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Intelligent Control Technologies for Smart Prosthetic and Orthotic Devices: A Systematic Review

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ABSTRACT

Smart prosthetic and orthotic systems are evolving from isolated assistive devices into closed-loop human–machine systems that integrate biological sensing, intelligent intent decoding, adaptive actuation, and sensory feedback. This systematic review brings together evidence from 70 sources on recent advances in intelligent prosthetic and orthotic systems. The reviewed approaches include the following: surface and high-density electromyography, peripheral neural interfaces, multimodal sensing, artificial intelligence, adaptive and reinforcement-learning-based control, sensory restoration, digital twins, cybersecurity, and clinical translation. The review was conducted and reported in accordance with the PRISMA 2020 guidelines. Records were retrieved from Scopus, PubMed/MEDLINE, and Web of Science and screened using predefined eligibility and scope criteria. Of the 312 records identified, 48 duplicates were removed, leaving 264 records for screening. Following the screening process, 115 full-text articles were assessed for eligibility, and 70 sources were ultimately included in the qualitative synthesis.

Collectively, the findings indicate that, the evidence points to a gradual shift from conventional, fixed myoelectric control toward more adaptive and multimodal control architectures. Approaches such as targeted muscle reinnervation, regenerative peripheral nerve interfaces, implanted electrodes, and bidirectional neural interfaces may improve signal specificity and expand the number of controllable degrees of freedom.

However, high decoding accuracy achieved under controlled laboratory conditions does not necessarily translate into meaningful clinical benefits. Important factors, including signal drift, the need for repeated recalibration, response latency, long-term stability, usability, cost, and performance during real-world activities, remain inconsistently evaluated across studies.

Based on these findings, the review proposes an end-to-end framework that links biological and environmental sensing with signal conditioning, user-intent interpretation, adaptive actuation, sensory feedback, and progressing from laboratory research and prototype development through validation and clinical testing to regulatory approval, clinical implementation, and ultimately real-world use.

The review also the review identifies several key priorities for future research, including standardized benchmarking protocols, longitudinal multicenter validation, interpretable and uncertainty-aware artificial intelligence, durable neural and sensing interfaces, cybersecurity, and patient-centered outcome measures. Therefore, addressing these areas will be essential for moving intelligent prosthetic and orthotic technologies from promising experimental systems toward reliable, clinically deployable solutions.

Index Terms: prosthetics and orthotics, myoelectric control, surface electromyography, neural interfaces, sensor fusion, artificial intelligence, reinforcement learning, sensory feedback, digital twins, clinical translation.

INTRODUCTION

Background and Motivation

Prosthetic and orthotic (P&O) technologies are increasingly conceived as integrated human–machine systems rather than isolated mechanical replacements. User acceptance, functional performance, comfort, and accommodation of biological and behavioral variability are therefore central engineering requirements. Recent evidence on prosthesis uses and user needs emphasizes that technical sophistication alone does not ensure sustained adoption, while neurointegrated lower-limb research increasingly frames prosthesis design around the user and the biological interface

This transition is enabled by advances in biological sensing, embedded computation, robotics, and neural engineering. Current systems can combine surface electromyography (sEMG) or high-density sEMG (HD-sEMG) with inertial, kinematic, visual, and ultrasound information, while adaptive controllers attempt to compensate for task and user variability at the hardware level, greater dexterity means that the prosthetic system has to handle a wider range of movements and control commands. As the number of possible movements increases, the system needs more reliable ways to understand the user's intentions and execute them safely [5], [10]– [16], [21]– [24], [33], [34]. sEMG remains a useful option because it is noninvasive and can be readily integrated into wearable devices. However, the quality of sEMG signals can change considerably depending on where the electrodes are placed, the user's physiological condition, interference from nearby muscles, and natural variations in the signal over time.

HD-sEMG and improved decomposition methods increase spatial information and can support more detailed neuromuscular characterization. Surgical interfaces—including targeted muscle reinnervation (TMR), regenerative peripheral nerve interfaces (RPNIs), and implanted electrodes—seek more specific pathways between residual neural activity and prosthetic control system. [6], [19], [25]- [27], [37]- [45], [36], [64]

Artificial intelligence (AI) represents another major driver of progress in the field of prosthetics and orthotics control. Rather than relying solely on traditional fixed pattern-recognition methods, recent advances increasingly use CNN-based decoding strategy, adaptive neural control technology, transfer learning, transformer models, and reinforcement learning to interpret user intent in order to improve control performance. Multimodal sensor fusion also provides the controller with a richer picture of the user's movement by bringing together complementary information from physiological, kinematic, inertial, visual, and ultrasound signals.

The third development is the movement toward closed-loop control. Artificial sensory feedback can be delivered through incidental, noninvasive, intraneural, or spinal stimulation, allowing information measured at the prosthetic interface to influence subsequent motor behavior. This establishes a systems perspective in which sensing, inference, actuation, and feedback are evaluated as a coupled control architecture. [15], [48]– [54], [69]

Research Gap and Contribution

Existing reviews commonly isolate myoelectric control, lower-limb powered prostheses, exoskeleton control, neural interfaces, or sensory feedback. The present evidence base instead permits an integrated analysis of how these layers interact and how engineering advances relate to clinical translation. A second gap concerns evaluation: studies report classification accuracy, trajectory estimation, gait performance, force estimation, sensory discrimination, and user outcomes using heterogeneous protocols, making direct comparison difficult. Although advanced neural interfaces, digital twins, explainable artificial intelligence (XAI), and connected systems have demonstrated significant promise, there is still limited long-term evidence confirming their reliability and effectiveness in today's routine clinical practice. [7], [11], [12], [16], [18], [49], [56], [61], [62], [65], [66], [70] This review therefore brings these developments together within a unified, end-to-end framework, by linking biological and environmental sensing with signal conditioning, intent interpretation, adaptive actuation, sensory feedback, and ultimately clinical application in order to address these gaps. In addition, the review highlights practical criteria for consistently assessing these technologies, including signal

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reliability and robustness, decoding and tracking accuracy, system response time as well as signal latency, recalibration needs, long-term stability, performance under real-world conditions, patient-centered outcomes, safety, and overall readiness for Clinical adoption

Aim and Objectives

The aim is to critically synthesize intelligent control strategies for smart P&O systems and identify the engineering conditions required for reliable clinical translation. The objectives are to: 1) map intelligent sensing and control approaches; 2) compare noninvasive and surgically mediated interfaces; 3) assess progression from conventional pattern recognition to adaptive deep and transformer-based decoding; 4) evaluate multimodal sensor fusion; 5) assess sensory feedback and bidirectional control; and 6) identify methodological, clinical, regulatory, economic, and cybersecurity barriers and define a research roadmap.

METHODS

Review Design

The review was conducted base on the PRISMA 2020 framework and used a qualitative narrative synthesis approach. However, a quantitative meta-analysis was not attempted because the included studies showed substantial heterogeneity in several key areas, including study design, participant populations, prosthetic and orthotic applications, sensing modalities, control strategies, outcome measures, and the extent of clinical validation.

Information Sources and Search Window

The search covered PubMed/MEDLINE, Scopus, and the Web of Science Core Collection for literature published between January 2016 and July 2026. Search concepts combined prosthetics and orthotics, powered lower-limb rehabilitation, biological and neural sensing, intelligent control, and clinical translation. Key terms included surface electromyography (sEMG), high-density surface electromyography (HD-sEMG), artificial intelligence (AI), targeted muscle reinnervation (TMR), deep learning, closed-loop control, sensor fusion, sensory feedback, reinforcement learning, adaptive control, clinical translation, and digital twins.

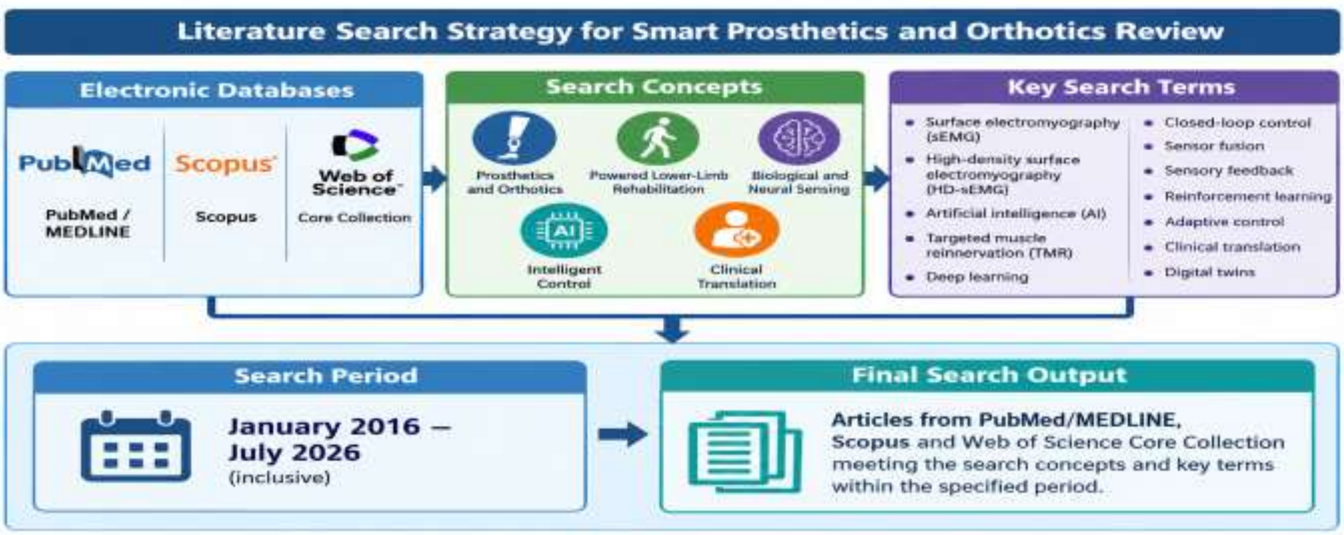

Figure 1. Infographic illustrating the literature search strategy generated using an AI-assisted image-generation tool based on the authors' predefined search strategy.

Search Concepts and Eligibility

Eligible sources addressed intelligent or adaptive control in upper-limb prostheses, lower-limb prostheses, orthoses, or powered rehabilitation systems and provided sufficient technical, clinical, human-use, or translational information for qualitative synthesis. Evidence classes included primary experimental

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investigations, clinical and human-use studies, engineering and technical reviews, systematic or scoping reviews, contextual or guideline evidence, preprints, and applied translational literature. Sources were excluded when they were duplicates, outside the specified publication window, unrelated to intelligent control or smart P&O applications, focused only on passive devices without an intelligent component, lacked sufficient information for synthesis, or were conference abstracts/editorials without adequate study detail.

Study Selection

The study-selection process was guided by the PRISMA 2020 guidelines to ensure that the systematic review was conducted and reported in a transparent, structured, and reproducible manner. A total of 312 records were identified through the database searches. After removal of 48 duplicate records, 264 unique records remained for title and abstract screening. Of these, 115 articles proceeded to full-text assessment. Forty-five records were subsequently excluded during full-text assessment, leaving 70 sources for the final qualitative synthesis. The retained evidence was intentionally heterogeneous and included primary experimental investigations, clinical and human-use studies, engineering and technical reviews, systematic and scoping reviews, contextual evidence, one preprint, and applied translational sources.

Stage	n	Description
Identification	312	Records identified
Duplicates	48	Removed
Screening	264	Title/abstract screened
Eligibility	115	Full texts assessed
Exclusion	45	Full texts excluded
Synthesis	70	Curated sources retained

Data Extraction and Quality Considerations

Data were extracted from the included studies based on key characteristics, including the following: study type and publication year, prosthetic or orthotic application, sensing or signal modality, control approach, main contribution, type of neural interface where applicable, sensory-feedback method, and reported limitations affecting translation into practice. The reported outcomes were then grouped into five broad categories. The first covered control and algorithmic performance, including classification accuracy, tracking error, response latency, and adaptation. The second focused on functional and biomechanical performance, such as task completion, gait performance, and movement quality. The third addressed human-centered outcomes, including comfort, usability, user satisfaction, acceptance, and cognitive or perceptual effects. The fourth considered safety and translational outcomes, including system robustness, stability, recalibration requirements, energy consumption, and adverse events. The fifth examined implementation and clinical-translation outcomes, including cost, maintenance requirements, user training, accessibility, long-term use, and performance in real-world settings.

RESULTS AND EVIDENCE SYNTHESIS

Evidence Profile

The 70 sources included in the review comprised 27 primary experimental studies, 15 clinical or human-use studies, 15 engineering and technical reviews, 4 systematic, scoping, or meta-analytic reviews, 5 landmark or contextual sources, 1 preprint, and 3 applied or translational studies.

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This distribution supports separate consideration of technological performance and clinical relevance rather than treating all evidence as equivalent.

Evidence class	n	Primary role
Primary experimental	27	Control, sEMG, AI, fusion, adaptive/RL, digital twins
Clinical/human use	15	Function, neural interfaces, sensory feedback, real-world use
Engineering/technical reviews	15	Technology synthesis and context
Systematic/scoping reviews/meta-analyses	4	Structured evidence synthesis
Landmark/contextual	5	Foundational technical context
Preprint	1	Emerging evidence
Applied/translational	3	Outcomes, economics, cybersecurity, regulation

Upper- and lower-limb prosthetic have distinct control requirements and are therefore best considered separately. Upper-limb prostheses mainly focus on dexterous grasping and the control of hand and arm movements across multiple degrees of freedom. In contrast, lower-limb prostheses must also support weight bearing while maintaining balance, coordinating gait timing, and adapting to interactions with the surrounding environment. Despite these differences, research in both areas increasingly highlights the importance of integrating the user's needs and experience, rather than focusing solely on device performance. Evidence on prosthetic use and user needs indicates that technical sophistication does not necessarily translate into sustained acceptance, while neurointegrated lower-limb research places increasing emphasis on biological compatibility and functional outcomes [1]– [4].

Over the years, there has been a rapid advance in the aspect of the lower limb prostheses. Despite the continuous improvement of each aspect of the already developed lower limb prostheses, there has also been a notable high rate of unfinished researches due to the need for a better understanding of human centered integration which is the psychosocial needs. However, the focus of many researchers shifted from device centered to having a patient satisfactory ready to use functional devices. Recent research tends towards high dexterity of degree of freedom for carrying out daily activities by the user. Additionally, a more standard grasping modes were added, real time sensor which connects to the joint angles of the fingers and the wrist, precision in design and a light weight prosthetic hands were achieved.

Upper-limb intelligent control has progressed from conventional direct myoelectric control toward pattern recognition, adaptive decoding, multimodal sensing, and neural interfaces. sEMG remains a practical noninvasive control signal, but electrode displacement, physiological variation, motion artefact, and inter-session signal drift can reduce reliability during everyday use. CNN-based and other learning-based approaches can improve movement-intent decoding, while self-recalibration and adaptive methods seek to reduce the need for repeated manual calibration [6], [19], [23]– [26], [45]. Clinical evidence involving TMR also indicates that pattern-recognition control can outperform direct control in selected users, although the generalizability of these findings remains constrained by study populations and experimental conditions [8].

Multimodal sensing further extends upper-limb control by combining biological signals with information about the device or external environment. Vision, ultrasound-based sonomyography, kinematic sensing, and other modalities can complement sEMG when individual signals are ambiguous or unstable. These approaches

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are particularly relevant to prosthetic hands that must infer both user intent and task context. The evidence suggests that multimodal systems can increase available information, but added sensors also increase computational, calibration, power, and integration requirements [21]– [24].

Over there years, it was seen that using control methods such as EMG tend to provide a weak signal which is due to artifacts motions. A more recent advance methods that was established are the use of vision sensors for generating information and the state the external environment. Additionally, regenerative peripheral nerve interfaces (RPNI) and targeted muscle reinnervation (TMR) shows promising in recent advances that were achieve, they serve to provide transected peripheral nerves through neuromuscular targets. Similarly, compact transformer-based hand gesture recognition (CT-HGR) was also proposed to overshadow the limitation that is related to most deep learning models which are the complexity of models, and signal processing [33], [45], [58], [59]. Moreover, one of the most challenging parts of the upper limb is the maintaining performance of the longitudinal robustness. Furthermore, using an enhance control accuracy approach such as adaptation and the use of machine learning has shown. Results prove that adaptation showed error which is notably from using a data set. [6], [10], [28], [30]

In addressing balance, gait timing, safe communication with the ground, joint coordination and load transfer, special control methods are required for lower limb prostheses and orthoses. The evidence retained which includes powered prosthetic control, online adaptive neural control, prosthetic controlled EMG driven, kinematic myoelectric fusion, assisted gait exoskeletons and robotic knee control [7], [10] – [16], [20], [21], [31]. Furthermore, these systems demonstrated how the lower limb control may not be assessed only through classification accuracy; rather, gait functionality, energy demand, performance tracking, stability and safety of user are evenly important.

Orthotic and rehabilitation-robotic systems constitute a distinct analytical category because their primary objective is often assistance or restoration of movement rather than replacement of a lost limb. Wearable ankle robots, gait-assistance exoskeletons, and adaptive robotic joints use sensing and intelligent control to regulate assistance according to task and user state [12]– [16], [31]. The literature therefore supports evaluating orthotic technologies using biomechanical and rehabilitation outcomes alongside controller performance.

In addition, a real-time study was done on the convolutional neural network bidirectional long-short term memory network (CNN-BiLSTM) model so as to forecast the joint angels of the knee. Moreover, the importance of the sEMG and the IMU signals with regards to the joint angle of the knee was predicted and for ensuring accuracy. In user's disability, the user safety, and stability is one level at which each prosthesis focuses on. Hence, the RL based is used rehabilitating the stability and effectiveness of the prosthetic. This RL based controller center of pressure (CoP) so as to maintain a stable state of motion during the rehabilitation. Furthermore, optimization algorithm is added to the generic transfemoral OpenSim model for prosthesis, it shows a reliable and fixed gait. Moreover, the integration of machinal sensors and EMG enhances the recognition of movements. In addition, inertial data was linked with the surface EMG so as to get more precise data for movements in the user lower limb. Lastly, another paper focuses on using deep reinforcement learning (DRL) and sensitivity and amplification control (SAC) methods to tackle the dynamics of movement in human exoskeleton interaction (HEI). [21], [31], [32], [34], [57]

sEMG remains the main noninvasive biological method of getting signals for myoelectric control given that it is relatively accessible and compatible with wearable systems. Moreso, deep learning methods, includes CNN architectures, can learn discriminative representations from multimodal EMGs, whilst transfer learning and adaptive approach addresses inter-end-user and variability inter-session [6], [19], [25], [26], [45], [64]. Additionally, HD-sEMG raises the spatial sampling and this will provide loaded data for intent decoding, nevertheless it also initiates more hardware and processing requirements [63]. These findings, promotes sEMG and HD-sEMG as one vital component of intelligent control, while emphasizing the need to report latency, robustness, performance of cross-session and recalibration rather than precision alone.

The sEMG still remains the main dominant noninvasive biological signal on the natural control methods base recognition pattern. Moreover, the natural control of prosthesis through sEMG proving a several number of amputees. The test relies on convolutional network for a certain number of hand movements. Deep neural networks results were consistent across amputees' participants. These has great potentials for enhancing the functionally and effectiveness of the quality of hand prosthesis. The utilization of HD-sEMG signals enhances the sampling mapping which has greatly enhances the representation of neuromuscular, data volume and complexity placement [19], [25]– [27], [63], [64]

A classifier base on CNN uses the short dimension latency which learns more about the direct representation of multichannel signals. Pre-processing, optimization and the net architecture have contributed to the simple analysis of the sEMG. The performance of the deep neural network has demonstrated that the network outperforms the intent of the decoding motor, giving effective output for the control of the signals coming from the EMG sensors. Moreover, transfer learning base parameter space addresses the challenge with sEMG classification. The results therefore, suggest that deep classifiers are best convenient for a cross subject of sEMG classification [6], [26], [28]– [30], [58], [59]

There is limitation on individual sensing modalities; Moreso, sensing fusion can lessen uncertainty by merging complementary information. the retained studies include ultrasound-based Sono-myography, kinetic myoelectric fusion, and controlled EMG vision [21] – [24]. Therefore, the multimodal architectures can enhance estimation of limb state or user intent, however, their functional value relies on placement of sensor, consumption of pawer, computational load, synchronization and robustness during real life experience.

The individual modalities have weaknesses nevertheless; fusion sensor compensate for that. A novel based feature model is designed to foretell the real-time accuracy of the prosthesis. Moreover, an ultrasound-based sensor was also introduced to determine the deformation of the muscle. Which is known as the sonomyography. This process is known to precisely classify an intended grasping of the individual hand and most especially people with the upper limb challenge. To further justify and approve the already established approached, dataset of the signals coming from the sEMG, there were three different objectives that were sets; comparison between conventional methods and the proposed methods, recognition robustness test, recognition of signals from the sEMG. In addition, some of the challenges that has been encountered over the years were lack of ready control, the deficiency in concurrent, sand lots more. Vision sensors remain one of the main sources of environmental sensing information which plays a major role in helping with the feeling of the prosthesis. Other models are the ANN, support vector machine (SVM), linear discriminate analysis (LDA) and k-nearest neighbor (KNN). [21]– [24], [33], [34]

Peripheral neural interfaces give additional pathways for increasing the specificity of biological control. More so, TMR and RPNI utilizes surgically modified or neural regenerated pathways to yield more informative signals control, whilst implanted electrodes can aid chronic recoding and two-ways communications [37] – [44]. In addition, clinical and translational evidence signifies great potential benefits in specificity and integration of the sensory motors, nevertheless, these techniques convey surgical, maintenance, biological and long-term requirements stability which differ essentially from noninvasive sEMG systems.

Just as the name implies; TMR, approach is surgical and muscle targeted which aid in producing a neural-machine interface that further give guidance to EMG signals for high level of myoelectric prostheses for amputees. Additionally, TMR shows promising in chronic post-amputation phantom prevention and treatment. Furthermore, it also helps with the pain developed in both the lower and the upper limb of an amputee. Moreover, it is a procedure used for nerve transfer procedure in relation to the phantom limb pain (PLP) in amputees. The loss of the upper limb has great consequences on a person because it affects the day-to-day activities. RPNIs is being implanted on amputees so as to record signals coming from the peripheral never so as to be able to create a working algorithm to build a stable prosthesis. Moreover, ultrasound computation of the RPHIs serves to be effective during the contraction and relaxation of the phantom finger flexion, which also mean that the RPNIs is an effective measure in reintervention of the amputee's hand prosthesis. Moreover, the signals from the RPNI are stable and quality, which makes it easier in decoding the grasping and finger movement, in addition, it also advantageous as it provides more data and are useful for regeneration of the nerve and as well as reinnervation of the muscle. [37]– [44]

Due to the fact that the brain go through a lot of changes from either the function and or the relentless even after the hand surgery. More reason why he Agonist-anatagonist myoneural interface (AMI) procedure tires

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to reestablish the physiological muscle agonist-antagonist responsive communication as well as the sensory feedback. This helps to facilitate the control motor. In addition, Lower limb amputation (LLA) damages the sensory communication between the two main parts of the body; the brain and the environment during activities. Moreover, the restoration of the sensory feedback is by assimilating the sensorimotor loop back into the sensory feedback. This way, the amputee would be able to have a well-developed neuroprosthesis which gives real time proprioceptive feedback. [46], [47]

Sensory feedback is progressively treated as an integral component of the closed loop prosthetic control preferably than optional additional. Moreso, artificial referred sensation, intraneural stimulation, two-ways directional interfaces, as well as integration of sensory motor systems seek to give more details on movement, contact and or prosthetic state of the user [15], [48], [49], [52], [69]. In addition, the long-term home use recommends that he integration of sensory motor can leverage the prosthetic's functions, perception and cognitive aspect [69]. Furthermore, the evidence, however, remains diverse in feedback modality, duration and reporting outcomes as well as directly limiting comparison across different studies.

the transformation of the sensory feedback has improved the way and manner the prosthetic control works., the interaction of the sensory motors, the bidirectional and one way command generation has also improved. The use of the artificial sensory feedback on an amputee has become promising in restoring the sensory feedback of the user. Some studies were focused on a closed loop-controlled prosthesis with distinct levels, which are definite to the direct impact it has on related feedback of the controlled motor framework. Furthermore, a non-invasive sensory feedback system was evaluated over the period of 4 weeks on an amputee, the results was based on an interview and the experience was the sensory feedback for touch that was experienced which was an addition to the already existing knowledge which was also one of the main challenges faced by many, even though there was a little instability of performance. In addition, the properties of psychometry of the auditory and as well as the visual feedback of the prosthesis was examined and later correlated to the vibro-tactile interface, and the results proved a remarkable inequity of the closing velocity of the prosthesis, which means that the results outrun the vibro-tactile interface.

Moreover, the prosthetic hand modulation was distinguished as though the unaffected hand. This work has enhanced the concurrent prosthetic hand regularities and the breadth neuromodulation. Additionally, another work was done in order to identify the different lower limb prosthetic need of the amputee, much attention was giving to the stability, safety, social integration, movement and sensory feedback which the overall experience was credible and applicable. Nevertheless, most of the recent designs of the prosthetic hands have different controllers to achieve a good degree of freedom. The neural machine interface helps to provide the sensory feedback and this help in the simulation of the prosthetic hand, this aims in rehabilitation of the perception of natural touch, and also enhances the prosthetic control. [48]– [54], [69]

Developing technologies comprises of transfer and deep learning, learning reinforcement, skin electronic, digital twins, cyber-security approaches, and connected medical device architectures. In addition, these emerging technologies may improve the sensing, simulations, adaptations and system level monitoring, however, the clinical utility relies more than validation beyond laboratory-controlled settings. Furthermore, AI-empowered medical devices also present requirements for security, transparency, governance and lifecycle monitoring [56], [60] – [66], [70].

Methodological quality and risk of bias varied across the evidence base. Primary engineering and clinical investigations generally reported quantitative performance measures, but validation strategies differed substantially. Common limitations included small cohorts, controlled laboratory conditions, heterogeneous outcome metrics, limited external or cross-session validation, and short follow-up periods. Review-level evidence was used primarily for contextual synthesis and was not treated as equivalent to primary experimental evidence. These limitations were considered when interpreting the strength and translational relevance of the findings.

More advances were made in the aspect of skin where an E-skin mechanization as established. This new potential has stagged advances in skin sensitivity interface, flexibility and many more through the use of Artificial Intelligence (AI). This rehabilitation can reshape the way and manner the amputees can feel their

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environments. Additionally, the advancements pin 6points the machine and human interaction through improved adaptive algorithms. In addition, the incorporation of Internet of Medical Thins (IoMT) with Internet of Things (IoT) in prosthesis have enhances the real-time data generation for patient rehabilitation and treatment. One of the challenges with it comes to AI, is Cybersecurity. This poses a great risk to Healthcare Cyber Physical Systems (CPS) reason being that everything will rest on communication wirelessly. To address this issue, the use of trustworthy signal jamming technologies has to be incorporated. This will help with the reach of the AI incorporated prostheses to be accepted in different reason for the beneficiaries, as many regions have to rigorously assess each medical devices under the medical decide regulation. [56], [65], [66], [70]

DISCUSSION

The data reveals advancement from the component level improvement towards intelligent controlled systems. Multimodal sensing, pattern recognition, Bayesian filtering, neural control and neural interfaces handles diverse stages of pathway control instead of representing interchangeable technologies. This aid in an end-to-end view linking to signal acquisition, internet inference, conditioning, sensory feedbacks and other outcomes.

Due to the amplitude limitation of the sEMG in the low-pass linear filtering, advances were made the overcome the limitation, which is the introduction Bayesian filter. This new approach offers a great advantage because it gives a more reliable results than the conventional approach that is used. Furthermore, the incorporation of intent recognition algorithm has transformed the lower limb prosthesis the use of mechanical sensors and EMG in powering the knee and the ankle prosthesis was efficient in generating simulated signals for improved prosthetic performance. Additionally, IMU, ultrasound-based sensors, and the bimodal sensory information, all have proven efficient over conventional sEMG signals. Moreover, the convolutional neural networks produce an accurate result when compared to the classical classification method, hence several factors such as optimization parameters, preprocessing and the net architecture are the basics for the sEMG data analysis. Furthermore, in contemporary muscle computer interfaces, there are distinct differences between the executable range of movement, and the control robustness, these two factors affects and or limit the total control of the prosthesis.

Therefore, one way to overcome such limitation is the use of multi-label machine learning method, this method breakdown complex movement of the hand prosthesis and makes it very simple. The rehabilitation of the prosthesis requires a method that can accurately help the amputee and moreover, the important indicator of the interface system, CoP also has shown to be promising. Some amputee showed stability of the gait through the model of transfemoral prosthesis, which means that the use of DRL promising as well. Other machine learning methods are SVM, LDA, ANN, LDA, KNN and non-negative factorization matrix have also been used for different grasping and movement recognition, while DLA is also used to integrate the simple correlation between the multiarticulate hand recognition and the sensor for gait stability. [19]– [24], [26]– [34]

The evidence does not support a simple hierarchy in which invasive interfaces universally replace sEMG. sEMG remains accessible and comparatively simple; HD-sEMG can increase spatial information without surgery; and TMR, RPNI, and implanted interfaces may provide greater specificity but impose surgical and long-term biological-management burdens [37]– [45], [63], [64]. Interface selection should therefore reflect intended function, required control dimensionality, acceptable invasiveness, clinical resources, maintenance, and evidence of durable benefit.

From Laboratory Accuracy to Clinical Effectiveness

Recognition accuracy is useful for algorithm development but does not establish clinical superiority. High performance may coexist with frequent recalibration, excessive power demand, poor robustness, or failure under daily-use conditions. Outcome frameworks and economic evaluation support broader endpoints including task completion, gait performance, long-term use, satisfaction, and cost-effectiveness. [2], [3], [53], [67], [68]

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Interface Selection as a Trade-Off

The evidence does not support a simple hierarchy in which invasive interfaces universally replace sEMG. sEMG remains accessible and comparatively simple; HD-sEMG increases information without surgery; TMR, RPNI, and implanted interfaces may provide greater specificity but impose surgical and long-term biological-management burdens. Interface selection should therefore reflect intended function, required control dimensionality, acceptable invasiveness, clinical resources, maintenance, and evidence of durable benefit.

Clinical Translation and Standardization

Translation is limited by small cohorts, specialized research settings, inconsistent validation, and heterogeneous outcome reporting. A common benchmark should report signal robustness, control latency, tracking error, recalibration burden, task performance, longitudinal use, patient-reported outcomes, and economic impact. AI-enabled devices additionally require lifecycle validation, transparency, monitoring, and cybersecurity controls. [65]– [70]

LIMITATIONS

The evidence base is heterogeneous and includes primary experimental studies, clinical and human-use studies, reviews, one preprint, and translational sources; it is therefore unsuitable for a single pooled effect estimate. The supplied review reports overall database counts and screening numbers, but the detailed database-specific search strings, deduplication logs, and individual exclusion decisions are not available at a level that permits independent reproduction of every screening decision. Substantial heterogeneity also exists in populations, prosthetic levels, sensing modalities, algorithms, and outcomes. Finally, several emerging technologies have limited longitudinal evidence, so conclusions about clinical readiness should be interpreted cautiously.

Research Agenda

Five priorities emerge. First, standardized benchmarking should combine signal robustness, latency, recalibration, control accuracy, task performance, and user-centered outcomes. Second, longitudinal multicenter validation is required to capture physiological adaptation, device wear, maintenance, and generalizability. Third, adaptive AI should incorporate safeguards, uncertainty estimation, and interpretable outputs. Fourth, neural interfaces should prioritize chronic stability, mechanical compatibility, signal quality, and practical implantation while noninvasive systems continue to improve spatial sampling and self-calibration. Fifth, future studies should integrate quality of life, acceptance, rehabilitation outcomes, cost-effectiveness, cybersecurity, privacy, energy efficiency, and maintainability into evaluation. [56], [65]– [70]

CONCLUSION

Intelligent prosthetics and orthotics are transitioning toward integrated human–machine systems that couple biological sensing, AI-based intent decoding, multimodal fusion, adaptive actuation, and sensory feedback. The 70-source evidence base demonstrates substantial progress across these layers, but technological maturity is not equivalent to clinical maturity. sEMG remains a practical foundation, while HD-sEMG and advanced processing increase information content; TMR, RPNI, implanted electrodes, and neuromusculoskeletal approaches offer higher-specificity pathways with greater clinical and biological demands; and deep, transfer, transformer, and reinforcement learning expand controller capability while leaving generalization and real-world robustness unresolved.

Future progress should therefore be judged not by isolated increases in laboratory accuracy, but by reliable, interpretable, safe, affordable, and durable closed-loop function demonstrated through longitudinal, multicenter, patient-centered evaluation.

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DECLARATIONS

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Conflict of Interest

The authors declare no competing financial or non-financial interests related to this work. Although advanced neural interfaces, digital twins, explainable AI (XAI), and connected systems have shown considerable promise, there is still limited evidence to demonstrate their long-term reliability and effectiveness in routine clinical settings. [7], [11], [12], [16], [18], [49], [56], [61], [62], [65], [66], [70] This review therefore brings these developments together within a unified, end-to-end framework that covers biological and environmental sensing, signal conditioning, intent interpretation, adaptive actuation, sensory feedback, and, ultimately, clinical application. It also highlights practical criteria that can be used consistently when evaluating different technologies, including signal reliability/robustness, decoding and tracking accuracy, system response time/signal latency, recalibration requirements, long-term stability, performance in real-world settings, patient-centered outcomes, safety, and overall readiness for clinical translation.

Data Availability

No new experimental dataset was generated. The evidence synthesized is derived from the published sources contained in the supplied master bibliography.

Ethical Approval

Ethical approval was not required because this study synthesizes previously published literature and does not involve new human-participant data.

Informed Consent: Not applicable.

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Author Contributions

Conceptualization: Maxwell James Stephen. Methodology: Maxwell James Stephen. Literature search: Taniyodi Izhar Oliver. Data curation: Taniyodi Izhar Oliver. Analysis: Maxwell James Stephen. Writing original draft: Maxwell James Stephen. Writing review and editing: Maxwell James Stephen. Supervision: Prof. Efrain Nwoye.

Abbreviations

Abbreviation	Full Term
AI	Artificial intelligence
CNN	Convolutional neural network
DoF	Degree of freedom
EMG	Electromyography
HD-sEMG	High-density surface electromyography

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HMI	Human–machine interaction
IMU	Inertial measurement unit
ML	Machine learning
P&O	Prosthetics and orthotics
PNI	Peripheral neural interface
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RPNI	Regenerative peripheral nerve interface
RL	Reinforcement learning
sEMG	Surface electromyography
TMR	Targeted muscle reinnervation
XAI	Explainable artificial intelligence

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Supplementary Material

Table S1. FULL 70- Reference Evidence Matrix

This supplementary table provides the study-level evidence matrix for all 70 sources in the revised Bibliography. The matrix is intended to support transparency of the review.

Reference base: Updated Master Bibliography, 70 retained references.

Ref.	Year	Study category	Domain	Primary technology / signal	AI / control	Principal contribution
1	2024	Review	Human–prosthesis integration	Neurointegrated lower-limb prosthesis	Biological/neural integration	Framework for user-centered neurointegrated lower-limb prosthesis development.
2	2026	Systematic review	Human–prosthesis integration	Upper-limb prostheses	Clinical translation	Synthesizes prosthetic needs reported by individuals with upper-limb loss.
3	2022	Clinical/human-use study	Human–prosthesis integration	Upper-limb prostheses	Device acceptance/use	Assesses current prosthetic usage and whether innovation has improved device acceptance.

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4	2021	Technical study	Upper-limb prosthetics	3-D-printed prosthetic sockets	Digital fabrication	Examines promises and pitfalls of additive manufacturing for prosthetic sockets.
5	2025	Experimental	Upper-limb prosthetics	19-DOF lightweight prosthetic hand	High-dexterity mechatronics	Demonstrates a lightweight high-dexterity prosthetic hand with human-level functional capabilities.
6	2017	Experimental	Upper-limb prosthetics	Surface EMG	CNN; self-recalibration	Demonstrates self-recalibrating sEMG pattern recognition for neuroprosthesis control.
7	2022	Systematic review	Lower-limb prosthetics	EMG-driven prostheses	EMG-driven control	Synthesizes EMG-driven control approaches for lower-limb prostheses.
8	2017	Randomized clinical trial	Upper-limb prosthetics	TMR + myoelectric control	Pattern recognition	Shows myoelectric pattern recognition outperforming direct control in selected TMR users.
9	2025	Comprehensive review	Upper-limb prosthetics	Robotic prosthetic hands; tactile sensors	Machine-learning EMG control	Reviews mechanisms, materials, tactile sensing, and ML-based EMG control.

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10	2022	Experimental	Lower-limb prosthetics	Powered transfemoral prosthesis	Adaptive neural network	Demonstrates real-time adaptation of an ANN controller during powered prosthesis use.
11	2020	Review	Lower-limb prosthetics	Multisensor prosthetic control	Sensor fusion	Reviews use of additional sensing modalities to enhance lower-limb prosthesis control.
12	2021	Review	Lower-limb exoskeletons	Gait-assist exoskeletons	Control strategies	Reviews control strategies for lower-limb exoskeleton gait assistance.
13	2019	Systematic review	Lower-limb rehabilitation	Wearable ankle robots	Assistive control	Reviews wearable ankle robots used for post-stroke gait rehabilitation.
14	2022	Experimental	Lower-limb robotics	Robotic knee	Actor–critic reinforcement learning	Applies actor–critic RL to knee tracking toward an intact-knee profile.
15	2022	Systematic review	Sensory feedback	Upper/lower-limb prostheses	Artificial referred sensation	Synthesizes evidence on artificial referred sensation in prosthesis users.
16	2023	Review	Lower-limb prosthetics	Powered lower-limb prostheses	Control strategies	Reviews state-of-the-art control methods for

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						powered lower-limb prostheses.
17	2020	Review	Human–prosthesis integration	Neuromusculoskeletal arm prostheses	Integrated control	Examines personal and social implications of intimately integrated bionic arms.
18	2024	Systematic review/meta-analysis	Peripheral neural interfaces	TMR and RPNI	Neural-interface translation	Compares TMR/RPNI with standard management for limb amputation outcomes.
19	2016	Experimental	Upper-limb prosthetics	Surface EMG	Bayesian filtering; proportional control	Uses Bayesian filtering for simultaneous and proportional prosthetic control.
20	2018	Experimental	Lower-limb prosthetics	Robotic lower-limb prosthesis	Online adaptive neural control	Demonstrates online adaptive neural control of a robotic lower-limb prosthesis.
21	2022	Experimental	Lower-limb biomechanics	Kinematic + myoelectric sensing	Signal fusion	Estimates knee joint angles continuously by fusing kinematic and myoelectric signals.
22	2022	Case study	Upper-limb prosthetics	Sonomyographic prosthesis	Ultrasound-based control	Demonstrates functional task performance using a sonomyographic prosthesis.

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23	2021	Experimental	Upper-limb prosthetics	Vision-based myoelectric hand	Bimodal EMG–vision control	Combines visual and myoelectric information for prosthetic hand control.
24	2022	Experimental	Upper-limb prosthetics	Surface EMG	Multi-Kalman filtering	Decodes arm kinematics from EMG using a multi-Kalman-filter approach.
25	2023	Review	sEMG and neural decoding	Surface EMG	Signal processing/control	Reviews trends, applications, and challenges of sEMG in prosthetic systems.
26	2016	Experimental/resource	sEMG and neural decoding	Surface EMG	CNN deep learning	Provides a CNN-based resource for movement classification from EMG for prosthetic hands.
27	2019	Experimental	sEMG and neural decoding	HD-sEMG	Spatial/temporal representation	Extracts multilabel movement information from raw HD-sEMG images.
28	2024	Experimental	Upper-limb prosthetics	Surface EMG	Deep learning; simultaneous decoding	Demonstrates real-time motor-intent decoding for simultaneous artificial-limb control.
29	2022	Survey	Wearable interfaces	Wearable EMG interfaces	Gesture-recognition algorithms	Surveys wearable interfaces and algorithms for

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						hand-gesture recognition.
30	2022	Comparative study	sEMG and neural decoding	Surface EMG	Transfer learning	Compares subject-to-subject transfer-learning methods for sEMG motion recognition.
31	2021	Experimental	Lower-limb exoskeletons	Exoskeleton	Reinforcement learning	Applies RL to control of a lower-extremity exoskeleton for squat assistance.
32	2021	Simulation/experimental	Lower-limb prosthetics	Physics-based musculoskeletal model	Deep reinforcement learning	Uses deep RL with physics-based musculoskeletal simulation for walking.
33	2024	Experimental	Upper-limb prosthetics	EMG + vision	Multimodal fusion	Infers grasp intent by fusing EMG and vision.
34	2021	Review	Lower-limb locomotion	sEMG + inertial sensors	Sensor fusion	Reviews the role of sEMG in fusion with inertial sensors for locomotion recognition and prediction.
35	2017	Experimental	Lower-limb biomechanics	Ultrasound + muscle model	Musculoskeletal force estimation	Compares Hill-type model predictions with ultrasound-based gastrocnemius force estimates.

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36	2019	Experimental	Lower-limb prosthetics	IMU	CNN intent recognition	Uses CNN-based IMU processing for locomotion intent recognition in an intelligent lower-limb prosthesis.
37	2025	Experimental	Peripheral neural interfaces	TMR	Myoelectric control	Compares two TMR approaches for improving myoelectric prosthetic control.
38	2025	Review	Peripheral neural interfaces	TMR	Clinical evidence/technique	Reviews evidence, indications, and surgical technique for TMR.
39	2019	Randomized clinical trial	Peripheral neural interfaces	TMR	Pain/neuroma treatment	Evaluates TMR for neuroma and phantom pain after major limb amputation.
40	2025	Preprint	Peripheral neural interfaces	Neuromuscular interface	Neural signal interface	Reports a robust neuromuscular interface aimed at restoring lost function after amputation.
41	2020	Experimental	Peripheral neural interfaces	RPNI	Real-time prosthetic control	Demonstrates real-time artificial-hand control using an RPNI.
42	2023	Experimental	Peripheral neural interfaces	Implanted electrodes	Electro-neuromuscular control	Demonstrates improved prosthetic control using surgically created

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						electro-neuromuscular constructs.
43	2023	Experimental	Peripheral neural interfaces	RPNI + implanted EMG	Long-term neural control	Reports long-term upper-extremity prosthetic control using RPNIs and implanted EMG electrodes.
44	2020	Clinical case	Peripheral neural interfaces	TMR + RPNI	Combined neural interface	Describes combined hand/peripheral-nerve TMR and vascularized pedicled RPNI.
45	2022	Experimental	Upper-limb prosthetics	Myoelectric hand	Neural-network proportional control	Analyzes neural-network-based proportional myoelectric hand prosthesis control.
46	2020	Experimental	Lower-limb prosthetics	Agonist–antagonist myoneural interface	Proprioceptive sensorimotor restoration	Shows preservation of proprioceptive sensorimotor neurophysiology with an agonist–antagonist interface.
47	2019	Experimental	Lower-limb prosthetics	Neurointegrated prosthesis	Sensorimotor integration	Demonstrates enhanced functional and cognitive integration of a lower-limb prosthesis.

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48	2021	Experimental	Sensory feedback	Intraneural stimulation	Percept encoding	Characterizes multiple cutaneous and proprioceptive percepts evoked by intraneural stimulation.
49	2020	Review	Sensory feedback	Upper-limb prostheses	Closed-loop sensory feedback	Reviews sensory feedback from a human motor-control perspective.
50	2020	Prospective study	Sensory feedback	Hand prostheses	Everyday sensory feedback	Evaluates sensory feedback in everyday prosthesis use.
51	2019	Experimental	Sensory feedback	Hand prosthesis	Incidental feedback	Characterizes incidental feedback sources during prosthetic grasping.
52	2018	Experimental	Sensory feedback	Bidirectional prosthesis	Biomimetic intraneural feedback	Shows biomimetic intraneural feedback can improve sensation naturalness, tactile sensitivity, and dexterity.
53	2022	Review	Human–prosthesis integration	Lower-limb prostheses	User-centered design	Reviews user needs that should drive lower-limb prosthesis development.
54	2022	Case study	Sensory feedback	Spinal cord stimulation	Closed-loop sensory discrimination	Demonstrates closed-loop lateral cervical spinal cord

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						stimulation for sensory discrimination.
55	2025	Review	Emerging technologies	Electronic skin	Tactile sensing/control	Reviews electronic-skin hardware, tactile sensing, control algorithms, and applications.
56	2026	Systematic review	AI and clinical translation	Healthcare AI	Explainable AI	Synthesizes XAI use cases and challenges across healthcare, including rehabilitation.
57	2023	Experimental	Lower-limb exoskeletons	Exoskeleton	Deep reinforcement learning	Adapts exoskeleton sensitivity for human performance augmentation using deep RL.
58	2023	Experimental	sEMG and neural decoding	HD-sEMG	Transformer	Applies transformer-based recognition to instantaneous and fused neural decomposition of HD-EMG.
59	2021	Review	Emerging technologies	Physics-based simulation	Simulation/modeling	Reviews the role of physics-based simulators in robotics.
60	2020	Systematic review	AI and robotics	Robotics	Reinforcement learning	Reviews RL-based robotics research over

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						the preceding decade.
61	2023	Experimental/methods	Digital twins	Myoelectric digital twin	Deep-learning data generation/modeling	Develops a myoelectric digital twin for fast and realistic modeling in deep learning.
62	2022	Scoping review	Digital twins	Physics-based digital twin + XR	Simulation and evaluation	Reviews digital-twin and extended-reality use for safety and ergonomics evaluation.
63	2026	Narrative review	Emerging sensing	Muscle-deformation sensing	Intelligent sensing	Reviews muscle-deformation sensing for upper-limb prosthetic control.
64	2019	Review	sEMG and neural decoding	Surface EMG	Pattern recognition	Reviews real-time EMG pattern-recognition control for hand prostheses.
65	2020	Survey/review	Cybersecurity	IoMT communications	Security/privacy	Reviews security threats and protections in Internet of Medical Things communications.
66	2024	Experimental/technical	Cybersecurity	Cyber-physical systems	Blockchain-backed detection	Presents blockchain-backed assault detection for cyber-physical systems.

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67	2023	Guideline/recommendations	Clinical translation	Lower-limb P&O outcomes	Outcome measurement	Provides patient-reported and performance-based outcome recommendations for lower-limb P&O.
68	2023	Economic evaluation	Clinical/economic translation	Upper-limb prostheses	Cost-effectiveness	Evaluates cost-effectiveness of multigrip versus standard myoelectric hands.
69	2020	Long-term home-use study	Sensory feedback	Bidirectional bionic arms	Sensory-motor integration	Reports functional, perceptual, and cognitive changes with long-term home use.
70	2023	Review	AI and clinical translation	Medical-device AI	AI governance/regulation	Reviews definitions, recommendations, and regulatory initiatives for AI in high-risk medical devices.