# Ergonomic Robotic Hip Exoskeleton Design with Integrated Second-Skin On-Body Sensing

Yash V. Mhaskar, Dongho Park, Aleksandar B. Bošković and Aaron J. Young

*Abstract*—**Robotic hip exoskeletons can reduce energy cost, improve gait symmetry, and enhance mobility, but success depends on accurate intent estimation. Current designs rely on rigid, device-mounted sensors that miss the body's complex dynamics, limiting generalizability. We introduce RHEx (Reinforcing Hip Exoskeleton), a modular, ergonomic system integrating a wearable sensor suit for device-agnostic sensing, improved actuator alignment, and enhanced comfort. RHEx was evaluated against a state-of-the-art hip exoskeleton with on-device sensors in three able-bodied participants performing level walking, ramp and stair ascent/descent, and sit-to-stand. RHEx preserved the user intent estimation accuracy under actuation: the full sensor suit model showed a $0.1\%$ drop versus $3.58\%$ for on-device models. User experience improved, with OPUS scores nearly $20\%$ higher (87.7 vs. 73.3), alongside gains in SUS (76.7 vs. 65.0) and RPSD (95.8 vs. 92.5). Alignment analyses revealed reduced actuator offset ($1.53\%$ improvement), supporting better joint tracking. Though limited by sample size, these findings highlight RHEx's potential to advance exoskeleton design by combining accurate, device-agnostic sensing with ergonomic adaptability for real-world use.**

*Index Terms*—**Wearable robotics, exoskeletons, torque estimation, assistive devices**

## I. Introduction

The last few decades have seen significant efforts in designing lower-limb robotic exoskeletons [1], [2] and exoskeleton controllers capable of assisting able-bodied [3], [4] and clinical populations [5], [6] with daily activities. Exoskeleton assistance has been shown to improve specific outcome measures when tailored for outcomes such as reduced energetic cost [7], increased walking speed [8], improved gait symmetry [6], and decreased muscle fatigue [9]. However, many of these exoskeleton control strategies are tested only for specific ambulatory conditions in a lab setting.

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To assist users with diverse ambulatory conditions in real-world settings, exoskeleton controllers increasingly employ end-to-end systems that estimate internal human joint mechanics [10], enabling adaptive assistance and reduced energetic cost [11]. These systems rely on on-device sensor data to infer the user's physiological state, which then informs real-time modulation of exoskeleton support. However, estimating biomechanical states from rigid exoskeleton sensors is challenging, as relative motion., soft-tissue deformation , and natural body movements, especially during actuation, can introduce significant errors [12]. In practice, researchers have typically collected training data with the device actuated, often using a stand-in controller before a deep learning system can be deployed [13] [11]. Additionally, such device-dependent data can only be leveraged for model training on devices with similar sensor orientations, necessitating the generation of transformation matrices based on sensor locations. This data collection process is time-consuming and labor-intensive for researchers, and can be particularly exhausting for participants, especially those in clinical populations.

An alternative approach to real-time data streaming has shown that a Second Skin system [14] can provide highly accurate, device-independent physiological data from users. This system requires the user to wear clothes with built-in sensors that replace the on-device sensor data. By simply wearing the Second Skin while performing the same set of tasks, users eliminate the need for device-specific measurements. As a result, large-scale datasets can be collected more efficiently across both able-bodied and clinical populations, a process our group has already demonstrated in prior studies.

To address these challenges, in this study, we have designed a Second-Skin-integrated Reinforcing Hip Exoskeleton (RHEx) and compared its effects to those of a state-of-the-art hip exoskeleton with on-device sensors [13]. RHEx enables collection of the required training dataset without users needing to wear the device during data acquisition; the exoskeleton is only donned when providing assistance.As mentioned earlier, models trained on on-device sensor data may experience reduced accuracy when applied to actuated exoskeleton control. We therefore hypothesize that the on-body sensor model with RHEx will show a smaller reduction in model accuracy under actuation compared to the on-device sensors based hip exoskeleton, when both are trained on unassisted biomechanics data.

While designing a wearable robotic device, overall performance must be considered alongside user comfort [15]
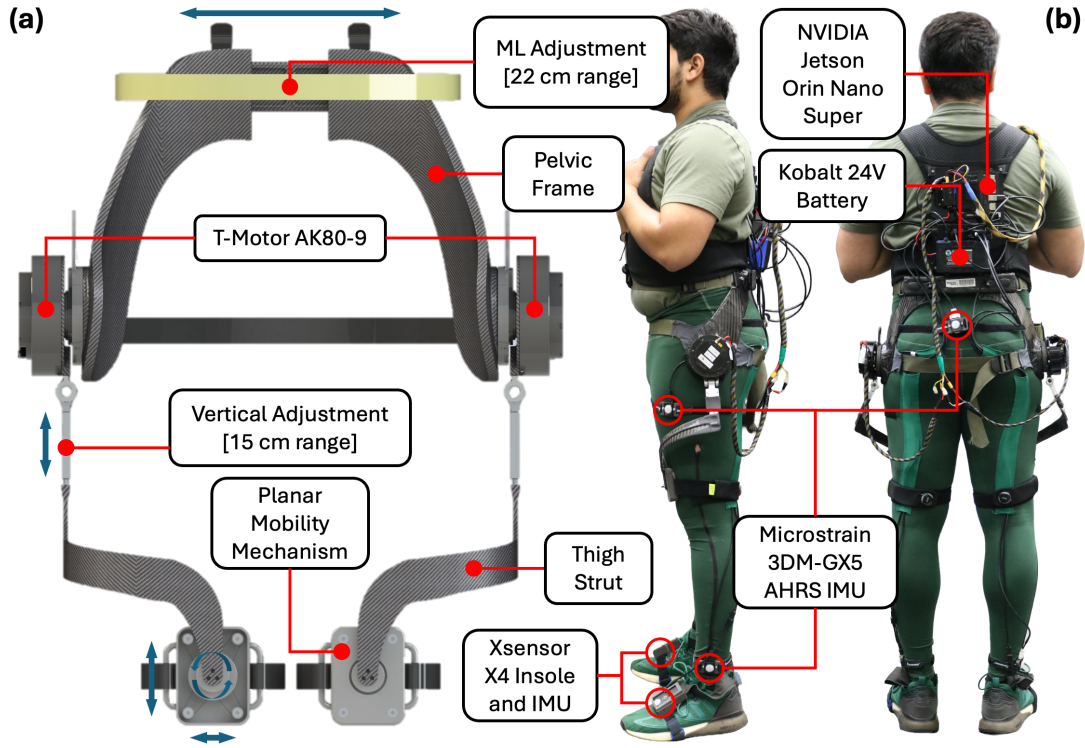
Fig. 1. (a) CAD model of RHEx; showcases the pelvic frame and its mediolateral (ML) adjustment, the actuators, the thigh strut and its vertical adjustment, and the planar mobility mechanism. (b) The fabricated and donned RHEx, with the second skin setup and mechatronics vest. The Second Skin setup includes the pelvis, thigh, shank, and foot IMU sensors, and the pressure insoles. The mechatronics vest includes the Jetson Orin Nano Super microcontroller and the Kobalt 24V 2mAh battery.

and usability [16]. Accordingly, RHEx was developed with a modular architecture incorporating adjustable components to accommodate users with diverse anthropometric dimensions. Its design conforms more naturally to the anatomical body, providing a secure yet comfortable fit, while the range of adjustability enhances usability across populations. We therefore hypothesize that RHEx will demonstrate superior user comfort and usability compared to the state-of-the-art hip exoskeleton [3].

A hip exoskeleton assists the user by generating flexion and extension torques about the hip joint through an actuator positioned around the waist. The effectiveness of this assistance depends on accurate alignment [17] between the actuator's rotational axis and the anatomical hip joint. To enhance this alignment, RHEx integrates refined strap and belt configurations designed to minimize actuator offset throughout movement. Consequently, we hypothesize that RHEx will exhibit reduced actuator alignment error relative to the on-device sensors based hip exoskeleton.

## II. HIP EXOSKELETON DESIGN

### A. Second Skin Sensor Suit

A Second Skin setup [14] was used to collect accelerations, angular velocities, and ground reaction forces from various locations on the user's body, as shown in Fig. 1. Five IMUs (Inertial Measurement Unit) (3DM-GX5-25, HBK

Microstrain, Williston, VT, USA) were placed on the pelvis, thighs, and shanks to obtain accelerations and angular velocities. XSENSOR X4 high-resolution pressure insoles with attached IMUs (XSENSOR Technology Corporation, Calgary, AB, Canada) were placed in the user's shoes to obtain ground reaction force readings. While incorporating various sensors and cables, the complete Second Skin setup weighs 0.81 kg, comparable to everyday clothing such as a pair of jeans [18].

### B. Mechanical Components

The pelvic frame [13] is fabricated by merging a lightweight carbon fiber base with precision nylon SLS-printed components. A custom nylon-carbon hybrid backplate allows smooth mediolateral adjustment as shown in Fig. 1. This modular design enables quick, tool-free, continuous adjustment as well as quick swapping for different sizes to accommodate hip widths of 26 cm to 48 cm. This hip width range covers the 1st percentile man and woman, as well as the 99th percentile man and woman [19].

The T-motor AK80-9 (CubeMars, Jiangxi Province, China) equipped actuator subassembly links the pelvic and thigh interfaces. This mechanism slots into the pelvic frame and is attached to the thigh struts via a custom-machined aluminum-carbon fiber hybrid mount. This actuator mount allows for natural adduction/abduction motion during use through a pas-

sive joint and also features a physical hardstop to ensure user safety.

The thigh interface subassembly features custom-machined aluminum-carbon fiber hybrid thigh struts that connect to the actuator mount through a locking slider mechanism. This design enables the thigh struts to be modular, allowing total discrete vertical adjustments of 15 cm as shown in Fig. 1. This adjustment and modular design range encompasses the 1 percentile man and woman, and the 99 percentile man and woman's thigh length [19]. A planar mobility mechanism at the end of each strut allows the point of torque application to shift relative to the hip joint center and reliably return to a neutral position after each displacement. The RHEx mechanical assembly, including actuators, straps, and interfaces, weighs 2.34 Kg.

### C. Electrical Components

The user wears a mechatronics vest as seen in Fig. 1, which houses the NVIDIA Jetson Orin Nano Super Microcontroller (NVIDIA, California, USA), USB hubs, the custom PCB, and the Kobalt 24-Volt Li-ion Compact Battery (Lowe's, North Carolina, USA). The microcontroller serves as the brain of the system, using sensor inputs to determine the desired hip motor torque. The custom PCB assists in motor communication and power distribution. The batteries are hot-swappable, allowing continuous device operation. The mechatronics vest, including the battery, weighs 1.35 Kg.

### D. Controller Software

The controller software collects sensor data via the Second Skin setup [14] and processes it with a TCN model to estimate biological hip joint moments [10]. These estimates are scaled and time-shifted using preset parameters to produce the desired motor torques [11] [13].

## III. METHODS

### A. Experimental Protocol

All participants consented to the experimental data collection, and the overall study was approved by the Institutional Review Board of the Georgia Institute of Technology. Three able-bodied individuals (gender: 3 male; age: 25.55 +/- 2.49 years; weight: 78.63 +/- 8.22 Kg; and height: 1.78 +/- 0.03 m) completed the experimental protocol that involved level ground walking (LG), ramp ascent (RA), and ramp descent (RD) at 1.1 m/s on the treadmill, along with stair ascent (SA), stair descent (SD) and sit-to-stand (S2S). These trials were conducted with our previous Hip Exoskeleton [3] and RHEx. A Vicon and Bertec setup was used to collect motion capture and ground reaction forces. The Second skin sensor [14] data was also collected and used by RHEx to provide real-time assistance.

### B. Sensor Models Comparison

The quality of assistance provided while using a hip moment estimation-based controller [11] depends directly on the accuracy of its underlying models. To evaluate this, we conducted an offline analysis comparing a model trained with on-device sensors to one trained with on-body sensors.

The on-device sensor model was trained on the corresponding fifteen subject dataset [13] using hip motor-encoder, thigh IMU, and shank IMU data. In constrast, the on-body sensors model was trained on the ten subject Second Skin dataset [14] along with five additional collections from a separate study, which included back, pelvis, thigh, shank, and foot IMU sensors and pressure insoles. To control for bias introduced by the greater number and distribution of sensors, we also trained a Reduced Sensor Model using only shank and thigh IMU data with estimated hip angle inputs. Finally, an All Sensor Model incorporating the full set of on-body sensors was trained to assess the maximum capability of the entire on-body sensors system.

All models were trained on unassisted data and evaluated on both unassisted and assisted novel subject datasets. In addition, the on-body Sensor models were tested online using RHEx during LG, RA, and RD tasks. Because the All Sensor model included pressure insoles, it was further evaluated on SA, SD, and S2S.

Model performance was quantified by calculating the percent decrease in $R^2$ between unassisted and assisted task-specific results. For each model, these task-specific decreases were averaged to obtain an overall measure of accuracy loss. This procedure was applied to both the on-device model and the on-body sensor models, enabling direct comparison of their robustness under actuation.

### C. Usability and Comfort Comparison

To compare RHEx and the previous device on the basis of usability and comfort, participants filled out a Device Session Survey, which included the System Usability Survey (SUS), Orthotics Prosthetics Users Survey (OPUS), and the Rating of Pain, Soreness, and Discomfort (RPSD) after using each exoskeleton for a session. After both device sessions, participants also completed a Session Comparison Survey, which allowed them to provide open feedback comparing the two devices and any specific scenarios where one device performed better than the other.

### D. Alignment Comparison

To compare the hip joint center alignment across the two devices, a marker was placed on the center of the actuators during the trials. The motion capture data were used to determine the center of rotation of the hip joint as well as its relative distance from the actuator marker. This was compared across multiple trials to determine whether RHEx improved hip joint center alignment.

## IV. RESULTS

### A. Sensor Models Comparison

The on-device model achieved an average $R^2$ of $0.64$ in the unassisted condition, but its performance dropped by $3.58\%$ under assisted conditions. In comparison, the on-body models performed better overall: the Reduced Sensor model averaged
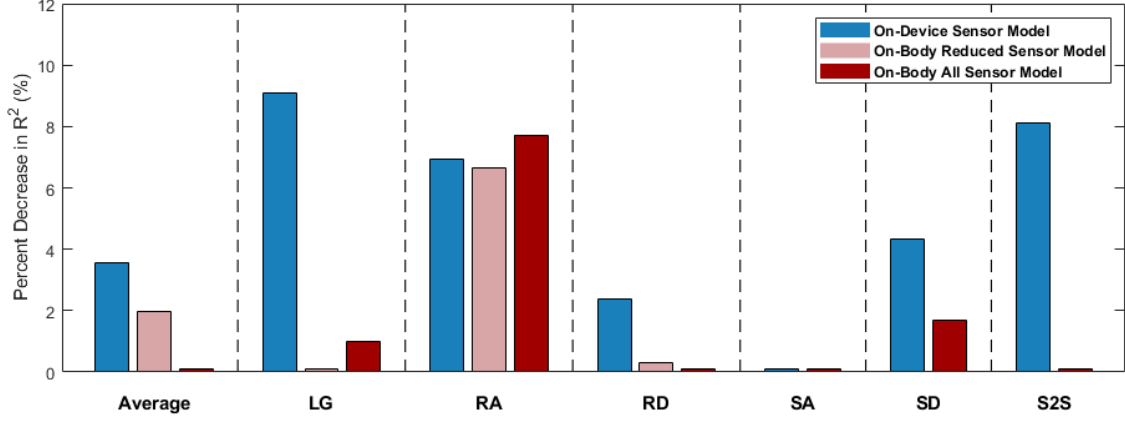
Fig. 2. Percent Decrease in $R^2$ for the on-device Sensor model (blue), on-body Reduced Sensor model (light red), and on-body All Sensor model (red) in various tasks. The on-device Sensor model and the on-body All Sensor model are tested on all tasks. The on-body Reduced Sensor model is tested on LG, RA, and RD tasks. The average percent decrease in $R^2$ is calculated based on the tested tasks for each model. Lower average percent decrease in $R^2$ corresponds to a more robust and generalizable model.

$R^2$ of 0.67 with only a 1.99% decrease, while the All Sensor model averaged $R^2$ of 0.72 and showed a negligible 0.10% decrease.

Task-level analysis revealed notable differences. For instance, in the LG task, the on-device model experienced one of the largest declines (9.1% decrease), whereas the Reduced Sensor model showed no decrease. Similarly, in the S2S task, the on-device model dropped by 8.1%, while the All Sensor model maintained its performance. Across all tested tasks, the Reduced Sensor model consistently exhibited smaller decreases than the on-device model. For tasks evaluated only with the All Sensor model, performance either matched the on-device model's stability or showed an even smaller decrease.

The All Sensor model was tested across all tasks; however, RA task results were based on only two subjects because Subject 3's online data was corrupted and excluded. Interestingly, RA was the only task where the on-device model outperformed the All Sensor model, though this finding is limited by the reduced dataset. In contrast, the SA task showed no decrease in $R^2$ for any model.

Overall, as illustrated in Fig. 2, the on-device model exhibited the highest average percent decrease in $R^2$ under assisted conditions. Both on-body models demonstrated greater robustness, with the Reduced Sensor model consistently outperforming the on-device model across cyclic tasks, and the All Sensor model showing near-complete resilience to assistance-related performance drops.

### B. Usability and Comfort Comparison

Survey results were analyzed to compare user perceptions of RHEx with those of the previous device across usability and comfort dimensions. RHEx achieved higher scores on all usability metrics, with a System Usability Scale (SUS) score of 76.7 compared to 65.0 for the previous device, and an OPUS score of 87.7 versus 73.3. This difference in OPUS scores was statistically significant, indicating a meaningful improvement

in perceived usability. RHEx also outperformed the previous device in RPSD (95.8 vs. 92.5). As illustrated in Fig. 3, the most pronounced usability improvements were observed in preferences for frequent use, simplicity and efficiency, ease of use, proper fitting, and manageable weight. Similarly, RHEx received higher ratings across all comfort-related questions. Fig. 4 highlights the areas with the greatest differences, where users found RHEx easier to wear, more aesthetically pleasing, less likely to cause wear and tear on clothing, free from irritation, and comfortable to wear without pain.

### C. Alignment Comparison

Motor joint alignment was assessed by measuring the distance between the post-processed hip joint center of rotation and the marker placed on the motor. This alignment metric was evaluated across all cyclic tasks for both RHEx and the previous device. Across tasks, RHEx consistently demonstrated better joint alignment, achieving an average 1.53% reduction in alignment error compared to the previous device.

## V. DISCUSSION

On-body sensor models exhibited a smaller drop in performance under assisted conditions compared to the on-device sensor model. For task-specific accuracies, the on-device sensor model showed substantial decreases, particularly in LG (9.1%) and S2S (8.1%). In contrast, the on-body Reduced Sensor model demonstrated a negligible decrease in LG, while the on-body All Sensor model showed a similarly minimal drop for the S2S task. Across all cyclic tasks, the on-body Reduced Sensor model consistently experienced smaller performance reductions than the on-device sensor model. For non-cyclic tasks, the on-body All Sensor model either matched negligible drops or outperformed the on-device model with lower decreases. Overall, the observed lower percent decrease in $R^2$ for both on-body sensor models suggests that the on-body configuration is more robust when applying models trained on
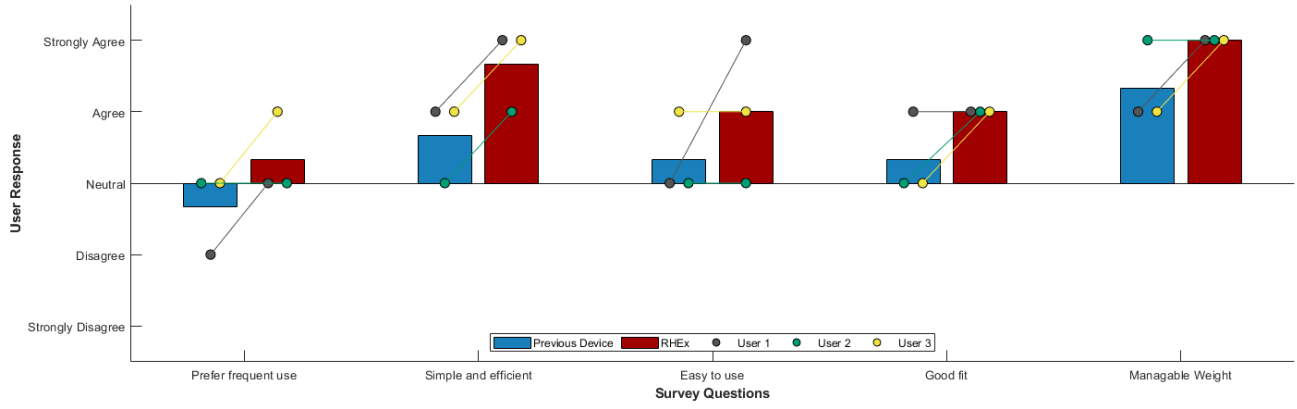
Fig. 3. Usability survey questions comparison between previous device (blue) and RHEx (red). The Y axis goes from "Strongly Disagree" to "Strongly Agree". These are the five most differing responses to the usability-related survey questions. The Subject-wise scores are provided as scatter points for Subject 1 (dark grey), Subject 2 (teal), and Subject 3 (yellow). A higher user response score corresponds to greater perceived usability.
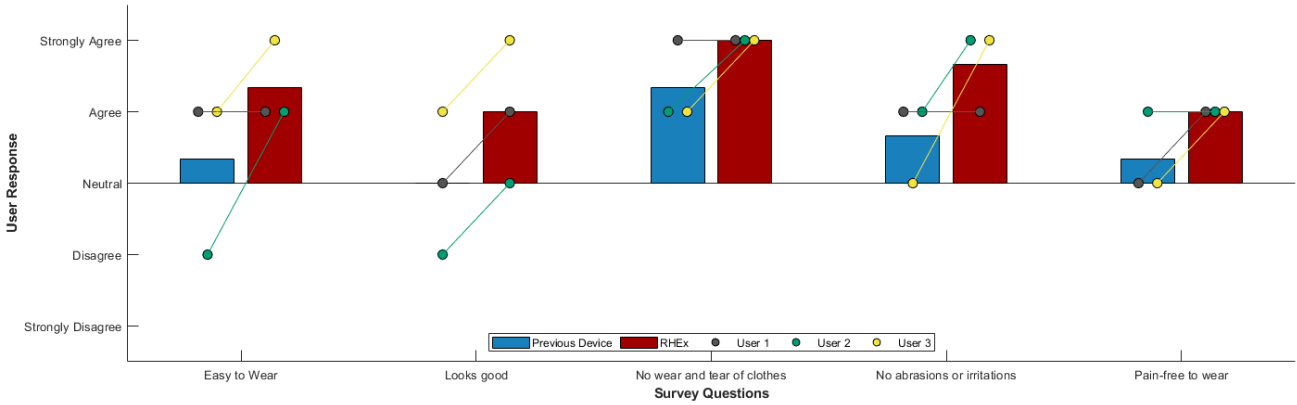


Fig. 4. Comfort survey questions comparison between the previous device (blue) and RHEx (red). The Y axis goes from "Strongly Disagree" to "Strongly Agree". These are the five most differing responses to the comfort-related survey questions. The Subject-wise scores are provided as scatter points for Subject 1 (dark grey), Subject 2 (teal), and Subject 3 (yellow). A higher user response score corresponds to greater perceived comfort.

unassisted biomechanics data to actively actuated exoskeleton control. These findings support our first hypothesis: on-body sensing in RHEx experiences less degradation in model accuracy than the on-device sensor-based hip exoskeleton under assisted conditions when trained on unassisted biomechanical data.

Such findings highlight the value of integrating on-body sensing into exoskeleton design, with RHEx being one of the first systems to implement this approach for the hip joint. Unlike on-device sensors, which are tightly coupled to specific hardware and require wearing the exoskeleton during data collection, on-body sensors enable device-agnostic data acquisition, including the ability to collect training data without the exoskeleton. This capability reduces participant fatigue and researcher workload during data collection, while also allowing the same dataset to be reused across multiple assistive platforms. As a result, model development becomes faster and more generalizable. Furthermore, on-body sensing mitigates performance degradation when transitioning from unassisted to assisted conditions, making it a more robust solution for real-world deployment. Collectively, these advantages position

on-body sensing as a critical design choice for next-generation exoskeletons aimed at adaptive and scalable control.

Across individual locomotion tasks, RA was the only condition where the on-body All Sensor model exhibited a greater percent decrease in $R^2$ compared to the on-device Sensor model. We attribute this anomaly to limited data availability, as only two subjects were included for RA due to data corruption in Subject 3's on-body All Sensor model RA recordings. With additional subject data, we expect the RA results to align with the consistent trends observed across other tasks. For SA, all models maintained stable accuracy with no degradation in $R^2$, representing a neutral outcome where neither the on-body nor the on-device configuration demonstrated an advantage.

User feedback collected through standardized instruments (SUS, OPUS, and RPSD) consistently favored RHEx over the on-device sensor-based hip exoskeleton across all survey dimensions. As illustrated in Fig. 3 and Fig. 4, core questions on usability and comfort revealed a clear preference for RHEx, reinforcing its ergonomic and user-friendly design. These findings support our second hypothesis that RHEx offers superior user comfort and usability compared to the previous

device, a critical factor for long-term adoption and real-world deployment.

RHEx demonstrated consistent improvements in joint alignment across all evaluated tasks, with an average reduction in alignment error of $1.53\%$ compared to the previous device. These results support our hypothesis that RHEx achieves lower actuator alignment error than the on-device sensor-based hip exoskeleton, although the improvement was smaller than anticipated, indicating the need for further refinement. Variability across subjects highlights the challenge of achieving uniform alignment due to anatomical differences, suggesting that an adaptable design accommodating diverse hip shapes and morphologies could further reduce error and enhance generalizability.

In summary, RHEx demonstrated advantages across multiple dimensions: improved robustness of sensor models under active assistive control, enhanced usability and comfort as reported by users, and consistent reductions in actuator alignment error. These outcomes collectively support our hypotheses and highlight the promise of on-body sensing as a device-agnostic approach for exoskeleton control. At the same time, several limitations temper these findings. The small, homogeneous subject population limited statistical power, and anomalies such as the RA condition underscore the need for larger and more diverse datasets to confirm model reliability. Similarly, while alignment improvements were consistent, their magnitude was smaller than anticipated, reflecting the challenge of accommodating anatomical variability. Therefore, future studies should include larger, more diverse subject cohorts to improve generalizability. Additional work is also needed to develop modular designs that accommodate a range of hip shapes and morphologies, thereby improving alignment, and to extend on-body sensing to additional joints to leverage more accurate physiological data. Taken together, this work positions RHEx as a step toward exoskeleton systems that combine accurate, device-independent sensing with ergonomic and adaptable design, ultimately advancing the transition of wearable robotics from controlled laboratory settings to real-world use by both able-bodied and clinical populations.

### REFERENCES

[1] A. J. Young and D. P. Ferris, "State of the art and future directions for lower limb robotic exoskeletons," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 2, pp. 171–182, 2017.

[2] G. S. Sawicki, O. N. Beck, I. Kang, and A. J. Young, "The exoskeleton expansion: improving walking and running economy," *Journal of NeuroEngineering and Rehabilitation*, vol. 17, no. 1, p. 25, Feb. 2020. [Online]. Available: https://doi.org/10.1186/s12984-020-00663-9

[3] D. Park, J. An, D. Lee, I. Kang, and A. J. Young, "Human-in-the-loop optimization of hip exoskeleton assistance during stair climbing," *IEEE Transactions on Biomedical Engineering*, vol. 72, no. 7, pp. 2147–2156, 2025.

[4] B. Lim, B. Choi, C. Roh, J. Lee, Y.-J. Kim, and Y. Lee, "Ultra-lightweight robotic hip exoskeleton with anti-phase torque symmetry for enhanced walking efficiency," *Scientific Reports*, vol. 15, no. 1, Mar. 2025, publisher: Nature Publishing Group. [Online]. Available: https://www.nature.com/articles/s41598-025-95599-2

[5] J. Zhang, N. V. Divekar, E. H. Hinojosa, and R. D. Gregg, "A task-agnostic hip exoskeleton for osteoarthritis pain relief: Energetic control across activities of daily life," *2025 International Conference On Rehabilitation Robotics (ICORR)*, pp. 1299–1306, 2025.

[6] L. N. Awad, J. Bae, K. O'Donnell, S. M. M. D. Rossi, K. Hendron, L. H. Sloot, P. Kudzia, S. Allen, K. G. Holt, T. D. Ellis, and C. J. Walsh, "A soft robotic exosuit improves walking in patients after stroke," *Science Translational Medicine*, vol. 9, no. 400, p. eaai9084, 2017. [Online]. Available: https://www.science.org/doi/abs/10.1126/scitranslmed.aai9084

[7] K. Seo, J. Lee, Y. Lee, T. Ha, and Y. Shim, "Fully autonomous hip exoskeleton saves metabolic cost of walking," *2016 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 4628–4635, 2016.

[8] D. Archangeli, M. K. Ishmael, and T. Lenzi, "Assistive powered hip exoskeleton improves self-selected walking speed in one individual with hemiparesis: A case study," *2022 International Conference on Rehabilitation Robotics (ICORR)*, pp. 1–6, 2022.

[9] N. V. Divekar, G. C. Thomas, A. R. Yerva, H. B. Frame, and R. D. Gregg, "A versatile knee exoskeleton mitigates quadriceps fatigue in lifting, lowering, and carrying tasks," *Science Robotics*, vol. 9, no. 94, p. eadr8282, 2024. [Online]. Available: https://www.science.org/doi/abs/10.1126/scirobotics.adr8282

[10] D. D. Molinaro, I. Kang, J. Camargo, M. C. Gombolay, and A. J. Young, "Subject-independent, biological hip moment estimation during multimodal overground ambulation using deep learning," *IEEE Transactions on Medical Robotics and Bionics*, vol. 4, no. 1, pp. 219–229, 2022.

[11] D. D. Molinaro, I. Kang, and A. J. Young, "Estimating human joint moments unifies exoskeleton control, reducing user effort," *Science Robotics*, vol. 9, no. 88, p. eadi8852, 2024. [Online]. Available: https://www.science.org/doi/abs/10.1126/scirobotics.adi8852

[12] W. S. Barrutia, A. Yumiceva, M.-L. Thompson, and D. P. Ferris, "Soft tissue can absorb surprising amounts of energy during knee exoskeleton use," *Journal of the Royal Society Interface*, vol. 21, no. 221, p. 20240539, 2024.

[13] D. D. Molinaro, K. L. Scherpereel, E. B. Schonhaut, G. Evangelopoulos, M. K. Shepherd, and A. J. Young, "Task-agnostic exoskeleton control via biological joint moment estimation," *Nature*, vol. 635, no. 8038, pp. 337–344, Nov. 2024, publisher: Nature Publishing Group. [Online]. Available: https://www.nature.com/articles/s41586-024-08157-7

[14] R. T. F. Casey, C. P. O. Nuesslein, F. Davenport, J. Wheeler, A. Mazumdar, G. Sawicki, and A. J. Young, "The second skin: A wearable sensor suite that enables real-time human biomechanics tracking through deep learning," *IEEE Transactions on Biomedical Engineering*, pp. 1–10, 2025.

[15] K. Mannion, E. Seguin, and M. Doumit, "A review of knee exoskeleton design aspects for improving user comfort," *2024 IEEE 4th International Conference on Human-Machine Systems (ICHMS)*, pp. 1–7, 2024.

[16] C. Basla, I. Hungerbühler, J. T. Meyer, P. Wolf, R. Riener, and M. Xiloyannis, "Usability of an exosuit in domestic and community environments," *Journal of NeuroEngineering and Rehabilitation*, vol. 19, no. 1, p. 131, Dec. 2022. [Online]. Available: https://doi.org/10.1186/s12984-022-01103-6

[17] A. MajidiRad, Y. Yihun, N. Hakansson, and A. Mitchell, "The Effect of Lower Limb Exoskeleton Alignment on Knee Rehabilitation Efficacy," *Healthcare*, vol. 10, no. 7, p. 1291, Jul. 2022. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC9320271/

[18] K. Jones, "How much does a pair of jeans weigh?" https://measuringly.com/how-much-does-pair-of-jeans-weigh/, July 24 2023, accessed: November 25, 2025.

[19] H. Dreyfuss, A. R. Tilley, and H. D. Associates, *The Measure of Man and Woman: Human Factors in Design*. New York: John Wiley & Sons, 2002.