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Systematic Review

Advances and Trends in Intelligent Lower-Limb Prostheses: A Systematic Review of Mechanical Design, Sensing, and Control

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ABSTRACT: Intelligent lower-limb prostheses are evolving from single-joint assistance toward coordinated, system-level control that supports cross-task adaptation, multimodal intent estimation, and verifiable safety. This systematic review surveys powered, semi-active, microprocessor-controlled, and related intelligent lower-limb prosthesis literature published between 1 January 2021 and 1 January 2026, spanning electromechanical design, sensing and human-machine interfaces, state/phase estimation, intent/terrain recognition, control and learning, evaluation endpoints, and translational considerations. Following a PRISMA-style workflow, 180 full-text reports were included and synthesized into a modular taxonomy covering clinical needs and endpoints; actuation and transmission; sensing and human-machine interfaces; phase/state estimation; intent/terrain recognition; impedance and trajectory control, including model predictive control; personalization with explicit safety constraints; real-world validation; and safety, reliability, and standardization. Emerging patterns include backdrivable low-impedance hardware, multimodal sensing with uncertainty-aware gating, and continuous phase-variable control, although the level of validation remains heterogeneous. Key gaps remain in endpoint consistency, external validity across users and contexts, and failure-mode reporting. We recommend benchmark protocols and system-level validation frameworks to support more reproducible evaluation and future clinical translation.

Keywords: Lower-limb prosthesis; Robotic prosthesis; Variable impedance; Gait phase; Intent recognition; Sensor fusion; Learning-based control; Real-world evaluation

1. Introduction

People with lower-limb amputation often walk with gait asymmetry, elevated metabolic cost, and reduced stability, particularly on uneven terrain and during activities of daily living (ADLs). Passive prostheses offer limited adaptability and cannot deliver net positive work; in contrast, microprocessor-controlled semi-active and powered systems can modulate damping and impedance and inject mechanical work at task-critical phases. Clinical translation, however, still hinges on compact high power-density hardware with low mechanical impedance, robust sensing and control under donning variability and sensor drift, and verifiable fail-safe behavior [1,2]. Accordingly, recent studies increasingly couple multimodal sensing, continuous phase variables, and learning-based adaptation to improve cross-task performance while maintaining safety.

Here, we synthesize advances in powered, semi-active, microprocessor-controlled, and related intelligent lower-limb prosthesis systems through a design, control, and evaluation lens, spanning architecture; sensing and interfaces; state/phase estimation and intent recognition; control and learning; and real-world validation. We also use a modular taxonomy to link clinical endpoints to implementation choices across these layers and discuss a layered safety stack for learning-enabled systems. Hip-level prostheses, especially hip disarticulation and hip-joint-level systems, are discussed separately as a high-consequence "stress test" because they add proximal DOFs, shift mass/inertia toward the trunk, and leave users with fewer compensatory strategies, making transition failures (sit-to-stand, turning, ramps/stairs) more consequential. Section 2 describes the review methodology; Section 3 synthesizes findings by module; and Section 4 discusses open challenges and future directions.

2. Methods

A systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.

2.1. Eligibility Criteria

English-language journal and conference reports published between 1 January 2021 and 1 January 2026 were considered eligible if they addressed powered, semi-active, microprocessor-controlled, or otherwise intelligent lower-limb prosthetic systems, or provided directly relevant evidence for their design, sensing, control, validation, prescription, safety, standardization, or clinical translation. Original research and technical reports were eligible when they reported at least one form of empirical, prototype-level, algorithmic, simulation, benchtop, hardware-in-the-loop, or human-subject/user-evidence support. Reviews, consensus papers, and perspectives were also included when they directly informed the taxonomy, clinical needs, endpoint selection, safety, standardization, or translational context, but they were coded separately from original research/technical reports.

2.2. Search Strategy and Study Selection

Scopus, PubMed, IEEE Xplore, and Web of Science were searched on 10 January 2026, covering publications from 1 January 2021 to 1 January 2026. Search strings were organized into four blocks: A (prosthesis-related terms), B (lower-limb anatomy and amputation level), C (intelligence/actuation/sensing/control/learning terms), and D (exclusion terms). The final query used the Boolean structure A AND B AND C NOT D. Database-specific syntax adaptations were applied where required, and the main search structure is described below.

An example query was: (prosthe* OR "artificial limb" OR "prosthetic limb" OR "prosthetic leg" OR "bionic leg") AND (knee OR transfemoral OR transtibial OR ankle OR foot OR leg OR "lower limb" OR lower-limb OR "lower extremity" OR lower-extremity OR "lower leg" OR lower-leg) AND (active OR robotic OR adaptive OR intelligent OR power OR bionic OR microprocessor OR "microprocessor-controlled" OR "microprocessor controlled" OR semiactive OR semi-active OR "semi active" OR mechatronic OR actuated OR "variable impedance" OR "variable damping" OR "intent recognition" OR "locomotion mode" OR "mode recognition" OR "gait phase" OR "phase estimation" OR "phase detection" OR "terrain recognition" OR "activity recognition" OR "pattern recognition" OR "sensor fusion" OR "machine learning" OR "deep learning" OR transformer OR "reinforcement learning" OR "online learning" OR "impedance control" OR "model predictive control" OR MPC OR "finite-state machine" OR FSM OR "human-in-the-loop" OR "shared control") AND NOT (replacement OR arthroplast* OR "joint replacement").

All records were exported to Zotero for deduplication and screening. Two reviewers independently performed title/abstract screening followed by full-text review; disagreements were resolved by discussion and, when required, adjudication by a third reviewer. Forward and backward citation chasing was performed, and the database search was updated on 10 January 2026. PRISMA accounting was as follows: 4850 records identified; 2310 duplicates removed (2540 unique records); 711 records removed before screening for other reasons (orthosis/exoskeleton, $n = 230$; non-prosthesis, $n = 481$); 1829 records screened; 1647 records excluded at title/abstract; and 180 full-text reports assessed and included in the synthesis (Figure 1).

The selected databases were intended to cover biomedical, rehabilitation, engineering, robotics, and computer-science-oriented literature. PubMed was used to capture biomedical and rehabilitation studies, IEEE Xplore to capture engineering and robotics reports, and Scopus and Web of Science to provide broader multidisciplinary coverage. Nevertheless, this database selection may have under-retrieved non-English publications, dissertations, patents, technical reports, industry white papers, and papers indexed only in databases such as ACM Digital Library or Google Scholar. This limitation was partly mitigated by backward and forward citation chasing.

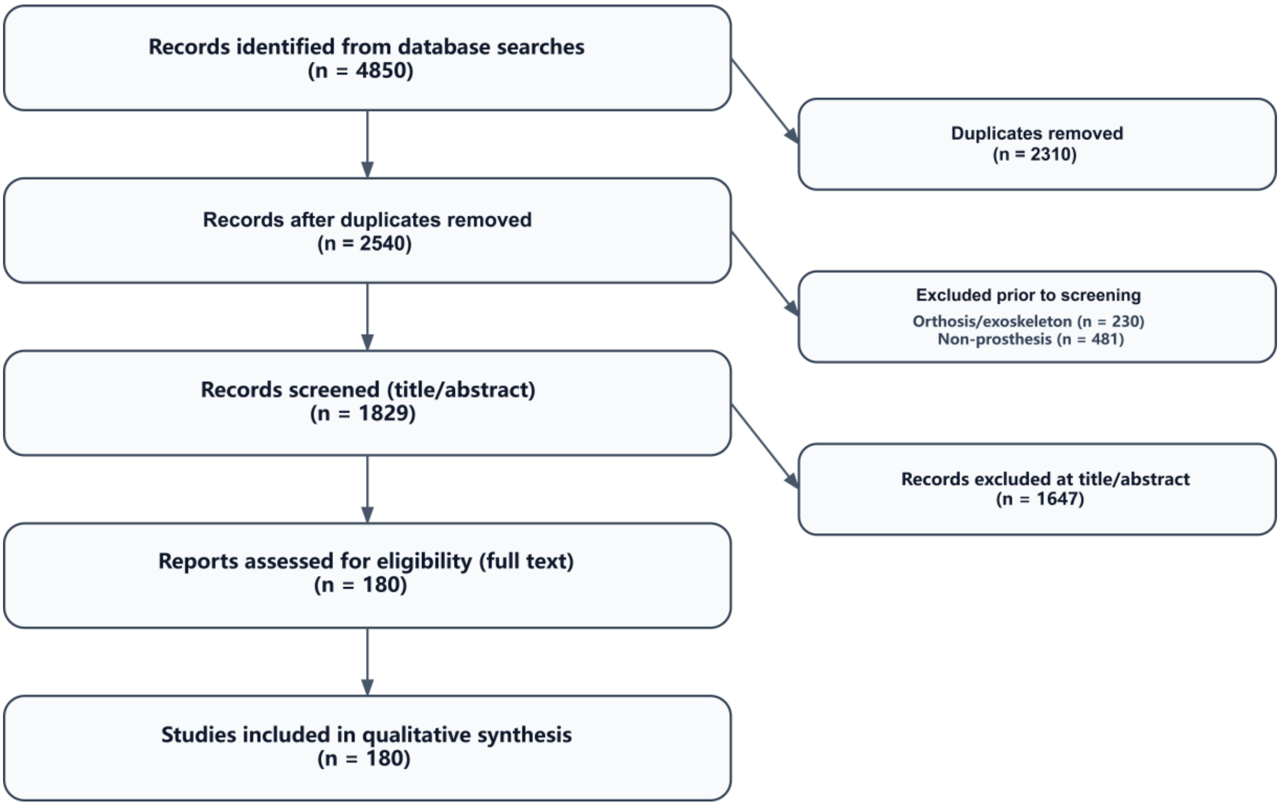

Figure 1. PRISMA-style flow diagram of study identification, screening, and inclusion.

2.3. Data Extraction and Synthesis

For each included report, the following items were extracted: device configuration (amputation level, joints, degrees of freedom [DOFs]), actuation and transmission, sensing modalities and human-machine interfaces (HMIs), estimation/recognition methods, control architecture, evaluation setting, and reported outcomes. Given substantial heterogeneity in devices, protocols, and endpoints, meta-analysis was not performed. Instead, a narrative synthesis was conducted and organized by electromechanical design, sensing and human-machine interfaces (HMIs), gait phase/state estimation, intent/mode/terrain recognition, control frameworks, learning-based personalization, and translational considerations (safety, reliability, and standardization).

2.4. Structured Coding of Included Reports

To improve transparency in the evidence synthesis, each included report was coded using a structured coding sheet. Coding fields included publication type (original research/technical report *vs*. review/consensus/perspective), primary research theme, primary validation setting, prosthesis/device class, joint/application level, sensing modality, control/algorithmic focus, and the manuscript module in which the report provided its most specific evidence. For reports that spanned multiple modules, one primary category was assigned according to the main objective and the strongest evidence contribution, while secondary tags were retained for internal audit. Original research/technical reports were further classified by primary validation setting as follows: human-subject or user-evidence study; benchtop, prototype, mechanical validation, or technical description; or algorithmic, simulation, or offline validation. Reviews, consensus papers, and perspectives were counted separately and were not included in the denominator for primary-theme and validation-setting percentages. When the title and abstract information were insufficient for unique classification, the full text and methods/results sections were checked. The aggregate coding results are summarized in Table 1.

Table 1. Quantitative characteristics of included reports.

Category	Subcategory	N	Percentage
All included reports	Total included reports	180	100.0%
Publication type	Original research or technical report	163	90.6% of 180
Publication type	Review, consensus, or perspective	17	9.4% of 180
Primary theme among original reports	Electromechanical architecture, actuation, or device design	43	26.4% of 163
Primary theme among original reports	Control, learning, or personalization	43	26.4% of 163
Primary theme among original reports	Clinical needs, endpoints, or user evidence	26	16.0% of 163
Primary theme among original reports	Sensing, human-machine interfaces, or feedback	21	12.9% of 163
Primary theme among original reports	Intent or terrain recognition	14	8.6% of 163
Primary theme among original reports	Phase or state estimation	11	6.7% of 163
Primary theme among original reports	Safety, reliability, or standardization	5	3.1% of 163
Primary validation setting among original reports	Human-subject or user-evidence study	99	60.7% of 163
Primary validation setting among original reports	Benchtop, prototype, mechanical validation, or technical description	33	20.2% of 163
Primary validation setting among original reports	Algorithmic, simulation, or offline validation	31	19.0% of 163

Note: Percentages for publication type were calculated using all 180 included reports as the denominator. Percentages for primary theme and primary validation setting were calculated using the 163 original research or technical reports as the denominator. Each original report was assigned one primary theme and one primary validation setting according to its main objective and strongest evidence contribution.

3. Results

3.1. Overview

This section summarizes the included reports by module and provides a quantitative overview of the evidence base before the narrative synthesis. Among the 180 included reports, 163 were original research or technical reports, and 17 were reviews, consensus papers, or perspectives. Among the 163 original research or technical reports, the main themes were electromechanical architecture, actuation, or device design (43/163, 26.4%); control, learning, or personalization (43/163, 26.4%); clinical needs, endpoints, or user evidence (26/163, 16.0%); sensing, human-machine interfaces, or feedback (21/163, 12.9%); intent or terrain recognition (14/163, 8.6%); phase or state estimation (11/163, 6.7%); and safety, reliability, or standardization (5/163, 3.1%). By primary validation setting, 99 reports included human-subject or user-evidence data (60.7%), 33 primarily reported benchtop, prototype, mechanical validation, or technical description (20.2%), and 31 relied mainly on algorithmic, simulation, or offline validation (19.0%). These quantitative distributions are summarized in Table 1.

Overall, the distribution of included reports indicates that the field remains weighted toward hardware/control development and short-term validation, whereas safety, standardization, and long-term real-world evidence remain comparatively underrepresented. Therefore, the following synthesis emphasizes not only reported technical advances but also differences in validation depth, clinical relevance, and translational readiness across modules.

Based on this quantitative overview, we organized the narrative synthesis using the modular taxonomy shown in Table 2, which maps each module to typical technical questions, evaluation endpoints, and representative studies. This taxonomy is used consistently throughout Sections 3.2–3.9 to connect clinical needs, implementation choices, and real-world validation evidence (Figure 2).

Table 2. Taxonomy of modules for intelligent lower-limb prosthesis research is reviewed in this paper.

Module	Typical Scope and Endpoints	Representative Topics/Examples
Clinical needs & endpoints	ADLs; gait symmetry; metabolic cost; safety/falls; patient-reported outcomes; task-specific performance.	Outcome mismatch across studies; task-dependent benefits.
Electromechanical architecture	Actuation/transmission; power density; backdrivability; low impedance/noise; mass/volume constraints.	Powered ankle/knee; SEA; QDD; modular, serviceable designs.
Sensing & human-machine interfaces	IMU/pressure/load/torque; EMG; vision/LiDAR; sensory feedback; donning/doffing robustness.	Multimodal fusion; confidence gating; low-burden sensor placement.
Phase/state estimation	Gait phase variables; continuous phase; event detection; latency and drift management.	Phase-variable models; hybrid observers; robust event detection.
Intent/mode/terrain recognition	Locomotion mode, terrain, transitions; generalization and dataset shift.	IMU+pressure recognition; EMG-assisted intent; context-aware transitions.
Control architectures	FSM impedance; variable impedance/admittance; trajectory/MPC; shared control; safe fallback.	Continuous control across tasks; adaptive impedance; transition handling.
Learning & personalization	HIL tuning; online adaptation; RL/safe learning; calibration burden.	HIL optimization; safe RL; multi-objective personalization.
End-user & real-world evaluation	Lab *vs*. outdoor validation; long-term wear; usability; reporting of adverse events.	Field trials; standardized protocols; reproducible benchmarks.
Safety, reliability & standardization	Fail-safe design; fault detection; degradation; logs/traceability; reporting standards.	Redundant braking; safe fallback; evaluation checklists.

(1) Hardware: lightweight, high power-density actuation and low-impedance/low-noise designs (e.g., a low-noise, highly backdrivable knee platform [3]), together with the ability to preserve backdrivability and compliance across multiple tasks (level walking, ramps, stairs, and sit-to-stand transitions), have become shared design objectives for next-generation powered prostheses [4–8].

(2) Sensing and interfaces: multimodal fusion (e.g., electromyography [EMG], plantar pressure, inertial measurement units [IMUs], and vision) is gradually replacing single-sensor thresholding, with growing emphasis on day-to-day stability, low latency, and deployable sensor placements [9–11]. In parallel, sensory feedback and neural interfaces are being explored to enhance embodiment and motor adaptation [12,13].

(3) Control: data-driven variable-impedance control, phase-variable trajectory generation, and unified control frameworks continue to emerge to reduce manual expert tuning and improve cross-context adaptation [14,15]. Learning-based methods and human-in-the-loop optimization further advance

personalization, typically accompanied by explicit discussion of safety constraints and fallback mechanisms [16–18].

In addition, recent reviews and new studies indicate that high-level inference and low-level control are converging toward "continuity" and "intermediate representations". On one hand, intent recognition based on noninvasive interfaces is expanding from discrete mode classification to continuous intent/trajectory regression, with an emphasis on online adaptation and drift compensation [19,20]. On the other hand, frameworks such as synergy representations and bi-level optimization attempt to unify human movement regularities, user adaptation, and controller optimization within a shared modeling language, enabling faster personalization [21,22].

(4) Validation and standards: An increasing number of studies evaluate multiple tasks with amputee participants and discuss standardized testing requirements and risk frameworks for neural-control and learning modules [23].

Recent systems extend sensing beyond onboard state to environment priors and continuous prediction: in-shoe electrodes estimate ground impedance [24], A-mode ultrasound and proximal sensing support continuous kinematic prediction [25,26], and vision provides obstacle look-ahead for feedforward trajectory updates [27]. For hip-level systems, reliable sensing often must capture trunk-pelvis motion and load transfer in addition to distal joint states, because whole-body coordination and safe transitions dominate performance and risk.

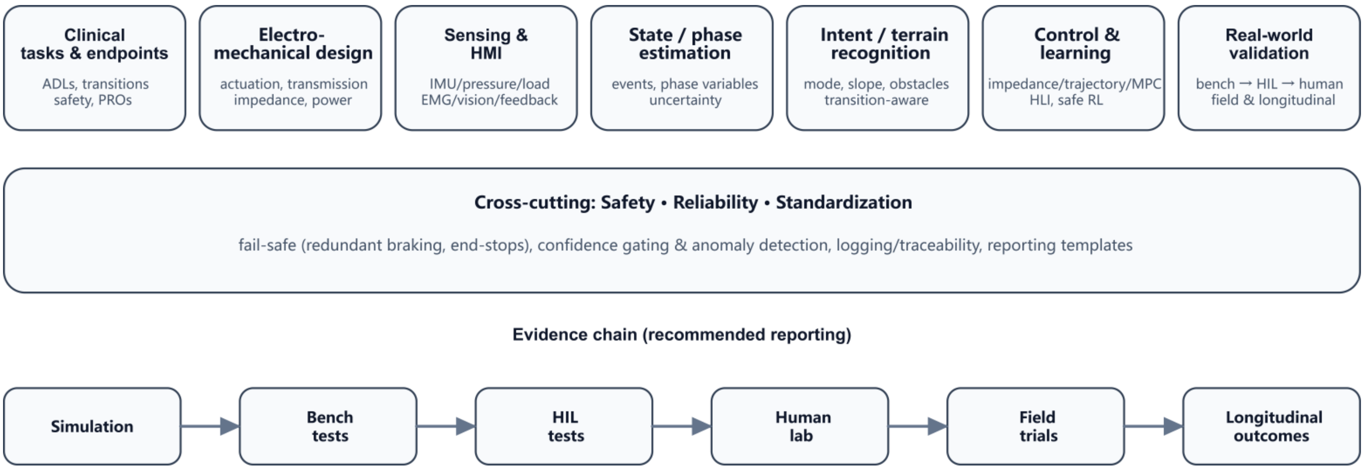

Figure 2. Modular taxonomy used in this review, linking clinical endpoints to hardware design, sensing/HMI, estimation and intent recognition, control and learning, validation, and safety/standardization. Hip-level systems are highlighted as a high-consequence stress test.

3.2. Clinical Needs and Evaluation Criteria

Section 3.2 maps common clinical tasks to outcome metrics and summarizes gaps that limit cross-study comparability.

3.2.1. Needs-to-Metrics Mapping

User priorities are consistent but heterogeneous. Manz et al. (56 studies; 8149 participants) identified stability/fall prevention, comfort (socket/skin), adaptability, fatigue, ease of use, and cost as core needs, with rankings depending on amputation level and activity [28]. Metrics should therefore be reported as a task set paired with endpoints (e.g., ramp/stair switching safety, tolerable mode errors) to enable comparable evidence.

3.2.2. Robustness, Variability, and Recovery Metrics

Metabolic cost and symmetry alone miss transition and perturbation demands. Lee et al. showed that task-redundant variability relates to usability: users preserve goal-equivalent variability to maintain task success, while non-goal-equivalent variability increases cost [29]. Controllers should regulate stability while allowing safe redundancy, and evaluations should include efficiency, stability, and recovery under transitions/perturbations.

3.2.3. Evidence Threads: Safety, Function, Experience

Clinical evidence emphasizes three themes. First, interface load and tissue health motivate pressure-aware design, socket monitoring, and adaptive fitting strategies [9,30–33]. Second, function beyond level walking requires evaluating transitions, stairs, and volitional shared control rather than level-ground walking alone [34–37]. Third, prescription and follow-up require clinically interpretable evidence, including user-priority surveys and consensus-based prescription guidance [28,38,39].

3.2.4. Real-World Gap and Long-Term Endpoints

Short-term laboratory evidence often favors quasi-passive/active powered components over purely passive devices, but the strength of evidence is still limited by small samples, methodological limitations (e.g., small samples, limited randomization/blinding), and short follow-up. A review by Lathouwers et al. included 34 studies and reported that quasi-passive and active powered components outperform passive devices on multiple functional and biomechanical measures; however, the overall evidence remains insufficient to directly support long-term clinical adoption. Future work must thus validate performance under real-world conditions across days/weeks and simultaneously report long-term outcomes such as falls/near-falls, pain, skin complications, and maintenance cost; otherwise, "better on average in the lab" may not translate into sustained clinical benefit [40].

3.2.5. Surveys and Fall-Related Endpoints

Surveys refine needs-to-metrics mapping. In 114 transfemoral users, priorities included stability, reduced fatigue, predictable/learnable control, comfort/skin health, weight/noise, reliability, and maintenance cost; preferences varied with activity and context [38]. Evaluations should pair functional outcomes with experiential measures (control, trust, learning burden) and explicitly report falls/near-falls. In six transfemoral users, King et al. induced prosthesis-side trips; observed falls and recovery kinematics highlight transient impedance and swing-clearance limits and motivate perturbation-stability tests and explicit "fall probability" reporting beyond standard gait metrics [41].

3.2.6. Mechanical Properties and Prescription

Foot/ankle stiffness classes affect energy, comfort, and contralateral knee loading, implying individualized trade-offs between performance and intact-limb protection [42,43]. Cubillos et al. reported reliability and minimal detectable change for stiffness measures, enabling credible pre/post comparisons across designs and controllers [44]. Property-validated personalized passive feet further stress linking measured mechanics to clinical endpoints with repeatable protocols [45].

3.2.7. Deployment and Backup Strategies

Clinical choices are often not a single device but a "primary device + backup device" strategy. A qualitative study by Young et al. compared practical considerations when using a microprocessor knee versus a non-microprocessor knee as a backup device, highlighting the real-world weight of cost, maintenance, environmental adaptability, and perceived safety. This indicates that implementation-level configuration strategies can substantially shape real-world outcomes and should be part of the technical discussion rather than treated as external noise [46].

The choice of clinical endpoints directly determines hardware specifications and controller optimization objectives. Future studies should report efficiency, stability, and safety under transitions/perturbations within a unified task set, and build a traceable mapping between engineering metrics and end-user endpoints. Systematic reporting of real-world and long-term outcomes (falls/near-falls, pain, skin complications, maintenance cost) is also essential to improve evidence comparability and clinical translatability.

3.3. Electromechanical Architecture, Actuation, and Power Transmission

Section 3.3 summarizes design trade-offs in actuation, transmission, compliance, and power that set achievable control performance and safety margins.

3.3.1. Wearable Power and Control Metrics

Reporting should therefore extend beyond peak output to include impedance/backdrivability, strength and fail-safe margins, endurance and thermal limits, sealing, and maintenance, since these factors set control bandwidth and real-world usability [4–8,47–66]. Adjacent actuator-engineering studies, such as high-dynamics servo-valve drivers for electrohydraulic actuation, may provide transferable component-level evidence but should not be interpreted as direct prosthesis validation [67].

3.3.2. Multi-Joint and Multi-DOF Topologies

Multi-joint assistance is valuable when it reproduces key biomechanical phases (early-stance knee flexion, plantarflexion push-off, toe rollover), reducing pelvic and contralateral compensation [4–6]. Added DOF increases mass, power draw, and failure risk; many designs therefore use underactuation, differentials, and series elasticity to trade peak power for stored energy and backdrivability. Safety constraints during stairs/ramps/transitions should bound topology choices [4–6,48].

3.3.3. Actuation and Transmission Trade-Offs

Actuation and transmission must balance high torque/power with low impedance/backdrivability, which sets the feasible control bandwidth and impedance/admittance strategies. Electro-hydraulic hybrids can deliver high damping and impact tolerance but add complexity and sealing/noise/efficiency burdens [50]. Screw drives and torque-sensitive actuators favor quieter, more backdrivable behavior. In practice, gear/belt/screw/differential layouts with compliant elements largely determine the achievable torque-backdrive trade-off and long-term serviceability [48].

3.3.4. Compliance and Energy Management

Compliance and energy-management mechanisms aim to increase safety and economy without increasing the wearing burden. Series elasticity, variable stiffness/damping, and assist-as-needed control reduce peak power and impact loads across speeds and tasks [49,68]. Low-power actuation integrated into ESAR feet further illustrates how energy management can be achieved without excessive distal burden [69]. Parallel springs and adjustable equilibrium positions provide interpretable ramp optimization, while quasi-passive designs use variable stiffness and energy regeneration for low power draw. Semi-active variable-stiffness feet show that speed-impedance coupling can improve gait with little added energy, but multi-task trade-offs should be reported [8,49,70–72]. Related passive-compliance concepts inspired by prosthetic-leg design may provide indirect mechanical-design insight, but such non-prosthetic applications should be treated as transferable rather than direct prosthesis evidence [73].

3.3.5. Foot Form Factor and Fitting

Foot-end form factor and clinical fitting strongly influence whether laboratory performance transfers robustly to real-world use. Foot-sized and self-contained powered ankle-foot designs aim to reduce volumetric intrusion and improve long-term wearability, while distal lightweighting and inertia optimization can lessen swing-phase burden and support rapid foot-ground interactions on complex terrain [5,53,58]. More importantly, explicitly incorporating socket alignment and residual-limb loading into mechanical objectives (e.g., co-optimizing powered plantarflexion push-off and alignment capability) can reduce the risk of “fitting variability → control mismatch”. This makes control strategies more robust to clinical fitting and long-term wearing conditions and elevates “easy to wear, easy to fit, easy to maintain” from peripheral considerations to design inputs [7,74].

3.3.6. System-Level Evidence and Benchmarks

Representative systems should link metrics to tasks and risk points, not only list parameters. Powered knees address early-stance knee flexion deficiency and obstacle negotiation, while modeling and optimization show that high peak torque can coexist with low backdrive; noise, size, and maintenance should be treated as primary metrics [3,48,54]. Powered ankle-feet demonstrate net positive work across tasks and enable sensitivity analyses. Quasi-passive and variable-stiffness designs, including parallel-spring and adjustable-equilibrium mechanisms, offer interpretable low-power adaptability [8,49,71,72,75,76]. Low-cost, preliminary, and non-powered mechanical systems further highlight the importance of serviceability, manufacturability, and clinically realistic fitting constraints [77–79]. As assistance scales to multi-joint coordination, requirements on structural validation, redundancy, and safety testing increase accordingly.

3.3.7. Hip-Level Constraints and Fail-Safety

Hip-level prostheses impose higher DOF and power demands, and failures during transitions (sit-to-stand, turning, ramps/stairs) have larger consequences. Compared with transfemoral designs, the absence of a residual femur reduces passive mechanical stabilization and shifts load transfer to pelvic interfaces, increasing sensitivity to donning variability and comfort constraints. Designs therefore prioritize proximal lightweighting and inertia shaping, backdrivable/high-peak-power actuation with serviceable transmissions, and architecture-level fail-safety (mechanical end-stops, redundant braking, and conservative degraded modes). System-level optimization under thermal/energy-density and interface constraints is needed to preserve headroom for coordinated hip-knee-ankle power allocation and transition control [80–86].

Together, backdrivability, compliance, and power density define the feasible set of control strategies, while noise, endurance, serviceability, and clinical fitting/alignment determine long-term usability and translatability. The next section turns to sensing and interfaces, explaining why day-to-day stability and low latency are prerequisites for closed-loop control and real-world robustness [4,48].

3.4. Sensing Systems and Human-Machine Interfaces

Section 3.4 reviews sensing modalities and human-machine interfaces for intent and state estimation under real-world drift, donning variability, and embedded real-time constraints.

3.4.1. Sensing Design and Evaluation

Sensing evaluation is shifting from offline accuracy to closed-loop, long-term usability. Key factors include cross-day drift (e.g., electrode shift and skin changes) [11,87], practical placement and maintenance workflows [9–11], and end-to-end real-time behavior (latency, dropouts, anomaly handling) that directly affects safety margins during transitions [88,89]. Studies should report drift, latency, anomalies, and failure modes alongside accuracy.

3.4.2. Biosignal Interfaces and Usability

Biosignal human-machine interfaces (HMIs) remain dominated by surface electromyography (sEMG), but the focus has shifted from offline decoding to drift-robust closed-loop use. Reviews cover paradigms from proportional control to pattern recognition and phase-variable/finite-state machine (FSM) coupling and consistently identify cross-day drift as the main clinical bottleneck [11,87,90]. Robustness improves by combining sEMG with complementary signals (force myography [FMG], bioimpedance, skin deformation) and with inertial measurement units (IMUs) and plantar pressure to form redundant feedforward/feedback channels with safety fallback [91]. For deployment, low channel count and embeddability often matter more than model complexity; single-electrode in-socket control with posture/contact constraints reduces mis-switching in stair tasks [92], and edge recurrent neural network (RNN) pipelines enable on-device inference [93]. Portable bionic-ankle and clinical sEMG-controlled systems further show why volitional control should be tested under amputee-specific conditions [94,95], while reusable dermal surface EMG may reduce signal-acquisition burden [96]. Continuous myoelectric or model-driven control can reduce switching burden but still requires drift handling and safety integration [97–99]. Overall, usability depends on online calibration, uncertainty gating, and verifiable fail-safe behavior [11,87,91,93,100].

3.4.3. Mechanical and Kinematic Sensing

Mechanical/kinematic sensing offers low latency and repeatability, making it a strong channel for phase/event estimation and safety fallback. IMU + pressure is a deployable backbone: rule-based IMU event detection achieved ≈10 ms timing error for heel strike/toe-off [101], and integrating pressure with inertial cues supports stable phase estimation in practical foot hardware [102]. Pressure also improves robustness when fused for gait-parameter estimation [9,101,102]. Load and force–moment sensing provides closed-loop variables for control and fault detection; compact force/moment measurement via elastomer deformation has been demonstrated [103]. A common strategy is to anchor stability and fallback on mechanical channels, then layer learning-based recognition or personalization modules on top.

3.4.4. Interface Health and Comfort

Interface health and comfort are safety-critical and should be measured and controlled. Textile pressure sensing enables long-term socket monitoring and links interface load to control parameters [9]. Passive fluid pads redistribute pressure without added control complexity [30], while residual-limb volume changes motivate continuous monitoring and adaptive fit [104]. Active pressure regulation has been demonstrated by estimating internal stress (finite element + support vector machine [SVM]) and modulating pressure via predictive control [33]. Studies should report interface-risk metrics and their sensitivity to control settings to support clinical translation.

3.4.5. Environment Sensing and Fusion

Environment sensing provides a feedforward look-ahead window, but gains depend on redundancy design and integration into real-time safety frameworks. Vision/depth fused with kinematics can support anticipatory terrain perception and smoother transitions [10,88,105]. To complement vision on wet/dry or material changes, shoe-sole electrodes can estimate ground impedance, though repeatability and safety specs need standardization [24]. A-mode ultrasound and proximal minimal sensing extend continuous state observation with low burden [25,26]. Practical stacks often use IMU/pressure/load for closed-loop stability and fallback, augmented by vision/ground-property/ultrasound for feedforward compensation with confidence gating.

3.4.6. Sensory Feedback and Bidirectional Prostheses

Sensory feedback is becoming a core system objective alongside intent decoding. Plantar somatosensory restoration or neural feedback can improve gait, speed perception, and motor adaptation, highlighting the need to co-design efferent (control) and afferent (feedback) pathways [12,13,106]. Because feedback effectiveness depends on controller bandwidth, delay, and stability, it should be optimized with the control architecture rather than added post hoc [13]. Integrable approaches such as TacLeg translate foot–ground contact and terrain cues into discriminable tactile feedback using soft tactile units and vision [107]. Bidirectional closed loops may also reduce cognitive burden and improve safety; thus they should be evaluated as system-level outcomes [57]. Recent haptic-feedback reviews also emphasize that feedback should be evaluated as a combined system-design, user-experience, and clinical-outcome problem [108].

Overall, stable real-world sensing sets the ceiling for estimation, intent recognition, and control. A practical approach is IMU/pressure/load as the low-latency backbone and safety fallback, with biosignals and environment sensing added through redundancy, drift handling, and confidence-gated degradation.

3.5. Gait Phase and State Estimation

Section 3.5 reviews real-time gait representations, from discrete events and finite-state machines to continuous phase variables that support unified control.

3.5.1. Discrete-to-Continuous Phase Variables

Discrete phase/event detection (e.g., heel-strike/toe-off [HS/TO]-triggered finite state machines [FSMs]) offers low latency and is easy to validate, making it suitable for controller switching triggers and safety fallback. However, under speed changes, terrain transitions, and day-to-day drift, it is prone to false triggers and switching jitter [101–103,109,110]. By contrast, continuous phase estimation directly outputs a continuous progress variable (typically normalized to 0–1 over a gait cycle), enabling smooth parameter updates and reducing discontinuities caused by discrete switching. Recent approaches implement continuous phase estimation using learning-based models (e.g., long short-term memory [LSTM] networks or temporal convolutional networks [TCNs]) and unified kinematics modeling across speeds and activities. However, their practical value hinges on cross-task robustness and stable deployment [111–114].

3.5.2. Phase-Based Trajectory Generation

A key advantage of the phase-variable framework is that it can close the loop among estimation, generation, and control: phase is not merely a label but an internal state that drives continuous changes in trajectories and impedance. Kim et al. proposed a real-time phase estimation and speed-adaptive trajectory generation method that combines sequential optimization with Kalman filtering to enable online adaptation across speeds while maintaining smoothness and stability [115].

3.5.3. Phase Variable Construction and Alignment

Phase-variable methods typically build a monotonic mapping between measurable kinematics (e.g., thigh angle) and gait progression, requiring consistent monotonicity and invertibility under varying speeds and slopes. Naeem et al. proposed an improved thigh-based phase-variable estimation method for knee-ankle coordinated prostheses, extending the usable range of conditions and improving alignment robustness [116].

3.5.4. Nonperiodic Tasks and Transitions

Phase modeling faces stronger nonlinearity and event heterogeneity in tasks such as stairs. Using stair descent as an example, Cha and Hur proposed a workflow to extend phase variables to nonlevel-ground tasks, providing a paradigm for transitioning from “level-ground usable” to “multi-task generalizable” phase estimation [117].

3.5.5. State Observation and Uncertainty

Beyond phase, an increasing body of work directly targets continuous kinematic/kinetic variables for estimation, providing finer-grained feedback for control. Ding et al. introduced an attention-based deep learning framework that uses wearable IMUs as input to estimate multi-dimensional kinematic/kinetic variables across multiple activities, highlighting the role of uncertainty-aware continuous observation for robust closed-loop control [112,118,119].

3.5.6. Minimal Sensing and Novel Inputs

Ultrasound provides an input channel for continuous kinematic prediction that is distinct from EMG. Mendez et al. used A-mode ultrasound to capture residual-limb muscle deformation features and trained a neural network to predict prosthetic-side knee/ankle position and velocity for transfemoral amputees, evaluating the approach on nine participants and demonstrating feasibility for continuous state estimation under realistic sensing constraints [25].

3.5.7. Benchmarking and Failure-Mode Reporting

Phase/state estimation is not an isolated module but the hub connecting sensing, control, and validation. In end-user experiments, estimation errors are often amplified into reduced comfort, degraded symmetry, or increased risk of incorrect switching. Therefore, studies should report robustness across tasks and days, explicitly document failure modes, and describe safety fallback mechanisms to support reuse and fair comparison across pipelines [101–103,113,115,117,118].

Continuous phase/state observation can provide smoother references and more natural task transitions, but its value hinges on cross-task and day-to-day stability, failure modes, and safe fallback. The next section discusses intent/mode/terrain recognition to clarify how high-level decisions should couple with phase/state estimation in a safety-aware manner.

3.6. Intent, Pattern, and Terrain Recognition

Section 3.6 reviews intent, mode, and terrain recognition methods, with emphasis on latency, robustness, and safe switching constraints.

3.6.1. Classification *vs*. Regression Formulations

Intent recognition includes both classification of discrete modes/terrains (e.g., level ground, ramp, stairs) and regression of continuous intent variables (e.g., walking speed, slope, continuous phase, or future joint trajectories/kinetics). Compared with pure classification, continuous regression can couple more naturally with phase variables and variable-impedance control, potentially reducing discontinuities and improving adaptability under gradual changes in task demands.

3.6.2. Wearable Signals and Temporal Models

Multimodal fusion of IMU with pressure and/or EMG remains the dominant route. While deep temporal models such as LSTM, TCN, and Transformers can improve offline performance, they also bring interpretability, drift, and out-of-distribution failure to the forefront of engineering translation, especially when sensor placement changes, skin conditions vary, or the environment differs from training. Recent work has also explored unified or adaptive locomotion-mode recognition and mode-unified intent estimation using wearable signals and deep temporal models, highlighting both performance potential and the need for robust generalization [120–124].

3.6.3. Transitions and Safety Fallback

Transitions are the time window where misclassification is most concentrated. Accordingly, practical systems often adopt hierarchical decisions and make safety fallback explicit. Narayan et al. performed real-time hierarchical classification with a convolutional neural network (CNN) in a hierarchical label space and achieved <2 ms embedded inference, trading model complexity for low latency and enabling conservative fallback behavior during uncertain transitions [125]. Complementary work has specifically targeted swing-phase detection and transition recognition for smoother multi-functional switching using wearable sensors, reinforcing the importance of transition-aware design [126,127].

3.6.4. Synergy Representations

Synergy modeling provides an intermediate layer for "low-dimensional representation to control mapping". By compressing high-dimensional sensing information into a small set of interpretable synergy coefficients, it can serve as features for intent recognition or be used directly to generate joint references or impedance parameters, thereby supporting transferability and reducing dependence on brittle, high-dimensional decision boundaries [21].

3.6.5. Terrain Perception Modalities

Vision/depth vision can provide anticipatory terrain classification and obstacle detection, offering the controller a feedforward time window, but it also introduces challenges such as occlusion, lighting sensitivity, power consumption, and privacy [10,128]. Li et al. stabilized the field of view with a two-DOF gimbal and LADRC, and coupled lightweight perception with locomotion control to improve robustness during outdoor transitions, illustrating a practical path toward vision-enabled prosthetic control under real-time constraints [105,129].

3.6.6. Edge Deployment and Lightweight Models

In prosthesis control, where real-time performance and power are highly constrained, lightweight models and feature engineering/optimization remain competitive. Zhang et al. combined node pruning with metaheuristic optimization to obtain an improved extreme learning machine (ELM), achieving multi-mode recognition with a very small model footprint while meeting embedded deployment requirements [130,131].

3.6.7. Hip-Level Implications for Recognition

Powered hip-disarticulation prostheses have higher degrees of freedom and higher-risk transitions (sit-to-stand, turning, stairs), making them more sensitive to control continuity, power allocation, and tolerance to incorrect switching. Because pelvic/trunk compensations and task boundaries can be less stereotyped, intent recognition for hip-level systems benefits from stronger uncertainty handling (confidence gating), conservative transition rules, and clearly defined fallback behaviors. Meng et al. proposed an SSA-LSTM-based locomotion mode recognition framework for powered hip-disarticulation prostheses, illustrating the need for safety-aware recognition under complex transitions [132].

3.7. Control Framework

Section 3.7 summarizes control architectures from impedance and trajectory control to model predictive control and hybrid schemes, focusing on unified control variables and task transitions.

3.7.1. Hierarchical Control and Safety Envelope

Control structures have evolved from the traditional FSM paradigm of "discrete states with fixed parameters" toward continuous parameterization, phase-driven modulation, and optimal-control formulations such as MPC or quadratic programming (QP). However, mainstream engineering practice is not to substitute stable mechanisms with optimization/learning, but to adopt a layered architecture: keep a verifiable safety layer, and allow adaptation to occur within bounded, interpretable modules. Tracking-control formulations that aim to reproduce target kinematics (e.g., intact-knee profiles) also provide useful methodological references for trajectory tracking and validation in wearable lower-limb devices [133].

3.7.2. Impedance/Admittance and Interaction Control

Variable impedance/admittance is a key handle for adapting across speeds, slopes, and tasks. The goal is to reduce user-specific hand tuning while allowing joint dynamics to change continuously with state and environment, thereby improving robustness on complex terrains. This is particularly emphasized for high-risk tasks such as stairs, where interaction forces, stability margins, and conservative fallback must be explicitly considered [14,134–137].

3.7.3. High-Risk Task Control

The difficulty of high-risk tasks is not simply "adding one more mode", but meeting stricter constraints on continuity, power allocation, and fallback behavior. Accordingly, many studies employ task-specific strategies to make the risk points explicit and verifiable [14,134]. For example, Marsh et al. developed a swing-assist controller to enhance knee flexion during the swing phase, thereby improving stair ambulation and demonstrating how targeted control can address a specific risk-dominant phase [138,139]. Impedance-based stair ambulation evaluations further stress the need to quantify stability and interaction forces under realistic transitions [140]. Similarly, unified variable-impedance strategies have been studied for sit-to-stand to improve loading symmetry and timing, illustrating that high-risk transitions require explicit objective definitions and safety-aware control structure [141].

3.7.4. Phase Variables and Virtual Constraints

Phase variables together with virtual constraints or reference-trajectory generation provide an "interpretable continuity": a single independent variable unifies trajectories, impedance, and factors such as speed/slope into a continuous coordinate system, reducing discontinuities induced by discrete switching [15,116,142,143]. This parameterization also supports smooth modulation across gradual changes in task demand and can be combined with model-based constraints to preserve stability.

3.7.5. Robust and MPC Control

In high-impact and strongly nonlinear scenarios such as foot strike and downhill/stair descent, robust control can still serve as a candidate safety layer. Memarzade et al. compensated dead zones and hysteresis using a disturbance observer and adopted fractional-order dynamic terminal sliding-mode control to improve tracking accuracy and robustness during shock absorption and high-variability interactions [144]. Related adaptive/neural-dynamics control and repetitive learning strategies have also been explored in prosthesis and prosthesis-simulation platforms, reinforcing the value of robustness-oriented design when hardware is non-ideal, and dynamics are uncertain [145–147].

3.7.6. Unified Control

Unified control frameworks aim to reduce reliance on explicit terrain/mode classification by shifting complexity from "classification accuracy" to robust design of continuous control laws and reliable event handling. Sullivan et al. proposed a unified controller that enables a powered knee-ankle prosthesis to execute multiple terrains without explicit mode classification, highlighting a direction where continuous control and verifiable transitions become primary design objectives [148–150].

3.7.7. Human Factors and Preferences

The quality of a control strategy is reflected not only in mechanical metrics such as torque and power, but also in learnability, interpretability, and subjective burden. Direct myoelectric control has also been explored as a means of modulating prosthetic ankle behavior [97], and Posh et al. compared FSM impedance control, DMC, and a switchable hybrid on the same robotic ankle platform [151].

3.7.8. Biologically Inspired Target Dynamics

To make impedance control "human-like" in a verifiable manner, quantifiable human target dynamics are needed. van der Kooij et al. identified equivalent hip/knee impedance during swing using a low-impedance exoskeleton perturbator and reported ranges across participants, providing measurable references for setting swing-phase impedance and evaluating biological plausibility [152].

3.7.9. Transition-Aware Control

Real-world difficulty is concentrated in transitions between activities and in continuous changes in speed/slope; thus, transitions should be treated as first-class objectives in both design and evaluation. Cheng et al. compared phase-based kinematic control that varies continuously over transition intervals with schemes that switch at discrete events, and reported that continuous schemes can improve comfort and stability without relying on hard switches under certain conditions [153].

3.7.10. Simulation and Offline Priors

To reduce iteration costs and risks from prototypes to human experiments, interpretable closed-loop simulation is becoming an indispensable intermediate layer in control engineering. Driessen et al. proposed a reduced-order closed-loop hybrid dynamics framework that unifies discrete events (e.g., contact/no-contact) with continuous dynamics, enabling systematic sensitivity analysis and risk screening before end-user testing [47].

3.7.11. Hip-Level Power and Fail-Safety

Because hip-disarticulation/hip-level systems have higher degrees of freedom and more severe consequences of transition failures, they more readily expose the tension among discrete mode switching, continuous phase progression, and multi-joint power distribution. Naïvely inheriting local FSM and impedance tuning from knee/ankle systems can amplify discontinuities at task boundaries and create unsafe corner cases when trunk-pelvis dynamics diverge from expected patterns. This motivates integrated system engineering that couples whole-body coordination maps, energy/power distribution across joints, and architecture-driven fail-safe logic (including "graceful exit" strategies) [154–159].

3.8. Learning Control and Individualization

Section 3.8 reviews personalization via learning and human-in-the-loop tuning, and outlines mechanisms to enforce safety constraints and fallback behavior.

3.8.1. Closed-Loop Personalization Landscape

From a broader review perspective, Bhoyar et al. summarized potential roles of AI in prosthetics across control, sensing and feedback, personalization, and remote monitoring [160].

3.8.2. Human-in-the-Loop Optimization

The core goal of human-in-the-loop (HIL) optimization and expedited tuning is to converge to more suitable impedance parameters or control policies within a limited number of walking trials, thereby reducing dependence on expert heuristics. At the same time, it must handle real-world learning effects such as fatigue, objective drift, and limited sample budgets, which can otherwise bias conclusions and undermine repeatability [16,18].

3.8.3. Clinical Objectives for Optimization

Compared with optimizing only metabolic cost or subjective preference, anchoring objectives to quantifiable clinical function metrics that relate to compensation and risk can better support a reproducible evidence chain. Li et al. used propulsion impulse symmetry as an optimization endpoint and proposed a hierarchical optimization framework to adjust control parameters, demonstrating how clinically interpretable targets can guide personalization while preserving safety [16,161].

3.8.4. Multimodal Closed Loops

Deployment of learning control often relies on observability and closed-loop correction, which increases the importance of multimodal sensing and feedback channels. Pi et al. coupled HIL tuning with sensory feedback: they estimated cadence from vertical ground reaction forces and used a D-SLIP-based framework to support collaborative control and adaptation, illustrating a direction where personalization and feedback co-evolve in a closed loop [162,163].

3.8.5. RL/IL with Physical Constraints

Optimization and learning-based methods, including hierarchical optimization, reinforcement learning, and imitation-learning-inspired policy generation, are being used to generate or refine control policies. The mainstream trend, however, is not purely data-driven control, but combining learning with physical models, structural priors, and explicit constraints to reduce unpredictable behaviors while improving transferability and safety [161,164–166].

3.8.6. End-to-End Learning and Distillation

As control targets shift from discrete mode switching to continuous multivariable control, end-to-end or multitask learning is increasingly used to distill expert rules into unified, deployable policies. This trend also strengthens the requirement for safety gating and fallback mechanisms. For example, Nuesslein and Young proposed a deep learning framework for end-to-end control, emphasizing that deployment must be coupled with confidence estimation, anomaly detection, and conservative fallback [123].

3.8.7. Co-Adaptation and Preference Learning

Learning control and individualization do not imply “handing everything to the algorithm”. Growing evidence suggests that user-controllable feedback channels and algorithm-adjustable control parameters must be co-designed. Fylstra et al. proposed a human-machine co-adaptation paradigm in which users can influence tuning through interpretable interaction channels, while the algorithm adapts parameters within safe bounds, highlighting preference-driven personalization as a system design problem [167,168].

3.8.8. Hip-Level Safety-Critical Endpoints

In hip-disarticulation/hip-level populations, compensation strategies are more heterogeneous, and transition tasks carry a higher risk. End-user validation of learning-based control should therefore include staged testing of high-risk activities (sit-to-stand, turning, ramps/stairs) and report safety-relevant endpoints such as falls/near-falls, recovery behavior after perturbations, and interface comfort over time; otherwise, laboratory gains may not translate to real-world safety [132,154,157,159,169].

Learning methods substantially increase the potential for personalization, but their translational feasibility depends on safety constraints and fallbacks, sample efficiency and trial design (including fatigue/drift management), and observability and edge deployability—not merely on network structure [16–18]. The next section returns to safety, reliability, and standardization as system-level prerequisites.

3.9. Safety, Reliability, and Standardization

From combined engineering and regulatory perspectives, this section summarizes key safety and reliability considerations for powered prostheses, including failure modes and risk boundaries, redundant braking and mechanical limits, degraded control and interpretable fallback, online fault detection and confidence estimation, logging and traceability, and standardized evaluation and reporting for regulatory pathways (Figure 3) [89,170–172].

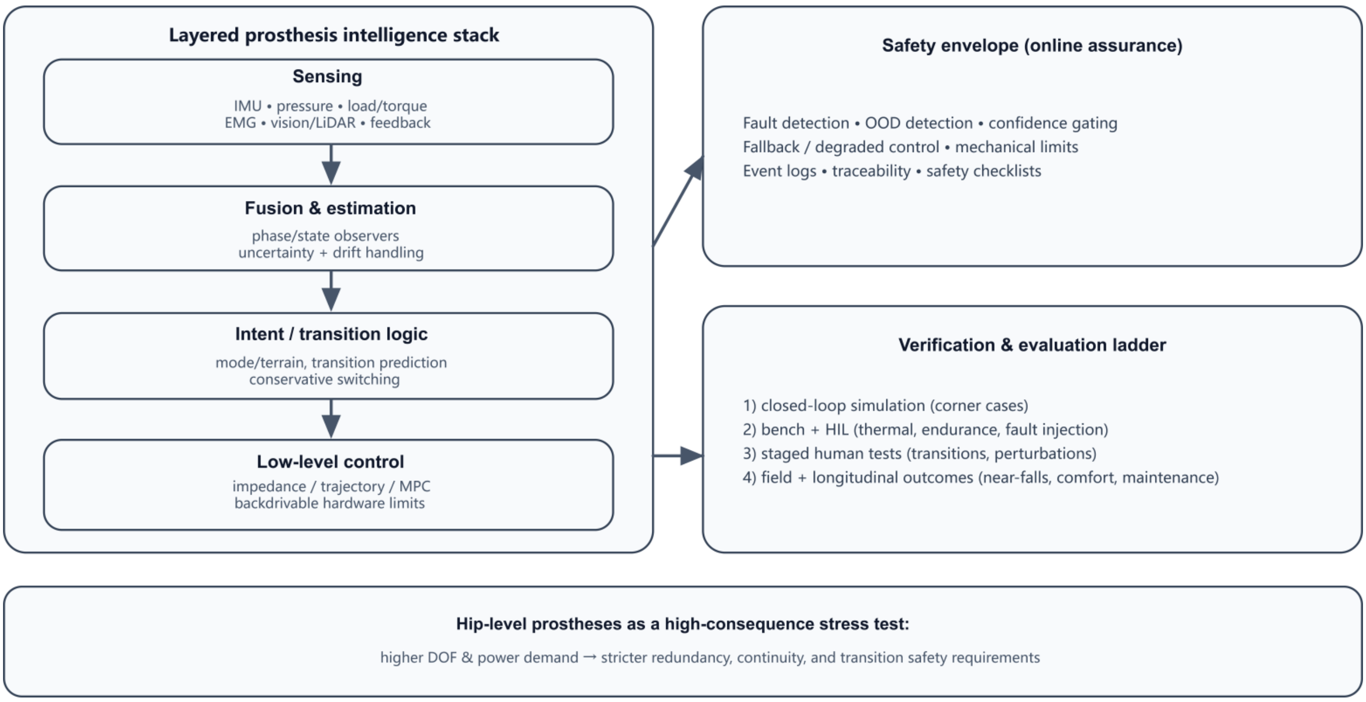

Figure 3. Layered safety/assurance stack for learning-enabled prostheses. A verifiable mechanical and low-level control core is complemented by online monitoring (fault detection, confidence gating), conservative fallback/degraded control, logging and traceability, and standardized evaluation to bound risk, especially for hip-level systems.

3.9.1. Hip-Level Fail-Safety

Fail-safe design for hip-level systems should be consequence-aware and architecture-driven, given the more severe consequences of failure and reduced available compensation. If critical actuation/transmission or sensing fails, proximal compensation margins are limited; beyond conventional strength and fatigue assessment, designs should incorporate redundant braking and/or mechanical locking, hard end-stops, and conservative degraded-control modes that maintain support and allow controlled task exit. Software should complement this with anomaly detection, confidence evaluation, and interpretable rollback logic (e.g., gate high-torque assistance unless state/intent confidence is sufficient) to bound risk during stairs, turning, and sit-to-stand [154–156,159,173].

3.9.2. Online Assurance and Traceability

Safety and reliability research commonly spans fault diagnosis, anomaly detection, redundancy and fallback mechanisms, risk assessment, and standardized testing. It also imposes stricter verifiability requirements on learning modules and neural control: risks of misrecognition or policy instability tend to concentrate during transitions and corner cases. Accordingly, online assurance mechanisms, such as confidence gating, out-of-distribution detection, and logging for traceability, should be treated as integral components of the control stack rather than optional add-ons [89,171,174,175].

3.9.3. Standardization and Reporting

On standardization, existing work has proposed roadmaps for neurally controlled prostheses, with a central demand to front-load testable performance/safety endpoints, risk categorization, and consistent reporting templates. Only when studies report under a unified set of tasks and failure scenarios, with consistent definitions (e.g., safety endpoints, transition errors, near-fall events), can evidence become comparable and support regulatory translation [42,171,172].

3.9.4. Reliability and Manufacturing

Mechanical reliability and manufacturing should be integrated into the same safety narrative because structure, control, and clinical outcomes are tightly coupled in powered prostheses. For example, the mechanical behavior and validation of 3D-printed prosthetic-foot components, together with changes in foot stiffness category, can meaningfully alter gait biomechanics, indicating that purely structural qualification is insufficient without closed-loop evaluation under realistic loading and control conditions [47,176].

3.9.5. Unified Verification

From a system-safety viewpoint, standardized mechanical tests and control safety are not independent paths. For instance, the powered hip-joint prototype reported by Brannen et al. included structural strength and mechanical validation; its significance is not only mechanical compliance but also providing a validated platform on which learning control and automatic mode switching can be assessed within a bounded safety envelope [154].

With the introduction of learning and neural interfaces, safety and standardization have shifted from optional extras to front-end constraints of system design. Future work should integrate confidence gating, anomaly detection, fallback strategies, and clinically interpretable reporting into a unified verification framework to support automatic transitions and learning control in real-world environments [42,89,171].

4. Open Challenges and Future Directions

Translation of intelligent lower-limb prostheses is increasingly constrained by system-level issues rather than isolated component performance. Even when actuation, sensing, or control performs well in controlled experiments, deployment often fails at the interfaces: robustness across days and environments, safe and reliable task transitions, and evidence that benefits persist in daily life. This section summarizes cross-cutting open challenges and outlines future directions toward clinically deployable systems. High-level amputations (hip-disarticulation/hip-joint-level) are used in subsection (6) as a high-consequence "stress test" that amplifies these bottlenecks.

(1) Real-world usability and long-term outcomes: End-user studies now cover a wider set of tasks, but they remain commonly limited by small sample sizes, short follow-up, and insufficient reporting of day-to-day stability. Future work should report traditional endpoints (e.g., metabolic cost and symmetry) alongside safety- and usability-relevant outcomes such as near-falls, task completion under fatigue, and longitudinal comfort. Reporting should be standardized to improve external validity. Notably, how endurance and fatigue endpoints are defined can substantially change the relative ranking of control strategies. Best et al. used the number of laps completed in a multi-task circuit as a primary endpoint, providing a practical template because it naturally integrates task diversity and fatigue into a single, interpretable outcome [34].

(2) System trade-offs among energy, weight, and form factor: Higher power density and lightweighting remain essential, but low noise, low mechanical impedance, and backdrivable compliance are equally important for comfort and bodily integration. Foot-size devices (e.g., ELSA) and low-power energy-management mechanisms illustrate opportunities to deliver useful assistance in constrained volumes, but they should be evaluated under realistic tasks and long-term wear constraints rather than short laboratory trials [5,8,49,72].

(3) Day-to-day robustness of sensing and interfaces: Cross-day drift driven by placement variability, skin condition, sweat, and environmental factors remains a primary deployment bottleneck. Studies should explicitly report calibration burden, drift/failure modes, real-time latency (e.g., <2 ms), and uncertainty-aware gating with conservative fallback control [9,11,89,125,175]. Vision can provide look-ahead but must address energy consumption, occlusion, and privacy; in practice, it is most credible when paired with proximal sensing rather than used alone [10,88,105]. Visuotactile designs (e.g., TacLeg) offer an intuitive pathway to translate look-ahead information into wearable feedback [107]. For EMG, electrode shift and fatigue are major sources of drift; mitigation strategies include improved electrodes, multimodal fusion, and online adaptation [87]. HDsEMG supports individualized calibration [177]. Low-channel volitional control and edge RNN pipelines are promising, but amputee validation and cross-day evidence remain necessary [92,93].

(4) Translational pathways for sensory closed loops and embodiment: Tactile and proprioceptive feedback can shape speed perception, motor adaptation, and long-term usability [12,13]. The bidirectional bionic-limb perspective argues that efferent and afferent pathways should be co-designed and co-evaluated; sensory return should therefore inform core control choices and endpoints rather than remain an add-on module [57]. Future studies should link feedback parameters to acceptability, learning curves, and functional outcomes under explicit safety and ethics constraints. Scalable options include peripheral haptics/vibration and integrable visuotactile devices such as TacLeg [107].

(5) Verifiable safety for learning-enabled modules: Reinforcement learning (RL) and human-in-the-loop (HIL) optimization can accelerate personalization, but they require explicit safety constraints, online monitoring, and reliable fallback behavior, together with standardized trial designs that limit fatigue and learning confounds [16,18]. Comfort and interface pressure can be optimized as measurable safety objectives, but they require longitudinal and cross-day evidence to be clinically persuasive [9,30,33].

Simulation RL reduces risk during exploration, yet still needs a credible sim-to-real validation chain [165]. End-to-end learned torque control can reduce rule tuning, but it increases demands on interpretability, fault diagnosis, and failure containment; it should be paired with uncertainty estimation, anomaly detection, conservative fallback, and sensitivity analyses grounded in structural testing [47,154].

(6) Whole-body coordination and validation platforms for hip-level systems (high-consequence case): Hip-disarticulation/hip-joint-level prostheses impose stricter constraints and higher consequences of failure, and therefore expose the hardest system-level bottlenecks. Key challenges include: (i) generating high peak power while limiting proximal mass/inertia and thermal burden; (ii) managing pelvic interface mechanics, donning variability, and long-term comfort/skin health; and (iii) achieving safe multi-task transitions with explicit fail-safe behavior under sensing/actuation uncertainty. Progress will likely require a staged validation toolchain—physics-based simulation, hardware-in-the-loop and bench testing (including failure injection), and carefully phased human studies—paired with conservative front-loaded safety strategies and transparent logging/traceability [159,169].

(7) Data, benchmarks, and standardization: Although standardization roadmaps have been discussed, cross-study comparability remains insufficient. Open datasets and unified task sets/reporting templates that span centers, devices, and days are urgently needed so that "hardware + sensing + control + learning + validation" can be evaluated and reproduced under a common yardstick. At a macro level, perspective and review articles have reviewed progress in lower-limb prostheses across materials, actuation, control, and clinical needs, emphasizing affordability, maintainability, and standardized evaluation as prerequisites for clinical adoption [178,179]. Benchmark-dataset mapping and open-source leg-prosthesis platforms may further support reusable evaluation resources [172,180].

5. Conclusions

This review synthesized recent progress in intelligent lower-limb prostheses through a system-level lens spanning electromechanical design, sensing and human-machine interfaces, phase/state estimation, intent recognition, control frameworks, learning-based personalization, and safety/standardization. Across these layers, the recent literature suggests a gradual shift from purely discrete mode switching toward continuous phase/state variables and variable-impedance behaviors enabled by multimodal sensing. However, translation to daily use is still constrained by endpoint mismatch, limited external validity across terrains and days, and insufficient reporting of failure modes and fallback behavior. Future advances may depend on integrated co-design of hardware and control, redundancy-aware sensing architectures, confidence-gated decision-making, and benchmarked evaluation protocols that connect laboratory metrics to real-world safety and long-term outcomes, especially for hip-level systems where consequences are amplified.

Statement of the Use of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the author(s) used ChatGPT (OpenAI) in order to improve the clarity, grammar, and readability of the text through language polishing and stylistic refinement. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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Author Contributions

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Ethics Statement

Not applicable. This article is a systematic review of previously published literature and did not involve any new studies with human participants or animals performed by any of the authors.

Informed Consent Statement

Not applicable. This study did not involve the recruitment of participants or the collection of identifiable personal data.

Data Availability Statement

No new data were generated or analyzed in this study. All information supporting the findings of this review is available within the article.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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