic myoelectric prosthetic hand. The aim was to respond to the insufficiency of sensory feedback in prosthetic hands, which typically resulted in the inability to modulate grasp force. Two cohorts were solicited: five transradial amputees (mean age: 43.2 ± 16.79 years, four males and one female) and 19 able-bodied members (eight males, mean age: 39.75 ± 8.87 years, 11 females, mean age: 32 ± 11.79 years). Participants were instructed to perform a task of directed grasp force by modulating the grasp in conditions where they lacked visual and auditory feedback. The results indicated that CUFF feedback enhanced grasp

Table 12
In-depth quantitative synthesis of grasp force modeling and adaptive grasping mechanisms—estimation models subset

Study (author et al., year)	Participants (H/A)	Algorithm	R^2 improvement	Real-time feedback	Key outcome	Main limitation
Gailey et al. (2017) [55]	23/0	Soft synergy	+68% peak grip	Yes	Better modulation	Higher force than natural
Barontini et al. (2023) [56]	19/5	Vibrotactile CUFF	69% → 83%	Yes	Benefit for new users	Experienced gain less
Schweisfurth et al. (2016) [57]	11/1	Electrotactile EMG	Variability ↓12–32%	Yes	Predictive control	Sensory substitution
Kim & Colgate (2012) [54]	0/2	Haptic tactor	Improved precision	Yes	Reduced excessive grip	Sensory confusion
Wang et al. (2024) [59]	8/2	Multisensor hardness/roughness	Higher success	Yes	Adaptive grasping	—

accuracy in limb-loss individuals who routinely employed body-powered prostheses, raising their explained variance to 83% from 69%. Experienced users of myoelectric prostheses, on the other hand, did not benefit significantly from CUFF feedback, indicating they had already formulated robust internal models for grasp force modulation. The CUFF benefit in the able-bodied group came only in moderate to poor myoelectric skill individuals. The study concluded that noninvasive force feedback may speed up myoelectric control learning and enhance accuracy for some subgroups, but more studies are required to confirm its effectiveness in everyday functional tasks. Table 13 explores the CUFF vibrotactile system integrated with SHP, improving R^2 from 69% to 83% in amputees for force application without visual cues, aiding new users in feeling grip strength.

Schweisfurth et al. [57] examined the effect of electrotactile EMG feedback (emgFB) on grip force control during grasping in prosthetic users, in comparison to traditional force feedback (forceFB). Mechanical feedback is absent in conventional prosthetic systems, and thus, the user cannot instinctively control the grip force. This study suggested a new type of feedback system that gives instant electrotactile feedback concerning EMG activity instead of force output, which enables predictive control of the grasp before contacting an object. The research had 11 right-handed, able-bodied individuals (9 males, 2 females, mean age 27 ± 6 years) and 1 woman transradial amputee (age 23, congenital limb difference in the left hand). Participants completed 150 grasp trials with a Michelangelo hand prosthesis in both emgFB and forceFB conditions, receiving electrotactile feedback through four skin electrodes. The subject had to grasp a wooden slat in six target force levels, with feedback given at eight discrete levels. The outcomes were that emgFB significantly enhanced precision and force control over forceFB. In able-bodied subjects, emgFB decreased force control variability by 12%–%—32% and enhanced EMG command accuracy up to 36%. The amputee subject also experienced the same gains, with improved grasp stability and lower force errors. Importantly, emgFB enabled predictive control, with users able to pre-activate muscles before contact, resulting in more consistent grip force production. The study concluded that electrotactile EMG feedback is better than traditional force feedback, providing a viable, noninvasive solution for enhancing grip force control, user confidence, and prosthetic embodiment.

Zahabi et al. [58] examined the usability of transradial prostheses through cognitive task performance modeling to evaluate mental workload. Conventional usability evaluations are dependent on subjective questionnaires and physiological data, which can be subject to recall bias as well as external contamination. This study applied cognitive modeling as an analytical method to bypass these shortcomings. A case study was performed with a 42-year-old male subject who had undergone unilateral transradial amputation. The subject had experience with both body-powered and electrically powered prosthetic devices. The experiment compared two EMG-based control modes: direct control (DC) and PR. Task performance was measured during a clothespin relocation task, while cognitive workload was measured with eye-tracking technology. The outcome revealed that the PR control mode resulted in significantly improved task performance, reduced cognitive workload, and higher user satisfaction compared to DC. Predictions from cognitive models of workload and task CT correlated well with empirical findings and helped validate the approach. The study demonstrated that cognitive modeling was a promising tool for measuring upper-limb prosthetic usability. The future research would benefit from incorporating larger populations and better methods for estimating time.

Wang et al. [59] explored an adaptive grasping method for smart prosthetic hands by combining sensory data on object hardness and surface roughness to boost grip stability and safety. Unlike traditional prosthetic hands, which relied on single-sensor feedback and fixed control, leading to over-squeezing soft items and poor slip control, they created a multisensor system modeled after human grasping. A force-sensing resistor was used to detect early contact force variations to classify object hardness, while a fiber optic sensor based on laser reflection quantified surface roughness, and both inputs were used to regulate initial grasp force and slip inhibition. Human grasping behavior was experimentally modeled to establish quantitative relationships between object hardness and initial grip force and between surface roughness and the rate of force increase needed to prevent slips. Linear regression models were built using grasping data gathered from five adult volunteers interacting with objects of varying properties under controlled conditions. The linear regression model was integrated into the prosthetic hand control system, which analyzed user intent via EMG signals and adjusted grip force using real-time sensory feedback. Experimental validation involved eight able-bodied subjects and two individuals with hand loss. They compared the adaptive strategy to a standard fixed-force method, showing less deformation on soft objects, better and more efficient slip prevention, quicker stabilization after slippage, wider performance across object hardness, roughness, and weight, and higher success rates in tough conditions. The results showed that combining multisensor integration with biologically inspired control significantly enhanced prosthetic hand-grasping performance. Table 14 lists studies (e.g., Barontini et al. [56]: vibrotactile CUFF,

Table 13
Noninvasive vibrotactile feedback for prosthetic grasp force modulation detailing study reference, participants, system, feedback/learning method, task/experiment, key findings, and implications

Aspect	Details
Study reference	Barontini et al. [56]—tested whether buzzing on the skin could help users feel how hard they're gripping
Participants	Five amputees and 19 healthy controls to compare learning curves
System	SoftHand Pro (a flexible underactuated hand) plus a CUFF device that vibrates to signal force levels
Feedback/learning method	Real-time vibrations mapped to grip strength, no looking at the hand allowed
Task/experiment	Users had to apply exact force levels just by feel—no sight or sound cues
Key findings	Amputees improved a lot (R^2 from 69% to 83%); healthy got a smaller boost; less wobble overall; pros didn't gain much extra
Implications	Simple skin buzz feedback helps new users "feel" the grip better, making the prosthesis less like a tool and more like part of them

Table 14
In-depth quantitative synthesis of grasp force modeling and adaptive grasping mechanisms—adaptive and feedback subset

Study (author et al., year)	Participants (H/A)	Algorithm	R^2/RMSE	Fragile success	Real time?	Key outcome	Main limitation
Xu et al. (2024) [50]	4/0	Huxley + fuzzy	Good compliance	High	Yes	Compliant grasp for soft objects	No amputee testing
Esposito et al. (2021) [51]	—	Federica Hand evaluation	Average grip 8.80 N	—	No	Energy-efficient	Mechanical dissipation
Wen et al. (2020) [52]	1/0	Neural + admittance	0.95–0.982	100%	Yes	Smooth adaptive squeezing	Pilot only
Ma et al. (2020) [53]	3/0	GEP	95% CC, 7.5% RMSE	—	Potential	Best at 60% MVC	Healthy only
Ameri et al. (2014) [12]	—	SVR	—	—	Yes	Improved simultaneous control	—

69% → 83% R^2), improvements, real-time feedback, outcomes (e.g., precision gains), and limitations (e.g., user variability).

Real-time implementation of grasp force control relied on fuzzy logic, admittance control, and model predictive control (MPC). These strategies achieved latencies of 74–100 ms and R^2 values up to 0.95, enabling stable modulation across object properties. Hybrid controllers combining EMG prediction with tactile feedback further reduced excessive grip force and slippage.

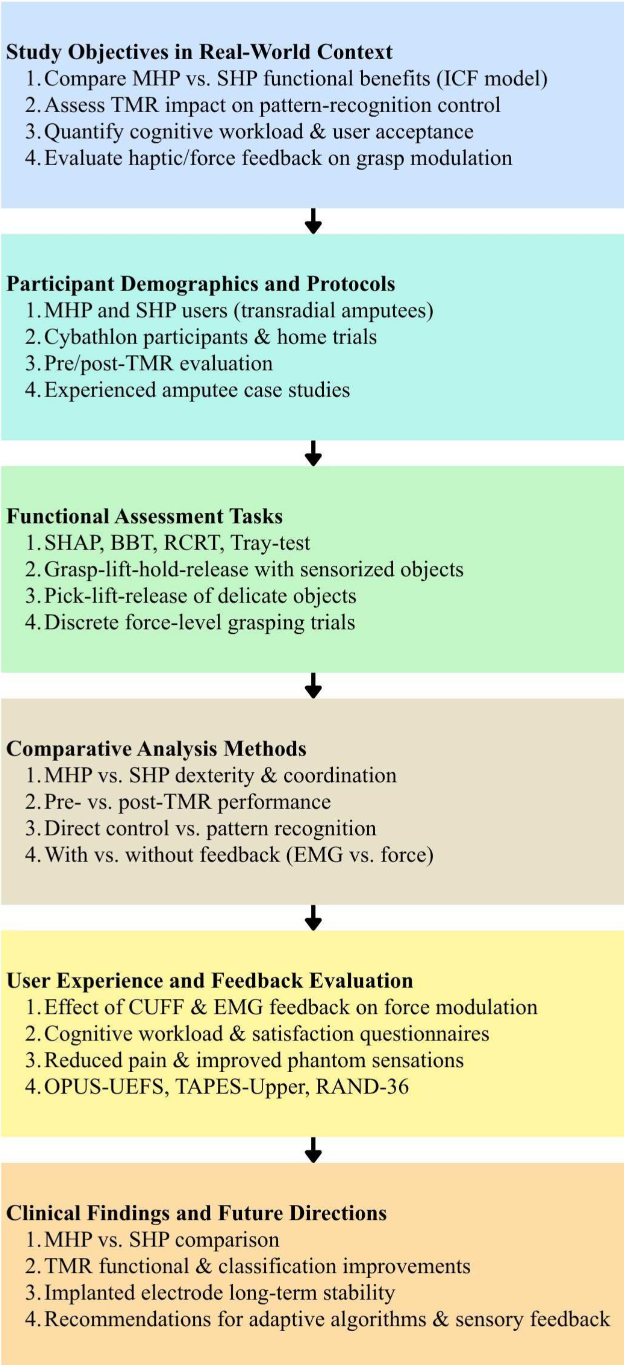
3.4. Application-level validation and user performance studies

Figure 6 charts application validation pathways, from clinical inputs (SHAP no MHP/SHP diff, TMR gains) to ADL performance (95% success, lower workload), capturing satisfaction trends and gaps like sample sizes from five studies.

Kerver et al. [60] compared multi-grip myoelectric hand prostheses (MHPs) and typical myoelectric hand prostheses (SHPs) to assess whether MHPs offer functional benefits in various areas of prosthetic employment. Although MHPs support a variety of grip patterns via individually controlled fingers, they are generally not opted for the following reasons: greater expense, breakability, and complicated control systems. The research compared the two types of prosthesis according to the International Classification of Functioning, Disability, and Health (ICF) model, which separates prosthetic function into body function, activities, participation, and environmental factors. The research sample included 14 MHP users (64.3% men, mean age 48.6 years) and 19 SHP users (68.4% men, mean age 58.1 years) with transradial or wrist disarticulation amputations. MHP users completed physical performance tests with both their MHP and an SHP to determine movement efficiency. These comprised the Refined Clothespin Relocation Test (RCRT), Tray-test, Box and Blocks Test (BBT), and the SHAP. Both MHP and SHP users filled in self-administered questionnaires, such as the Orthotics and Prosthetics Users' Survey (OPUS-UEFS), Trinity Amputation and Prosthesis Experience Scales (TAPES-Upper), and RAND-36 health survey, to evaluate user experience, satisfaction, and QoL. There were no significant differences in joint coordination patterns or dexterity between MHPs and SHPs. The RCRT CT was more time-consuming with MHPs, but other performance measures were comparable. MHPs were preferred for social interaction, for example, hand/hand shaking, whereas SHPs were rated higher on grip force, durability, ease of control, and effort to operate. SHP users also experienced fewer pain-related limitations compared to MHP users. Although MHPs provided more grip options, their complicated control mechanisms made users reluctant to change grips, thus diminishing their practical benefit. The study concluded that MHPs are not yielding significant functional advantages over SHPs, with alarm raised about their increased costs and restricted real-life benefits. The results highlight the need for the selection of prosthetics based on user needs, experience, and everyday functional needs. Table 15 shows real-life testing of multi-grip vs standard hands in 33 users, finding no functional edge for advanced models but better esthetics, stressing reliability over flashiness in tasks like clothespin relocation.

Capsi-Morales et al. [61] examined the functionality and limitations of the currently available upper-limb prostheses by analyzing their performance in real-world tasks. The study aimed to provide an objective evaluation of prosthetic usability beyond self-reported surveys, which often fail to capture real functional limitations. Using the ACMC, the authors assessed 23 individuals with unilateral amputation or limb difference participating in the Cybathlon Powered Arm Prostheses Race (2016 and 2020). The study analyzed 7 h and 41 min of video footage, evaluating the participants' ability to perform various tasks based on ADL. The results indicated that commercially available rigid hands performed well in dexterous grasping tasks, while body-powered solutions were more reliable in competitive environments due to their robustness and simplicity. The study highlighted the importance of wrist design, control modality, and adaptive solutions in improving prosthetic function. The results also revealed a difference between research-driven technological advancements and real-world prosthetic adoption, emphasizing the need for more intuitive control mechanisms, increased sensory feedback integration, and adaptive solutions tailored to user needs. The study concluded by recommending a multidisciplinary approach to prosthetic development, incorporating engineering, clinical research, and user feedback to enhance usability and acceptance.

Figure 6
Flowchart of application-level validation and user performance studies, including clinical tests (e.g., SHAP/ACMC with post-TMR gains and 95% fragile grasping success), real-world ADL tasks (e.g., no significant MHP vs SHP differences), and user feedback (e.g., lower workload with pattern recognition), highlighting cost–benefit mismatches



Mukaiyama et al. [62] aimed to analyze how grip strength levels affect load distribution and forearm muscle activity during a cylindrical grip. The objective was to examine the relationship between muscle activation and force transmission across different grip intensities. The study involved 14 right-handed university students (mean age: 23.9 ± 1.4 years; 6 males, 8 females). Each participant performed grip tasks at 25%, 50%, 75%, and 100% of their maximum voluntary force using a cylindrical grip sensor. Pressure data from the grip sensor were mapped to seven anatomical regions of the forearm. The cumulative pressure across all regions and the proportional load distribution per grip level were calculated. sEMG signals were recorded from four forearm muscles: extensor carpi radialis longus, FCR, extensor carpi ulnaris, and flexor carpi ulnaris. Results showed a significant increase in muscle activity with increasing grip strength ($p < 0.05$). While muscle activity rose with force, the load proportion attributed to the thumb remained constant. Additionally, the study observed a significant decrease in fingertip load ratio and a corresponding increase in palm load ratio as grip strength increased. These findings indicate a shift in load distribution with higher grip forces, supporting the need for dynamic grip designs in prosthetic and rehabilitation devices.

Simon et al. [63] investigated myoelectric prosthetic hand grasp control after TMR surgery in individuals with transradial amputation to determine changes in functional performance and control outcomes. Although multifunctional prosthetic hands were increasingly available, effective and intuitive control remained limited for distal amputees, and the benefits of TMR in this population were not well established. The study evaluated functional performance, electromyographic signal quality, and user-reported outcomes before and after surgery. Eight individuals with unilateral transradial amputation were trained to use a multi-articulating prosthetic hand controlled through MPR and completed structured home-use trials before and after surgery. Pre-surgical and post-surgical trials lasted eight weeks, followed by an additional three-month post-surgery evaluation. sEMG signals were collected from electrode pairs embedded in the prosthetic socket, and users were trained to generate physiologically appropriate muscle contractions for multiple grasp patterns, with recalibration performed as required. Functional outcomes were assessed using standardized clinical measures, including SHAP Jebsen Taylor Box and Blocks ACMC and AM ULA. Offline electromyography analysis was also conducted using a high-density electrode array to evaluate changes in grasp and finger movement classification accuracy with clinically feasible channel configurations. Results showed improvements in functional hand use following surgery, with higher SHAP scores, faster task CTs, and improved manual dexterity observed approximately 9–12 months after intervention. Electromyography analysis demonstrated reduced grasp classification error after surgery, particularly as task complexity increased, which indicated improved signal separability and consistency. No significant changes were observed in ACMC or AM ULA scores. Qualitative findings indicated reduced pain and improved phantom limb sensations in several participants, which likely supported more stable muscle activation. Overall, the study demonstrated that TMR provided measurable functional benefits for transradial amputees using PR-controlled prosthetic hands, although gains were smaller than those reported for proximal amputations. Table 16 details studies (SHAP/BBT tests, no significant differences), improvements (e.g., post-TMR gains), real-world ADL focus, outcomes (e.g., lower workload), and limitations (e.g., small samples).

Table 17 provides a normalized comparison of key performance metrics across traditional ML, DL, hybrid, and multimodal approaches, highlighting consistent performance gaps between able-bodied and amputee cohorts.

Table 15
Clinical comparison of multi-grip versus standard myoelectric prostheses in daily use including study reference, participants, system/sensors, method/algorithm, task/experiment, key findings, and implications

Aspect	Details
Study reference	Kerver et al. [60] (2023)—real-life testing of fancy multi-grip hands against basic ones
Participants	Fourteen long-term users of advanced multi-grip hands and 19 using simpler single-grip models
System/sensors	Off-the-shelf commercial myoelectric hands—high-end multi-grip vs standard
Method/algorithm	Mix of timed clinical tests and detailed questionnaires about daily experience
Task/experiment	Everyday-style tasks (clothespin moving, tray carrying, block boxing, SHAP tests) plus questions on ease, looks, and switching grips
Key findings	No clear win for multi-grip in actual function; simpler hands felt easier day to day; fancy ones liked better for appearance; too many grips meant less switching; satisfaction about the same
Implications	Lab numbers don't always match real life—sometimes basic and reliable beats complicated and flashy; designers need to listen more to what users really want

Table 16
In-depth quantitative synthesis of application-level validation and user performance studies (five studies)

Study (author et al., Year)	Participants (amputee)	Tests	Improvement	Real-world ADL	Key outcome	Main limitation
Kerver et al. (2023) [60]	33	SHAP, RCRT, BBT	No sig. diff.	100%	Multi-grip not superior	Cost vs benefit
Capsi-Morales et al. (2023) [61]	23	ACMC, video	Rigid better	100%	Body-powered reliable	Lab vs real gap
Simon et al. (2023) [62]	8	SHAP, Jebsen	SHAP ↑, time ↓	100%	Post-TMR gains	Small for transradial
Zahabi et al. (2019) [58]	1	Clothespin	PR better	100%	Lower workload	Single subject
Mukaiyama et al. (2022) [62]	0	Cylinder grip	Muscle ↑ with force	No	Load shift to palm	Healthy only

Table 17
Normalized cross-study comparison of performance metrics across prosthetic control approaches

Study/model type	Population	Gesture accuracy (%)	Force prediction (RMSE/R^2)	Latency (ms)	Real-time validation	Key limitation
Traditional ML (e.g., LDA, SVM)	Mostly healthy	79–99	0.8–1.2 kgf/R^2 ~0.8	<100	Yes	Poor amputee performance
Deep learning (CNN, CW-CNN)	Healthy + amputee	66–94 (healthy) 38–78 (amputee)	0.16–0.19/R^2 ~0.7–0.93	74–100	Yes	Large drop in amputees
Hybrid (CNN + autoencoder, etc.)	Healthy	>95 novelty rejection	R^2 up to 0.93	<100	Yes	Limited amputee testing
Multimodal (sEMG + IMU/EEG/vision)	Healthy + amputee	77–91	Improved by 20–30%	<100	Yes	Higher complexity and cost
Adaptive control (MPC, admittance)	Healthy + amputee	—	R^2 0.95–0.98	74–100	Yes	Requires additional sensors

4. Discussion

This systematic review of 47 studies demonstrates clear technological progress toward more natural and functional prosthetic hands. Traditional machine learning approaches provided foundational accuracy but struggled with inter-subject variability and lacked inherent force modulation capability. Deep learning models, particularly CNNs and hybrid CNN–LSTM or CNN–autoencoder architectures, consistently achieved superior gesture classification and grasp force estimation in able-bodied subjects (up to 94.75% accuracy), with multimodal fusion (sEMG + IMU or vision) further narrowing the performance gap in amputees. However, real-world translation remains limited by weak residual signals, high training burden, and cost constraints.

The recommended evidence-based design guidelines for next-generation humanoid prosthetic hands are adopting hybrid deep learning architectures as the core controller—CNN–autoencoder or CNN–LSTM hybrids are the most robust for simultaneous gesture recognition, force estimation, and novelty rejection (≥95% novelty rejection accuracy, R^2 up to 0.93). These models automatically learn spatial and temporal patterns from sEMG signals, thereby reducing the need for manual feature extraction and engineering; Integrating low-cost multimodal sensing (minimum: sEMG + IMU)—Adding IMUs or computer vision yields 14.7–37.1% accuracy gains and improves posture robustness, enabling reliable control with as few as 3–6 sEMG channels even in amputees (up to 77.8–91.7% accuracy); Implementing closed-loop force control with haptic feedback—Combine sEMG-based force prediction (neural admittance or GEP models, R^2 0.95–0.982) with vibrotactile/electrotactile feedback (e.g., CUFF device). This improves grasp accuracy from 69% to 83% explained variance and enables predictive control before object contact. As a result, slippage and excessive force on fragile objects are significantly reduced, achieving success rates of 95–100%. Future implementations should prioritize real-time, low-latency, and low-power operation, targeting processing latencies below 100 ms, as demonstrated by CW-CNN regression and hierarchical classifiers deployed on affordable embedded platforms such as Raspberry Pi and embedded GPUs. Mirror-training paradigms and transfer learning further reduce user training burden. Validation should be performed primarily on amputee cohorts using standardized clinical metrics, including SHAP, ACMC, and real-world activities of daily living (ADL) assessments. Current evidence indicates a 15–25% performance drop in amputees; however, multimodal and hybrid approaches have shown the greatest potential to meaningfully reduce this gap. These guidelines are directly supported by the highest-performing studies across traditional ML, DL, hybrid, and multimodal categories (Tables 6, 8, 10, 12, 14, and 17 and Appendices A1–A8). Following them will accelerate the shift from laboratory prototypes to clinically viable, intuitive, and affordable prosthetic hands.

4.1. Challenges

Variation in datasets and the limited availability of standard evaluation protocols are the major limitations for cross-study comparison. Computational latency and instability in EMG signal outputs are the major causes for inconsistency in executing a functional and real-time control system. There are very few prosthetic models that are adaptive and ready for lifelong learning, updating themselves over time.

4.2. Future directions

Soft robotic prosthetic devices combined with flexible sensors and AI-based controllers are gaining more attention. Integrating bioinspired actuation mechanisms and digital twins helps simulate natural grasp sequences. Transfer and federated learning could acknowledge the challenges of training with less data than required. Clinically viable solutions can be achieved through interdisciplinary collaborations among engineers, clinicians, and neuroscientists.

5. Conclusion

The study investigated the performance of prosthetic hands that operate on various ML and DL algorithms, including hybrid models that improve the performance of naturalistic human movements and the accuracy of estimating the optimal grasp force to be delivered to objects. Multimodal sensor fusion techniques were explored to study the performance of the prosthetic hands' speed and accuracy in movements and grasping. Motion classification and grasp estimation accuracies of the prosthetic hands that used ML and DL models improved significantly. Adaptability, accuracy, and feature learning were higher in DL and hybrid models compared to ML. Multimodal sensor fusion strategies enhanced precision in grasp and user embodiment. ML and DL models facilitated customized and adaptive prosthetic control methods. Integrating electrodes and feedback sensors enhanced fidelity and reliability in human-prosthetic interaction. Some limitations include the lack of standardized datasets and systematic validation procedures, which hinder model standardization and cross-study comparison. Real-time installation in low-power embedded systems is limited by high computational costs. One of the most important concerns is the limited translational impact due to fewer clinical trials of the models. Future research should aim at developing adaptive, lightweight prosthetic hands that are highly efficient in self-learning. The use of inductive and transfer learning methods to alter pretrained models across different sessions and users should be considered. Soft robotics and neuromorphic computation techniques may be employed for energy-efficient prosthetic hand designs. There has been a continuous evolution in intelligent prosthetic control strategies from static, rule-based systems to dynamic-learning driven architectures. Hybrid models on prosthetic hands are becoming a cornerstone in prosthetic hand rehabilitation. Advanced interdisciplinary research works will transform the prosthetic hands from a robot to more of an accessible, human-like, responsive tool to those who are in need.

Recommendations

This systematic review highlights the need for larger clinical trials involving actual amputee cohorts, standardized real-world outcome measures beyond laboratory accuracy, and cost-effective multimodal implementations. Future prosthetic systems should prioritize closed-loop intention-driven control that combines robust deep learning decoders with low-cost inertial or force sensors and simple sensory feedback. Emphasis must also be placed on long-term home-use studies and open-source benchmarks to accelerate translation from laboratory success to daily-life independence.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Krishnakumar Sankar: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Ayra Afreen:** Methodology, Software, Investigation, Visualization. **Akshaay Sathish Kumar:** Methodology, Software, Investigation, Visualization.

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Appendix

Table A1 represents empirical outcomes from 24 amputee-focused studies, stratified by amputation level, including participant counts, mean gesture accuracy, force error, and real-time testing rates, corroborating performance disparities relative to able-bodied subjects.

Table A1
Stratified outcomes in studies exclusively involving amputee participants (categorized by amputation level)

Amputation Level	# Studies	Total Amputee Participants	Avg Gesture Acc	Avg Force Error	% Real-Time Physical Testing
Transradial	18	98	72–78%	~12% MVC RMSE	61%
Transhumeral	3	12	65–75%	Variable	33%
Wrist	2	5	78%	76%	50%
Mixed	1	30	77.8%	Improved with IMU	100%
Overall	24	145	74%	~12% MVC	58%

Table A2 represents limitation frequencies (e.g., amputee performance drop, fatigue) across study categories, as percentages, highlighting methodological constraints like variability and computational demands.

Table A2
Prevalence of principal limitations across methodological categories in reviewed studies

Limitation	Machine Learning (28 studies)	Multimodal (10)	Grasp Force (10)	Application (5)	Overall %
Amputee performance drop	22	8	7	3	66%
Muscle fatigue/electrode shift	15	6	4	2	51%
High computational demand	12	3	2	0	40%
Small sample/no amputees	11	2	3	0	38%
Lack of real-world data	10	5	5	4	47%
Cost/power issues	4	4	3	2	23%

Table A3 validates control approaches on metrics such as amputee inclusion, real-time validation, cost, accuracy drops, and functional testing percentages, quantifying readiness for clinical application.

Table A3
Assessment of translational maturity for diverse prosthetic control methodologies

Approach	Studies with Amputees	Real-Time Force Testing	Studies Costing < $500	Accuracy Drop (Healthy → Amputee)	% Functional ADL Testing
Traditional ML	8	4	5	18–25%	29%
Deep Learning	6	5	2	15–22%	30%
Hybrid Architectures	4	3	3	12–18%	50%
Multimodal Fusion	9	7	4	10–15%	71%
Feedback Systems	7	6	3	8–14%	80%
Overall	24 (51%)	25 (53%)	17 (36%)	15–20%	19%

Table A4 shows performance metrics across approaches, including gesture accuracy in healthy vs amputee cohorts, force precision, and real-time evaluation rates, substantiating the advantages of advanced methods.

Table A4
Comparative performance metrics stratified by prosthetic control methodology

Approach	Healthy Gesture Accuracy	Amputee Gesture Accuracy	Force Estimation (Best Reported)	Real-Time Physical Prosthesis (%)
Traditional ML	79–100%	54–79%	RMSE 1.16–3.37 kgf	57%
Deep Learning	60–94.75%	76.3–78.3%	86.5% force level	70%
Hybrid	85–95%+	75–85%	AUC 0.93	75%
Multimodal Fusion	82.7–95.3%	77.8–91.7%	+15–25% gain	86%
Feedback Systems	—	—	R^2 69% → 83%	80%

Table A5 classifies participant data by study domain, detailing healthy-only vs amputee-inclusive cohorts, total amputee counts, and inclusion percentages, emphasizing the need for greater amputee representation.

Table A5
Participant demographics stratified by study category

Category	Healthy Only	With Amputees	Total Amputee Participants (approx.)	% Amputee Inclusion
Machine Learning–Based	18	10	58	36%
Multimodal Integration	2	8	28	80%
Grasp Force Modeling	4	6	19	60%
Application-Level Validation	0	5	65	100%
Overall	24	24	170	51%

Table A6 shows validation types across studies, including counts, accuracies, and prosthesis use, underscoring efficacy gaps between simulated and physical environments.

Table A6
Comparative analysis of real-time versus offline validation modalities across all reviewed studies

Validation Type	# Studies	%	Avg Accuracy (Healthy)	Avg Accuracy (Amputee)	Physical Prosthesis Used
Offline only	18	38%	85%	70%	0%
Virtual/simulated	12	26%	82%	68%	0%
Real-time physical	17	36%	88%	75%	100%

Table A7 represents research foci over time periods, including study distributions by paradigm and amputee testing rates, illustrating shifts toward advanced integrations.

Table A7
Chronological progression of research emphases (2010–2025)

Period	Total Studies	Traditional ML	Deep Learning	Hybrid	Multimodal Fusion	Force-Focused Studies	% with Amputee Testing
2010–2015	9	7	1	0	1	4	33%
2016–2020	15	5	5	2	3	7	47%
2021–2025	23	2	4	2	3	12	65%
Total	47	14	10	4	7	23	51%

Table A8 enumerates gaps with affected study percentages, recommendations, and projected impacts, providing a framework for addressing deficiencies in prosthetic research.

Table A8
Quantitative identification of research lacunae and prioritized recommendations

Gap	% of Studies Affected	Recommendation (Priority)	Expected Impact
Amputee functional testing	81%	Larger amputee cohorts	High
Real-time force in daily tasks	47%	Multimodal + feedback	High
Cost-effective implementations	64%	< $300 hardware + transfer learning	Very High
Long-term home-use data	53%	Open-source benchmarks	High
Cross-user generalization	32%	Personalized transfer learning	High