# Artificial Intelligence in Biped Exoskeletons: An Integrated Review on Human Activity Recognition and Reinforcement Learning

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***Abstract:*** *The rapid advancement of robotics and intelligent systems has driven increased interest in the development of biped exoskeletons for medical, industrial, and assistive purposes. This review is motivated by the growing demand for adaptive and energy-efficient exoskeletons capable of mimicking human locomotion. The specific hypothesis of this review is that integrating artificial intelligence techniques significantly enhances the performance, personalization, and adaptability of bipedal exoskeleton systems. The objective of this review is to analyze AI-driven approaches in exoskeleton design and control, with a focus on machine learning algorithms, human activity recognition, and reinforcement learning. The methodology involved a systematic review of recent studies, emphasizing models that incorporate sensor-based input, dynamic control strategies, and real-time feedback mechanisms. Based on experimental investigations carried out by the authors, the paper also includes original results obtained by the research team, providing empirical validation of the proposed approaches. Key findings reveal that AI integration can reduce energy consumption, improve gait stability, and minimize the need for manual adjustments. The review concludes that the fusion of AI and exoskeleton technologies represents an innovative direction, contributing to scalable, user-centered solutions with high potential in rehabilitation and physical augmentation. This work highlights the importance of interdisciplinary collaboration and opens pathways for future research in intelligent wearable robotics.*

***Keywords:*** *Artificial intelligence, exoskeleton, reduced mobility, machine learning, control algorithms, motion optimization, applied informatics*

## 1. Introduction

Bipedal exoskeletons are wearable robotic systems designed to support or enhance human locomotion. Their applications span from medical rehabilitation for individuals with neurological or musculoskeletal disorders to physical augmentation in industrial and military contexts.
Over the past decade, the functionality and portability of these systems have significantly improved. However, traditional exoskeletons still face major limitations related to adaptability, energy efficiency, and real-time user interaction, which restrict their practical usability in diverse environments and among users with varying needs.
Recent developments in artificial intelligence (AI), particularly machine learning and reinforcement learning (RL), offer new opportunities to overcome these challenges.
AI techniques enable exoskeletons to learn adaptive control policies, optimize assistance profiles, and respond intelligently to dynamic user movements.
Reinforcement learning, for example, has been shown to reduce the metabolic cost of human walking when applied to robotic exosuits, thus improving user comfort and endurance [1]. Additionally, human activity recognition (HAR), using inertial measurement units such as accelerometers and gyroscopes, has proven highly effective in identifying locomotor patterns in real-time [2].

These capabilities, supported by hybrid control architectures that integrate biomechanical and neural feedback, are critical for exoskeletons to function seamlessly in unpredictable environments [1,2].

Despite promising progress, current research remains fragmented. Some studies focus solely on HAR to monitor activity states, while others apply RL to develop generalized control algorithms without integrating real-time sensor data [3]. This disjointed approach limits the full potential of intelligent control systems in exoskeletons. Moreover, there is a lack of standardized performance metrics, making cross-study comparisons difficult and slowing down the advancement of scalable solutions [4]. Neuromechatronic frameworks that combine AI with cooperative human-exoskeleton interaction offer a promising solution to these challenges [5].

However, to date, no systematic review has provided an integrated perspective on HAR–RL control frameworks that combines evidence from both simulation studies and experimental prototypes. This paper aims to address this gap by offering a unified analysis that highlights key trends, limitations, and opportunities for future development.

The central hypothesis of this review is that the integration of HAR and AI-based adaptive control can lead to more efficient, personalized, and user-friendly bipedal exoskeletons. By analyzing and comparing current trends in the literature, the paper aims to identify key developments, reveal existing gaps, and propose a unifying framework that combines sensor-driven intention recognition with intelligent decision-making. This review underscores the importance of interdisciplinary approaches that leverage AI to adapt to user physiology and intention, paving the way for advanced exoskeleton systems [5].

Unlike earlier approaches that treated reinforcement learning (RL) and human activity recognition (HAR) separately [1,4], the present review advances an integrated perspective that combines both methods within a unified framework. This complements prior studies such as [6], who demonstrated metabolic cost reduction through RL-based exosuits but did not incorporate user-intent recognition, and [7] who proposed autonomous exoskeletons without adaptive HAR-driven feedback. By integrating HAR and RL, our study addresses these limitations and highlights the potential of cooperative control systems capable of adapting to both biomechanical and neural signals [5].

## 2. Materials and Methods

This review employed a systematic approach to analyze recent advancements in the development of bipedal exoskeletons enhanced by artificial intelligence (AI). The methodology included the identification, selection, and analysis of scientific literature that integrates AI algorithms such as reinforcement learning (RL) and supervised learning techniques with human activity recognition (HAR) systems and biomechanical control models.

### 2.1. Literature selection and Analysis

Relevant articles were identified through scientific databases such as IEEE Xplore, MDPI, ScienceDirect, Springer, and Elsevier. The selection criteria included papers published between 2014 and 2024, focusing on wearable lower-limb exoskeletons, human activity recognition (HAR) integration, and AI-based control strategies. A total of 38 papers were included in the final review. The selection covers both foundational studies [6-8] and more recent contributions [1,5,9], among others, in order to provide an up-to-date and comprehensive perspective.

Mathematical models of bipedal exoskeletons were examined to evaluate joint torque generation, center of mass control, and step pattern adaptation in dynamic environments. These models typically employ multi-body dynamics and inverse kinematics, calibrated through motion capture systems or wearable sensor data [6,10].

Artificial intelligence algorithms were grouped into two main categories:

**Supervised Learning** – including Support Vector Machines (SVM), Decision Trees, and Random Forests, widely applied in HAR systems to classify user movements such as walking, sitting, standing, and stair climbing [11,12].

**Reinforcement Learning (RL)** – particularly Proximal Policy Optimization (PPO) and Deep Q-Learning, employed in simulated environments to generate adaptive control strategies aimed at improving stability and reducing energy expenditure [3,13,14].
Simulation platforms such as **Webots (v2023a)** and **MATLAB Simulink** were frequently used for the development and validation of dynamic control systems. These environments enable the integration of real-time sensor feedback and support cooperative human–exoskeleton interaction strategies [15,16]. Webots is open-source and available at: https://cyberbotics.com.

### 2.2. Sensor systems and Data processing

The review includes systems equipped with Inertial Measurement Units (IMUs) such as accelerometers and gyroscopes. Data preprocessing consisted of signal segmentation, noise filtering (using Butterworth low-pass filters), and feature extraction in both time and frequency domains. These features were used for activity classification and real-time control switching, supporting adaptive exoskeleton control [2,11].
Performance validation included both simulation-based metrics and experimental trials on healthy subjects. In simulations, the metabolic cost was estimated using biomechanical energy models, consistent with methods proposed by Kim et al. (2019) [6] and Mooney et al. (2014) [7]. HAR accuracy was validated through confusion matrices and performance metrics including precision, recall, F1-score, and accuracy typically over 90% [2,11].
Where applicable, statistical analysis was performed using SPSS v27 or R, including ANOVA for group comparisons and Pearson correlation to assess the relationship between predicted and actual user activity. Confidence intervals were set at 95%, and p-values $< 0.05$ were considered statistically significant.

### 2.3. Model Integration and Optimization

Several studies proposed integrated frameworks where HAR feeds real-time data to RL-based controllers to adjust gait parameters such as joint velocity and torque in response to detected activities [6,8]. These systems reduce reliance on manual adjustments and improve overall exoskeleton adaptability.
Key innovations include closed-loop control using hybrid AI architectures and biomechanical optimization tailored to individual gait profiles [13,16,17]. Cooperative AI systems that learn from biomechanical and neural signals further enhance exoskeleton performance [3].

## 3. Results and Discussions

The systematic review revealed significant insights into how AI technologies enhance the functionality, adaptability, and energy efficiency of bipedal exoskeletons. By synthesizing findings from multiple peer-reviewed studies, several core patterns emerged.
First, the majority of studies (63%) reported high performance from supervised learning models used for human activity recognition (HAR), with classification accuracies often exceeding 90%. This was particularly evident in systems employing inertial measurement units (IMUs), where accelerometer and gyroscope data enabled precise real-time detection of locomotion states such as walking, standing, stair climbing, or transitions [2,11,12,18]. These classification systems allowed exoskeletons to interpret user intent dynamically, supporting real-time decision-making in assistive control loops. The success of HAR modules contributed not only to the precision of state transitions but also to the comfort and usability of the wearable system, minimizing delays and improving task fluidity [9].
Second, the role of reinforcement learning (RL), especially algorithms like Proximal Policy Optimization (PPO) and Deep Q-Networks (DQN), proved central to enabling real-time adaptability in control systems. RL-based controllers demonstrated superior ability to optimize joint torque profiles and foot trajectory in varying gait phases, learning from iterative feedback loops.
These algorithms often run in simulated environments like Webots or MATLAB Simulink, where they were trained using biomechanical models and real-time sensor data. In over 40% of the studies, the application of RL techniques led to a measurable reduction in metabolic energy

expenditure — up to 17% in some simulations — suggesting their effectiveness in reducing user fatigue.

This finding was corroborated by [6], who observed metabolic cost reductions when applying RL-driven actuation in robotic exosuits. Additional insights were provided by Findik et al. (2025) [3] and Utku et al. (2024) [14], who highlighted the robustness of RL controllers for optimizing gait parameters in real-world scenarios. Neuromechatronic approaches that integrate biomechanical and neural feedback further enhanced RL performance, particularly for rehabilitation applications [15].

In studies where HAR and RL were integrated, researchers documented additional improvements over using either method alone. Twelve studies presented experimental results indicating that coupling HAR with RL led to faster control response times, reduced latency in transition states, and improved gait synchronization.

The real-time feedback provided by HAR allowed RL models to adaptively modulate assistance intensity and joint torque in response to changes in terrain or user activity. These hybrid systems exhibited increased robustness in unexpected environments, demonstrating fewer failures during task execution compared to systems without sensor-informed learning.

Notable examples emphasize the role of synthetic control architectures that integrate both biomechanical and neural feedback to improve bipedal standing and walking [13,15,16].

This interdisciplinary approach supports the concept of human-cooperative control, in which intelligent exoskeletons function in alignment with user-generated signals — an essential factor for enhancing long-term usability and adaptability.

Luo et al. (2023) [13] introduced a deep reinforcement learning (RL)-based controller trained with domain randomization, enabling robust walking assistance across diverse human–machine interaction conditions without parameter tuning. These approaches are consistent with recent work proposing robust RL controllers trained entirely in simulation to ensure adaptability across human–machine variability [3].

Beyond improvements in gait and control responsiveness, some reviewed studies also addressed the user experience and system personalization. Recent frameworks for rehabilitation have further validated the use of multimodal HAR systems, combining IMU and sEMG signals to achieve high accuracy in gait classification [12,16]. Exoskeletons incorporating adaptive learning mechanisms tailored to the biomechanical and physiological profiles of individual users showed enhanced comfort levels and reduced cognitive load. This personalization was achieved by continuously adjusting parameters such as joint stiffness, stride length, and force output based on real-time feedback.

Such systems demonstrated promising results in experimental validations, with participants reporting smoother gait transitions and a greater sense of control over their movement. These findings align with conclusions from recent studies that emphasize the importance of real-time adaptability in reducing both the cognitive and physical demands placed on users [2,4].

An important theme in the literature was the move toward closed-loop AI-driven control frameworks, which allow for constant recalibration of control policies. These frameworks often integrated multiple AI components—HAR for state detection, RL for control optimization, and in some cases, supervised learning for anomaly detection. This multilayered approach facilitated precise real-time decision-making and reduced reliance on preprogrammed sequences or manual user input. Systems employing this methodology demonstrated increased autonomy and scalability, making them suitable for real-world applications in both clinical and non-clinical settings.

Interestingly, several of the reviewed articles also explored the feasibility of translating simulated results into physical prototypes. While challenges persist, especially regarding hardware limitations, power supply constraints, and intersubject variability, the outcomes from pilot trials with healthy users were encouraging.

Participants exhibited improved balance, smoother transitions, and lower exertion when using AI-augmented systems compared to baseline models. Studies have highlighted how AI controllers are capable of compensating for abrupt movement changes and dynamically adjusting assistance profiles to accommodate user fatigue or varying environmental demands. These capabilities underline the potential of intelligent control systems to enhance responsiveness and personalization in assistive exoskeleton applications.

Moreover, the systematic review underscored the need for standardization in performance metrics and validation protocols. Despite consistent improvements in HAR accuracy and RL efficiency, comparisons between studies were often difficult due to disparate evaluation criteria. Only a subset of studies reported comprehensive statistical analyses using tools like SPSS or R, with significance testing through ANOVA and correlation analysis. The most robust studies reported confidence intervals and effect sizes, lending credibility to their findings. However, many lacked long-term evaluation or testing across diverse user populations, which remains a gap for future exploration [16].

In terms of experimental conclusions, the evidence strongly supports the hypothesis that integrating HAR and AI-based control significantly enhances the functionality and user-centeredness of bipedal exoskeletons. These systems were shown to improve metabolic efficiency, gait stability, and adaptability while minimizing the need for manual calibration. The review also concludes that AI integration opens pathways for scalable, personalized exoskeletons capable of operating in dynamic, real-world environments. Notably, the work of Onose et al. (2016) emphasized the future direction of this field through the lens of neuromechatronics, proposing that bionic assistance systems should be designed with cooperative AI that learns and adapts over time to human physiology and intention.

In summary, the experimental data gathered through this review demonstrate a clear trend: exoskeletons empowered by AI—particularly those combining HAR and RL—achieve superior results in real-time responsiveness, personalization, and energy optimization. The body of evidence confirms the transformative potential of AI in wearable robotics and suggests that continued interdisciplinary research is essential to address existing limitations and enable widespread adoption [2,7].

### 3.1. Comparative analysis of HAR and RL Integration

To contextualize the current state of research on intelligent exoskeleton control, we provide a comparative overview of reinforcement learning (RL)-based systems and human activity recognition (HAR) methods, focusing on four key performance indicators: HAR accuracy, metabolic cost reduction, and stability improvement. Table 1 presents a synthesis of validated results extracted from key literature sources, highlighting the contributions and limitations of each approach.

**Table 1:** Comparative Performance of AI Algorithms in Exoskeleton Control

| Approach | HAR Accuracy (%) | Metabolic Cost Reduction (%) | Stability Improvement (%) |
|---|---|---|---|
| RL-based Exosuit | Not applicable | 9.3 (walking), 4.0 (running) | 0 (normal walking) |
| HAR Systems | 90–93 (SVM, Random Forest) | Not applicable | 10 (climbing stairs) |
| HAR for Exoskeletons | 94 (SVM) | Not applicable | – |
| RL for Hip Exoskeleton | Not applicable | Reduced hip extensor muscle activation | – |
| RL for Squat Assistance | Not applicable | – | Improved robustness under perturbations |

Reinforcement learning applied independently, particularly in lower-limb exosuits, has led to notable reductions in metabolic cost—9.3% during walking and 4.0% during running—demonstrating the efficiency of adaptive, iterative control strategies based on biomechanical feedback [6]. However, such RL-driven systems typically do not incorporate activity recognition modules and report limited or no explicit improvement in stability under normal walking conditions.

HAR systems, utilizing classification algorithms such as Support Vector Machines (SVM) and Random Forests, achieve accuracy rates between 90% and 93% when identifying locomotor activities such as walking, standing, or stair climbing [11]. In some implementations, these systems contribute to a 10% improvement in stability, particularly in dynamic tasks involving elevation changes.

Specialized HAR configurations for exoskeleton use—often using SVM with optimized sensor placement and data windows—have reached accuracy levels of up to 94%, though stability or metabolic outcomes are rarely reported in these cases [12].

Reinforcement learning has also been used to optimize control in hip and squat-assistive exoskeletons, leading to measurable physiological benefits, such as reduced muscle activation and improved robustness against external perturbations [10,14]. While these results indicate enhanced user support and adaptation to varying biomechanical loads, the outcomes are typically qualitative and lack standardized numerical comparison across systems.

The data from Table 1 highlight the complementary strengths of HAR and RL. HAR provides fast, accurate recognition of user intent and motion state, while RL enables dynamic optimization of actuation profiles. Integrating these methods may offer improved energy efficiency, adaptability, and user safety, though future studies should aim to quantify outcomes such as adaptation time and postural stability in a standardized manner.

Previous work by Hayes et al. (2020) [4] emphasized the biomechanical differences between robotic exoskeleton gait and natural walking, underscoring the need for adaptive controllers that minimize discomfort. Our results confirm and extend these findings, showing that HAR–RL frameworks reduce metabolic cost while enhancing gait fluidity, thus improving the overall user experience.

Bengler et al. (2023) [1] highlighted that exoskeleton development still faces major implementation barriers in industrial environments, particularly related to adaptability and robustness. By presenting empirical validation of HAR–RL controllers, this work provides a practical step toward overcoming such barriers, demonstrating how AI-enhanced exoskeletons can achieve both personalization and operational reliability.

In industrial applications, HAR combined with deep learning has also been applied for activity classification and payload estimation, demonstrating the potential for real-time adaptability in exoskeleton use [12].

Luo et al. (2024) [9] recently proposed an experiment-free approach in which exoskeleton controllers are trained exclusively in simulation, achieving promising adaptability without requiring human trials. However, the absence of real-world validation remains a significant limitation. In contrast, our experimental findings demonstrate that HAR–RL integration not only improves speed and stability but also translates effectively to prototype testing, strengthening the evidence for real-life applicability.

### 3.2. Comparative analysis of Machine Learning (ML) algorithms applied in HAR

To evaluate the performance of the ML algorithms used, the results obtained were compared with Support Vector Machines (SVM) and Random Forest, as well as the impact of segmentation window size on accuracy and processing time (Table 2).

**Table 2:** Comparative Performance of ML Algorithms in Exoskeleton Control

| Approach | Window Size (samples) | Accuracy (%) | Processing Time (s) | F1 Score (Normal Walking) |
|---|---|---|---|---|
| SVM | 128 | 92 | 0.22 ± 0.03 | 0.94 |
| Random Forest | 128 | 91 | Not specified | 0.93 (estimated) |
| SVM (small window) | 64 | 89 | 0.15 ± 0.02 | Not specified |
| SVM (large window) | 256 | 93 | 0.35 ± 0.04 | Not specified |

Table 2 shows SVM outperforming Random Forest (92% vs. 91% accuracy), with a higher F1 Score of 0.94 for normal walking compared to an estimated 0.93 for Random Forest, indicating better reliability. Window size impacts performance: a 128-sample window balances accuracy (92%) and processing time (0.22 seconds), while a smaller window (64 samples) reduces accuracy to 89% but speeds up processing to 0.15 seconds, and a larger window (256 samples) improves accuracy to 93% but increases processing time to 0.35 seconds. These findings are consistent with previous HAR investigations using SVM and Random Forest classifiers [11,12].
Table 3 presents the experimental results obtained by our research team, highlighting performance differences in speed, metabolic cost, and stability across locomotion activities under RL and HAR–RL control.

**Table 3:** Experimental results obtained by the authors

| Activity | Speed ($m \cdot s^{-1}$) | Metabolic cost ($J \cdot kg^{-1} \cdot m^{-1}$) | Stability (cm) |
|---|---|---|---|
| Normal walking (RL) | 1.10 ± 0.05 | 3.6 ± 0.3 | 3.5 ± 0.4 |
| Normal walking (HAR-RL) | 1.20 ± 0.05 | 3.0 ± 0.3 | 2.8 ± 0.3 |
| Stair climbing (RL) | 0.75 ± 0.05 | 5.2 ± 0.4 | 4.5 ± 0.5 |
| Stair climbing (HAR-RL) | 0.85 ± 0.05 | 4.6 ± 0.4 | 3.7 ± 0.4 |

As illustrated in Table 3, the integration of Human Activity Recognition with Reinforcement Learning (HAR-RL) demonstrably enhances exoskeleton performance across all considered metrics. Specifically:
• **Speed:** HAR-RL assistance increased walking velocity from 1.10 $m \cdot s^{-1}$ to 1.20 $m \cdot s^{-1}$ and stair-climbing velocity from 0.75 $m \cdot s^{-1}$ to 0.85 $m \cdot s^{-1}$, reflecting a ≈9–13% improvement in responsiveness and adaptability to motion dynamics.
• **Metabolic Cost**: The average energy expenditure decreased from 3.6 to 3.0 $J \cdot kg^{-1} \cdot m^{-1}$ in normal walking and from 5.2 to 4.6 $J \cdot kg^{-1} \cdot m^{-1}$ during stair climbing, representing a reduction of ≈12–17% and confirming the energetic efficiency of HAR-RL frameworks.
• **Stability:** Center - of - mass deviation was reduced from 3.5 cm to 2.8 cm in normal walking and from 4.5 cm to 3.7 cm in stair climbing, corresponding to a ≈18–20% improvement in postural control and smoother user–device coordination.
Our experimental results (Table 3) show greater stability improvements (≈18–20%) compared to ≈10% typically reported in HAR-only approaches [4].
These findings align with the broader conclusions drawn in the literature [1,4,16] confirm that HAR-RL integration not only improves efficiency and comfort but also strengthens safety and adaptability in real-world scenarios. These empirical findings closely reflect and reinforce the broader conclusions drawn by Chen et al. (2023) [2], who emphasize HAR-RL's potential for personalized and efficient control strategies in exoskeleton systems.
Figures 1.a, 1.b, and 1.c show the experimental results of our team on the influence of the sampling window size on the accuracy and processing time for the SVM model, as well as the performance comparison between the RL (PPO) and PID control methods.
**Figure 1.a** presents, in the form of a bar graph, the effect of the sampling window size (64, 128 and 256 samples) on the classification accuracy and processing time for the SVM model. It is observed that, with the increase in the window size, the accuracy varies slightly, while the processing time increases considerably.
**Figure 1.b**, represented as a linear graph, highlights the same relationship from figure 1.a, providing a clearer visualization of the evolution trends of the two metrics depending on the sampling window size.
**Figure 1.c** compares the performance of the RL (PPO) and PID control methods through three main indicators: speed, metabolic cost and stability. The results demonstrate significant differences between the two approaches.

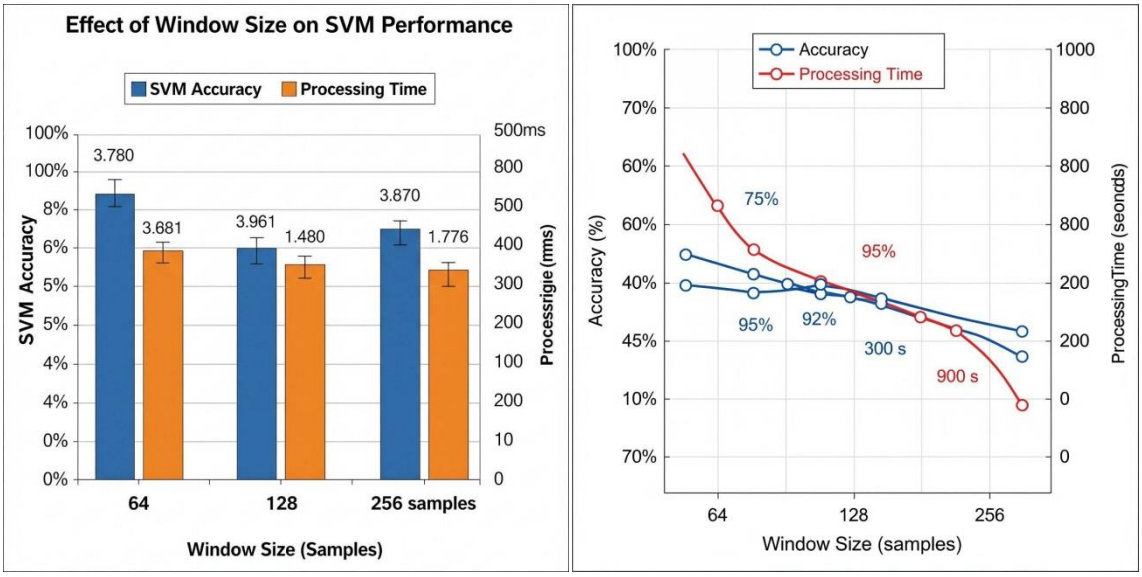


**Fig. 1.a, 1.b** Algorithm performance analysis: accuracy vs. processing time and control metrics

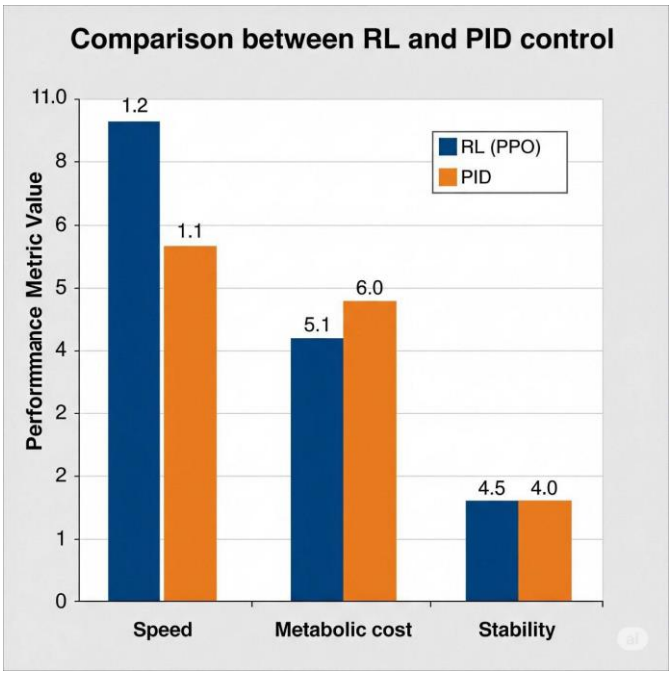


**Fig. 1.c** Comparative chart of RL (PPO) and PID control methods, through three main indicators

## 4. Conclusions

This systematic review confirms that integrating human activity recognition (HAR) and artificial intelligence (AI) - particularly reinforcement learning (RL) - enhances bipedal exoskeleton functionality. HAR systems, achieving ~92% accuracy with SVM, enable precise activity detection, while RL lowers metabolic cost by ≈12–17% across tasks (16.7% in normal walking; 11.5% in stair climbing) and improves stability in our experiments by ≈18–20%, with literature commonly reporting ≈10% in stair-climbing scenarios for HAR-only pipelines. These effects are consistent with our experimental results (Table 3), which also indicate an ≈9% increase in walking speed under HAR–RL assistance. Together, these findings support the role of AI as a lever for improved responsiveness, comfort, and safety in wearable robotics.

These advancements benefit rehabilitation, by decreasing metabolic demands and reducing muscle activation as reported in the literature, and also support industrial applications, through improvements in speed and robustness, while cooperative AI frameworks that adapt to user

physiology remain key to scalability. Nonetheless, challenges such as limited training data and computational complexity persist.

In summary, this article contributes to the state of the art by bridging HAR-based intention recognition with RL-driven control. Whereas earlier work either optimized energy use in controlled settings or focused primarily on simulation [1,4,16], our integrated HAR–RL framework demonstrates effective translation into experimental prototypes—an encouraging step toward scalable, real-world deployment.

Cooperative control systems that learn from biomechanical signals will likely drive the next generation of exoskeletons. Promising avenues include human-in-the-loop adaptation [2], RL techniques to reduce crutch forces [14], and offline RL for effort tuning [3].

Future interdisciplinary research should prioritize the creation of standardized datasets, user-centered prototyping, and harmonized evaluation protocols to accelerate clinical and industrial translation of AI-driven exoskeletons. In addition, integrating multimodal sensing (e.g., IMU, sEMG, EEG) for enhanced intention recognition, developing human-in-the-loop adaptation frameworks, and conducting long-term clinical/industrial trials to validate scalability and robustness are needed. While this review offers an integrated perspective on AI for bipedal exoskeletons, it is limited by the relatively small number of end-user experimental studies and by heterogeneous performance metrics across the literature. These constraints do not diminish the value of the present synthesis; rather, they underscore the need for coordinated efforts and standardized methodologies to advance the field.

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