

Research Article

Wind-Normalized Southeast Asian 100-m Sprint Performances and a Conceptual Framework for AI-Powered Exoskeletons

Edgar Jeevan Danaraj* 

College of Engineering, Nanyang Technological University, Singapore

Abstract

This study has two distinct components. First, an empirical secondary analysis applies a quadratic wind-normalization model to 20 recorded Southeast Asian (SEA) men's 100-m performances for which official times and wind readings were available in the compiled dataset. The mean official time was 10.399 ± 0.177 s and the mean model-adjusted time was 10.379 ± 0.185 s. The adjustment changes the relative ordering of some performances, illustrating how wind conditions can affect historical comparisons. Second, the paper presents a conceptual framework for an AI-powered lower-limb exoskeleton using inertial sensing, temporal-convolutional and recurrent neural-network components, athlete-specific digital twins, phase-specific assistance, and independent safety supervision. No exoskeleton intervention or athlete trial was conducted in this study; therefore, its proposed effects on sprint kinematics, performance, neuromuscular function, and injury risk remain hypotheses requiring controlled validation. The combined contribution is a wind-adjusted regional performance analysis and a technology proposal motivated by the training and performance questions that such comparisons raise.

Keywords

100-m Sprint, Southeast Asian Sprinting, Wind Normalization, Sprint Biomechanics, Resisted Sprint Training, Assisted Sprint Training, Artificial Intelligence, Wearable Robotics

1. Introduction

Sprint performance comparisons across historical periods and geographic locations must account for environmental factors, particularly horizontal wind velocity and air density [1]. A tailwind can reduce aerodynamic resistance and may improve recorded 100-m times, whereas a headwind can increase resistance [2]. Consequently, raw race times recorded under different wind conditions are not directly equivalent. A wind-normalization model can provide an estimate of the time under

a reference wind condition, but the result remains model-dependent and should not be interpreted as a direct measurement of an athlete's underlying physiological capacity.

The first component of this study is a secondary analysis of 20 Southeast Asian men's 100-m performances listed in the compiled dataset, covering athletes from Thailand, Indonesia, Malaysia, Singapore, and the Philippines. The analysis applies a quadratic correction to the recorded fully automatic timing (FAT) result using the associated wind reading. The purpose

*Correspondence: Edgar Jeevan Danaraj (edgar.jd@ntu.edu.sg)



is to describe how model-based adjustment changes comparisons among the listed performances, not to establish definitive regional rankings or infer a physiological plateau. The second component is a conceptual proposal for AI-guided lower-limb exoskeleton assistance. The wind-adjusted analysis provides a performance-benchmarking context for discussing possible training needs; it does not itself demonstrate that an exoskeleton would address those needs.

Lower-limb exoskeletons have been studied primarily in rehabilitation and gait-assistance contexts, including for people with neuromuscular impairments [5]. Building on this broader wearable-robotics field, this paper outlines conceptual sprint-assistance architecture using inertial sensing, athlete-specific movement references, phase-aware control, and independent safety limits. Architecture is a proposal rather than a tested device or intervention. Its ability to alter sprint mechanics or improve performance has not been established here and would require staged feasibility testing and controlled experiments.

Study Design and Data Analysis

This manuscript uses a two-part design: (1) a descriptive secondary analysis of a compiled table of 20 men's 100-m performances and (2) a conceptual engineering framework for a possible AI-powered sprint exoskeleton. The two parts are linked as context and proposal, not as a single experiment. No athlete was recruited, no exoskeleton was built or tested, and no intervention outcomes were collected.

For each listed performance, the official time T and reported wind reading W were entered into $T_0 = T + \alpha (W - \beta W^2)$, using $\alpha = 0.050$ and $\beta = 0.0556$ as the selected empirical coefficients. Positive W denotes a tailwind and negative W a headwind. The analysis reports descriptive means and standard deviations for official and adjusted times and orders the performances by calculated T_0 ; it does not conduct inferential statistical testing. The compiled manuscript table supplies the records used for the calculations. Because primary timing sheets and wind-gauge records were not available for independent checking of every entry in the supplied materials, the source data and rankings require record-by-record verification against authoritative competition sources before definitive use.

2. The Sprint Gait Cycle: Kinematics and Kinetics

To accurately quantify the impact of environmental factors and technological training interventions, a fundamental understanding of the running gait cycle and its underlying neuromuscular mechanics is required. While walking is defined by continuous ground contact and a double-support phase, running and sprinting introduce a double-float phase where both feet are entirely airborne. As a sprinter's velocity increases, the duration of the stance phase decreases exponentially, while the time spent in the flight phase increases, requiring the musculoskeletal system to absorb and generate immense forces in fractions of a second. The sprint gait cycle (Figure 1) begins with initial contact and is broadly divided into the stance phase and the swing phase. The stance phase is further subdivided into absorption (braking) and generation (propulsion). During maximum velocity sprinting, the ground reaction force (GRF) exerted at the center of pressure can surge to 250% to 300% of the athlete's body weight, necessitating exceptional structural integrity and balance. Kinematically, the sprint cycle demands extreme ranges of motion. At initial ground contact, the hip is typically positioned at approximately 50 degrees of flexion, immediately transitioning into aggressive extension through the stance phase, reaching up to 10 degrees of hyperextension precisely at toe-off to maximize forward propulsion.

Simultaneously, the knee flexes to roughly 40 degrees upon heel strike, absorbs the impact by flexing to 60 degrees during the loading response, and subsequently extends to propel the center of mass forward. During the ensuing flight and initial swing phase, elite sprint mechanics demand a rapid, high-heel recovery where the knee flexes to a maximum of 125 degrees, snapping the foot closely under the hamstring to reduce the moment of inertia and accelerate the forward swing of the femur. The ankle joints endure similar extremes, transitioning from 10 degrees of dorsiflexion to rapid plantarflexion reaching a maximum of 25 degrees immediately following toe-off.

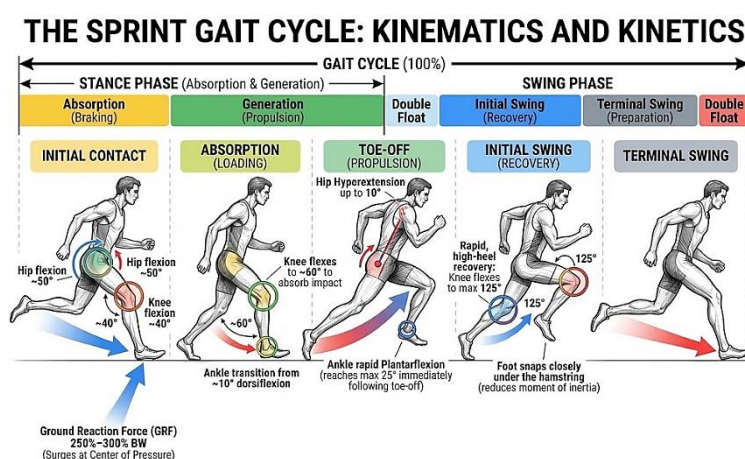


Figure 1. Biomechanical Phases and Joint Kinematics of Maximum Velocity Sprinting.

2.1. Neuromuscular Activation Profiles

The timing and amplitude of muscle activation, measurable via surface electromyography (EMG), dictate the efficiency of the kinematic transitions [6]. In elite sprinting, the neuromuscular system operates at its absolute physiological limit, with muscle contractions occurring just milliseconds prior to and immediately following ground contact to stiffen the lower limb joints. The gluteus maximus and gluteus medius activate intensely during the late swing and early stance phases to drive the thigh backward and stabilize the pelvis. The quadriceps group (vastus lateralis, rectus femoris) functions eccentrically during the initial 10% of the stance phase to arrest the downward velocity of the center of mass, before switching to a concentric action in the final 20% of the swing phase to prepare for the subsequent ground strike. Crucially, the medial hamstrings are active both during the early stance phase to assist in powerful hip extension, and during the late swing phase to eccentrically decelerate the rapidly extending tibia.

This eccentric deceleration is the primary mechanism of hamstring strain injuries (HSI), an inherent risk when athletes attempt to artificially push their limb velocities beyond their neuromuscular capacity through unregulated overspeed training [7]. Furthermore, the core acts as a vital conduit for force transfer, utilizing a diagonal elastic support strategy. This mechanism relies on counter-pelvic rotation and spinal engine mechanics to seamlessly distribute and transmit force between the upper and lower control zones, ensuring that power generated by the lower limbs is not dissipated by excessive torso oscillation. Any training intervention, whether it be dragging a heavy sled or wearing an active robotic suit, directly interferes with these delicate kinematic variables and neuromuscular activation timings, necessitating rigorous biomechanical monitoring.

2.2. The Physics of Aerodynamic Drag and Wind Assistance

Recorded 100-m times reflect both an athlete's performance and the environmental conditions during the race. Aerodynamic drag depends on the relative motion of the runner and the surrounding air [2]. In this study, recorded times are adjusted to a zero-wind reference using the empirical quadratic model described below. This correction is an analytical estimate; it does not account for every factor that can affect comparability, including altitude, track and timing conditions, footwear, competition context, or differences in data quality.

$$T_0 = T + \alpha (W - \beta W^2) \quad (1)$$

Where:

- 1) T is the official fully automatic timing (FAT) result in seconds.
- 2) W is the reported wind reading in m/s; positive values

indicate a tailwind, and negative values indicate a headwind.

- 3) α is the linear empirical coefficient, set to $0.050 \text{ s} \cdot \text{m}^{-1}$ for the model used in this analysis.
- 4) β is the quadratic coefficient, set to $0.0556 \text{ s} \cdot \text{m}^{-1}$, so that the term βW^2 has the same units as W. These coefficients are model assumptions adopted for the present calculations, not coefficients estimated from the 20 performances.

Under this framework, a maximum legal tailwind of +2.0 m/s corresponds to a modeled time reduction of approximately 0.10 to 0.11 seconds, a mathematical adjustment that can completely alter the outcome and historical ranking of elite competitions.

3. Model Sensitivity, Measurement Uncertainty, and Altitude Effects

The model is sensitive to wind-measurement precision and to the selected correction coefficients. Wind readings are commonly reported to 0.1 m/s, so rounding and short-term fluctuations may affect calculated zero-wind estimates. The uncertainty values discussed here are model-based sensitivity estimates rather than confidence intervals derived from repeated measurements. The analysis is descriptive: it reports the mean and standard deviation of the listed official and adjusted times and compares their ordering. No inferential hypothesis test was conducted. Accordingly, small differences between adjusted times should not be treated as statistically significant.

Altitude can also affect aerodynamic resistance because air density generally decreases with elevation [8]. The dataset includes performances from venues at different elevations, but the wind correction applied here does not normalize for altitude. The adjusted times therefore represent zero-wind equivalents under the selected model, not fully standardized sea-level equivalents. Comparisons involving venues at substantially different elevations should be interpreted cautiously.

3.1. Southeast Asian Men's 100-m Sprint Analytics (Up to 2026)

The dataset contains 20 performances from the five countries represented in Table 1. For each entry, the listed variables are athlete, nation, official time, wind reading, venue, date, and calculated zero-wind equivalent. The manuscript's compiled table is the analysis dataset; the primary timing sheets and wind-gauge records were not available within the materials used for this revision for independent verification of every entry. The rankings should therefore be read as results of this compiled dataset and model, and individual records should be checked against authoritative competition results before being treated as definitive.

Table 1. Southeast Asian men's all-time 100 m ranking by zero-wind equivalent time (Linthorne model).

Rank (Normalized)	Athletes (Nation)	Official Time (s)	Wind (m/s)	Zero-Wind Eq. T0 (s)	Hypothetical +2.0 m/s Eq. (s)	Competition Venue & Date
1	Puripol Boonson (THA)	9.90	+0.1	9.905	9.816	Nagoya, JPN (25 Sep 2026)
2	Muhd. Azeem Fahmi (MAS)	10.09	+0.2	10.100	10.011	Cali, COL (1 Aug 2022)
3	Lalu Muhammad Zohri (INA)	10.03	+1.7	10.107	10.018	Osaka, JPN (19 May 2019)
4	Eric Cray (PHI)	10.25	0.0	10.250	10.161	Singapore (13 Jun 2015)
5	Reanchai Seecharwong (THA)	10.29	-0.5	10.264	10.175	Kuala Lumpur, MAS (12 Sep 2001)
6	Reanchai Seecharwong (THA)	10.23	+1.9	10.315	10.226	Bangkok, THA (13 Dec 1998)
7	U. K. Shyam (SGP)	10.37	-0.5	10.344	10.255	Kuala Lumpur, MAS (12 Sep 2001)
8	Marc Brian Louis (SGP)	10.27	+2.0	10.359	10.270	Hangzhou, CHN (30 Sep 2023)
9	Reanchai Seecharwong (THA)	10.31	+1.6	10.383	10.294	Bangkok, THA (14 Dec 1998)
10	Marc Brian Louis (SGP)	10.37	+0.4	10.390	10.301	Nagoya, JPN (25 Sep 2026)
11	Kongdech Natanee (THA)	10.45	-0.5	10.424	10.335	Kuala Lumpur, MAS (12 Sep 2001)
12	U. K. Shyam (SGP)	10.37	+1.8	10.451	10.362	Beijing, CHN (27 Aug 2001)
13	C. Kunalan (SGP)	10.38	+2.0	10.469	10.380	Mexico City, MEX (13 Oct 1968)
14	Calvin Kang L. Loong (SGP)	10.47	0.0	10.470	10.381	Singapore (9 Jun 2015)
15	Gary Yeo Foo Ee (SGP)	10.44	+1.1	10.492	10.403	Vientiane, LAO (15 Dec 2012)
16	Kongdech Natanee (THA)	10.41	+1.9	10.495	10.406	Almaty, KAZ (23 Jun 2001)
17	Muhd. Elfi Mustapa (SGP)	10.56	-0.4	10.540	10.451	Singapore (25 Jul 2010)
18	Muhd. Amirudin Jamal (MAS)	10.46	+2.0	10.549	10.460	Kuala Lumpur, MAS (19 Oct 2013)
19	Haron Mundir (INA)	10.57	+0.9	10.613	10.524	Jakarta, INA (16 Sep 1987)
20	M. Naqib Asmin (MAS)	10.57	+2.0	10.659	10.570	Taipei, TPE (12 Jun 2014)

3.2. Statistical Summary

For the 20 listed performances, the mean official time is 10.399 ± 0.177 s and the mean model-adjusted zero-wind time is 10.379 ± 0.185 s (mean $\pm$ standard deviation). These descriptive summaries characterize this selected dataset only; they do not establish a population-level estimate for Southeast Asian sprinters. The hypothetical +2.0 m/s column is an extrapolated model scenario and should not be interpreted as an observed race result or an athlete's demonstrated capability.

For example, the listed 10.37-s performance by U. K. Shyam under a reported -0.5 m/s headwind yields a model-adjusted value of 10.344 s, while Marc Brian Louis's listed 10.27-s performance under +2.0 m/s yields 10.359 s. Under the chosen correction model, these estimates are close and their ordering differs from the raw times. This comparison illustrates the potential importance of environmental adjustment, but it does not establish which athlete delivered the superior biomechanical effort; that conclusion would require additional performance and measurement data.



Figure 2. 21st SEA Games in Kuala Lumpur, 2001. 100-m Final (-0.5 m/s Headwind): Reanchai Seeharwong (right), 10.29 s and U. K. Shyam (left), 10.37 s. (source: Bridgeman Images).

Puripol Boonson's listed 9.90-s performance under a reported +0.1 m/s wind yields a model-adjusted value of 9.905 s in this dataset. The hypothetical +2.0 m/s estimate is a mathematical extrapolation, not a prediction of the time the athlete would necessarily achieve under those conditions. The dataset is too limited and heterogeneous to support the conclusion that regional sprint performance has plateaued.

The adjusted results should not be used to claim a fixed performance gap between Southeast Asian sprinters and the global elite, or to infer that conventional training has reached a physiological limit. Instead, they demonstrate that wind conditions can affect comparisons and provide a descriptive benchmark for considering future research. The following sections review resisted and assisted sprint training before outlining a conceptual AI-exoskeleton framework; no direct comparison of these interventions was conducted in this study.

4. Traditional Sprint Augmentation: Resistance Vs. Assistance

Sprint augmentation relies on mapping an athlete's physical profile to see how well they generate power across different running speeds. Sprinting is naturally limited because an athlete cannot produce maximum force when moving at maximum speed.

Trainers analyze this balance to find specific weaknesses, identifying whether an individual struggles with initial power out of the blocks or maintaining speed at the end of a sprint. By pinpointing these gaps, trainers apply targeted solutions—using weighted resistance to build powerful acceleration, or high-speed assistance to improve running velocity.

Sprint training is often discussed in terms of force-velocity and power-velocity relationships [9]. These concepts help describe how force production changes with movement velocity, but the relationship varies with the athlete, task, and measurement method. They provide background for the following discussion of resisted and assisted sprint training; this manuscript does not measure individual force-velocity profiles.

4.1. The Mechanics and Limitations of Resisted Sprint Training (RST)

Resisted sprint training (RST) includes sled towing, parachute resistance, and motorized resistance devices. External resistance can increase the horizontal force demand during acceleration, although the effects on sprint mechanics depend on load, athlete, and protocol [3]. The figure illustrates a common resisted-sprint setup; it is not evidence from an intervention conducted as part of this study.

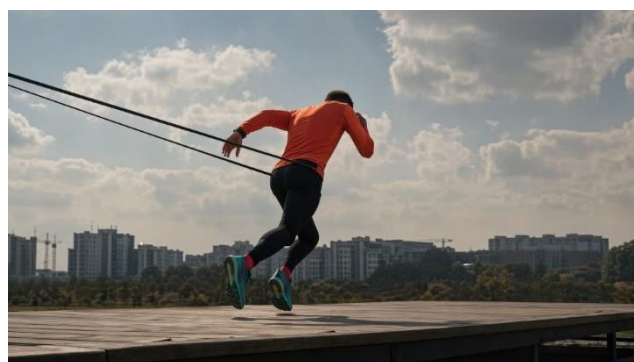


Figure 3. An athlete engaged in resisted sprint training (RST), demonstrating the forward lean required to overcome horizontal resistance.

Research suggests that resisted sprint training can improve acceleration under some loading conditions, while heavier

loads can alter running kinematics and increase ground-contact duration [7]. The magnitude and direction of these effects depend on the protocol and athlete. The present manuscript did not collect electromyography or ground-contact measurements, so these mechanisms are discussed from the cited literature rather than presented as new findings.

RST emphasizes force production under additional load and may not reproduce the mechanics of maximal-velocity sprinting. However, the claim that it necessarily causes central-nervous-system maladaptation or makes athletes sluggish is stronger than the evidence presented here supports. Training effects should be evaluated in relation to load, volume, and transfer to the athlete's target sprint phase [7, 10].

4.2. The Perils of Assisted Sprint Training (AST) and Overspeed Protocols

Assisted sprint training (AST), or overspeed training, uses elastic towing or other assistance to expose athletes to running speeds above their usual unassisted speed [11]. Such protocols can change step length, flight time, and ground-contact time, but the response depends on the assistance level and athlete. Excessive assistance may disrupt coordination or promote overstriding; therefore, progression and monitoring are important. The 110% threshold is sometimes used as a practical coaching guideline, but it should not be treated here as a universally validated safety boundary [4, 12].

Overstriding and high-speed running may increase demands on the hamstrings, particularly during late swing, but the specific injury risk depends on multiple interacting factors [4, 6]. The present study did not measure muscle forces, injury incidence, or the effects of towing assistance. AST is therefore discussed as a training approach with potential benefits and risks, not as an intervention whose injury outcomes are evaluated by this study.

5. Kinematic Optimization via AI-Powered Lower-Limb Exoskeletons

The limitations of RST and AST motivate interest in assistance strategies that can respond to an athlete's movement rather than applying a fixed external load. This paper proposes a conceptual lower-limb exoskeleton architecture using phase-aware, joint-level assistance. Existing rehabilitation exoskeleton research provides relevant background [5], but it does not establish that current devices can safely deliver the forces, speeds, or control precision required for maximal sprinting. The proposed athletic application remains unvalidated.

5.1. Predictive AI Architecture and the Digital Twin

A possible control architecture could combine wearable in-

ertial measurement units (IMUs) with a Temporal Convolutional Network (TCN) and a Gated Recurrent Unit (GRU) to estimate gait phase and movement state. This is a proposed design choice, not a tested or benchmarked model in the present study. Its classification accuracy, latency, robustness, and performance under sprint-specific loads would need to be evaluated experimentally before any assistance is delivered to an athlete.

An athlete-specific digital twin or sprint signature could be developed from high-frame-rate video, motion capture, and wearable sensors, subject to calibration and measurement uncertainty. The reference could then be used to identify deviations in joint angles or timing. Any controller should treat the reference as an individualized comparison target rather than an ideal template that must be imposed on every athlete; athlete-to-athlete variation and natural adaptation must be retained.

5.2. The Gait-Phase Correction Factor (GCF) and Late-Cadence Assist

In the proposed framework, assistance would be triggered only when the estimated gait phase and measured kinematics satisfies pre-defined criteria. A Gait-Phase Correction Factor (GCF) is suggested as a design concept for expressing phase-weighted deviations from an athlete-specific reference; it has not been validated in this study. Its definition, weighting coefficients, and thresholds would need to be specified and calibrated in future work.

$$GCF(\phi) = w_h \cdot e_h(\phi) + w_k \cdot e_k(\phi) + w_a \cdot e_a(\phi) + w_f \cdot e_f(\phi) + w_s \cdot e_s(\phi) \quad (2)$$

Here, the gait-phase variable denotes the percentage of the gait cycle, and the error terms would represent measured deviations in selected kinematic variables relative to the athlete-specific reference. The exact variables, normalization, and weighting would need to be defined before the equation could be implemented or independently reproduced.

One possible application is a late-cadence assistance mode intended to investigate whether phase-specific hip or knee assistance could help maintain leg-switch timing during the final portion of a sprint. The timing, torque magnitude, and direction of assistance are hypotheses for future testing, not established interventions. Feasibility testing would first need to assess comfort, actuator response, coordination, and safety at submaximal speeds before progression to maximal sprinting.

5.3. Multi-Objective Loss Functions and Safety Supervision

The proposed controller could use a multi-objective loss function to balance kinematic tracking with constraints on posture, left-right symmetry, and foot placement. This is a design proposal; the equation and its weights require formal

specification and validation before it can be interpreted as an operational controller.

$$L = \lambda_1 L_{stride} + \lambda_2 L_{phase} + \lambda_3 L_{posture} + \lambda_4 L_{footstrike} + \lambda_5 L_{cadence} + \dots + \lambda_9 L_{gate-correction} \quad (3)$$

Each individual L term measures a different aspect of sprint performance, while each λ is a weighting coefficient that determines how strongly that aspect influences the total loss.

L is the total loss function; L_{stride} is the stride-kinematics tracking error; L_{phase} is the gait-phase estimation or tracking error; $L_{posture}$ is the deviation from the target sprinting posture; $L_{footstrike}$ is the deviation from the desired foot-strike

mechanics; and λ terms are the weighting coefficients assigned to individual objectives.

Such a framework would require an independent safety supervisor that can reject or interrupt controller commands. The safeguards listed in Table 2 are proposed engineering controls, not proven injury-prevention measures. Their effectiveness would need to be assessed through bench testing, simulation, and staged human-subject studies under appropriate ethical and safety oversight.

Furthermore, to mitigate the catastrophic hamstring injuries associated with traditional overspeed training [7], the neural network cannot directly command unrestricted motor torque. All requests are filtered through an independent Safety Supervisor micro-controller.

Table 2. Proposed Safety Supervisor Protocols: Intended Operational Functions and Risk Controls.

Safety Supervisor Protocol	Operational Function	Injury Prevention Mechanism
Torque Limitation	Proposed limit on peak motor current based on pre-validated engineering and biomechanical constraints.	Intended to limit actuator output that could contribute to excessive muscular or tendon loading; effectiveness requires validation.
Joint-Angle Bounds	Proposed cutoffs to keep commanded joint motion within individually configured anatomical bounds.	Intended to keep commanded motion within configured joint-angle limits; safe limits require individual calibration.
Velocity Limiter	Proposed cap on the angular velocity of robotic actuators.	Intended to constrain actuator speed; its effect on overstriding and injury risk remains untested.
Symmetry Monitoring	Proposed monitoring of left-right differences in stride length and ground-contact time.	May flag left-right asymmetry for review or shutdown; it cannot independently diagnose fatigue or predict injury.
Phase Plausibility	Proposed check of requested assistance against the estimated sprint phase and contact state.	Intended to reject commands inconsistent with estimated gait phase; detection performance requires validation.

5.4. Comparative Discussion: The Exoskeletal Advantage

The wind-normalized results describe variation within the compiled dataset but do not demonstrate a regional performance plateau or identify a causal training deficit. The proposed exoskeleton framework is a separate, conceptual response to questions about how sprint-specific assistance might be studied. The connection between the two components is therefore motivational and exploratory: the performance analysis provides context, while the technology section defines hypotheses and design requirements for future research.

RST can be useful for developing acceleration-specific

force production, but the extent to which it transfers to upright maximal-velocity sprinting depends on the training protocol and athlete [3, 7, 10]. AST can expose athletes to higher running speeds, while excessive assistance may disrupt mechanics [4, 11, 12]. Neither method was experimentally compared with an exoskeleton in this study.

No comparative exoskeleton trials were conducted for this manuscript, and no observed 30%-40% reduction in gait-cycle time or improvement in race performance can be reported. The proposed architecture may be evaluated in future studies using pre-registered outcomes such as gait-phase classification accuracy, joint kinematics, ground-contact time, symmetry, athlete comfort, adverse events, and electronically timed sprint performance. Until such data is collected, any performance benefit remains hypothetical.

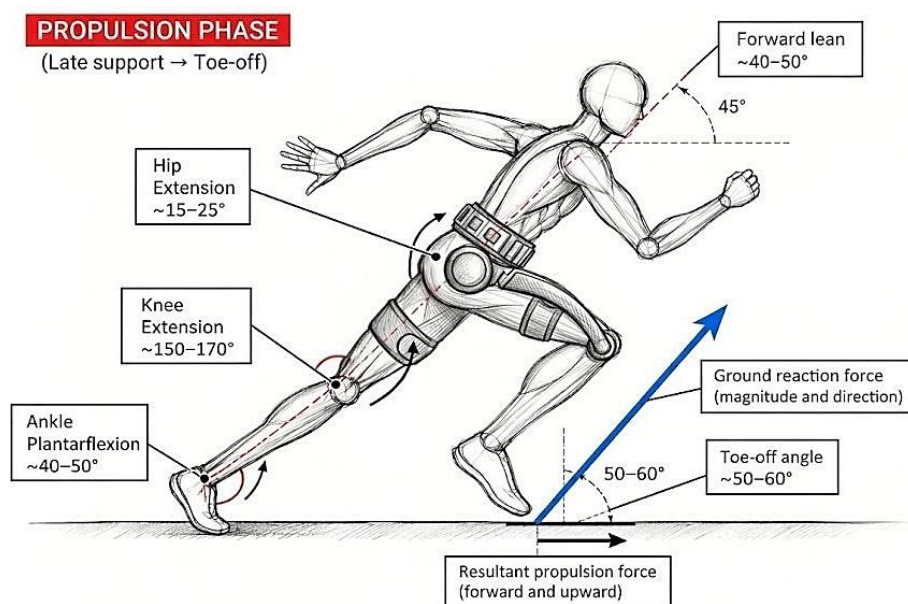


Figure 4. Presents a conceptual illustration of possible exoskeleton-assisted propulsion, not a tested prototype or validated operating mode. The image should not be interpreted as evidence that the proposed system can safely achieve supramaximal speed or reduce hamstring injury risk.

The proposed system could be investigated as a motor-learning aid, but this manuscript contains no participant testing, subjective feedback, or evidence that an exoskeleton accelerates neuroplasticity or reduces perceived effort. These claims have therefore been framed as research questions rather than findings. Any future study should examine whether assistance preserves natural coordination and whether effects persist after the device is removed.

The proposed controller could be assessed against conventional training in a controlled study, but no exoskeleton group, resisted-training comparator group, or post-intervention sprint data were included in the present work. No statistical trend or superiority claim can therefore be made. A future comparison should report sample size, protocol, effect estimates, uncertainty intervals, and adverse events.

6. Conclusion

This study combines a descriptive, model-based analysis of 20 listed Southeast Asian men's 100-m performances with a conceptual proposal for AI-guided sprint assistance. The wind-normalization results show how a quadratic adjustment can change comparisons among recorded performances, while also depending on the selected coefficients and the accuracy of the underlying times and wind readings. The compiled dataset and the lack of independent source verification for every entry limit the certainty of the rankings.

The analysis does not establish a regional performance plateau, a physiological ceiling, or the superiority of any training method. The review of resisted and assisted sprint training provides context for considering alternative approaches, but the manuscript includes no direct intervention or comparative

training data.

The AI-powered exoskeleton architecture is a hypothesis-generating framework that combines potential inertial sensing, athlete-specific movement references, phase-aware control, and independent safety supervision. Its feasibility, effects on sprint kinematics and race performance, and any injury-related implications remain unknown. Future work should first verify the historical performance dataset and make the normalization calculations reproducible, then evaluate the proposed controller through simulation, bench testing, and ethically approved staged human studies. The present contribution is thus the integration of a descriptive wind-adjustment analysis with a clearly identified conceptual technology proposal, rather than evidence of demonstrated exoskeleton efficacy.

Declaration of Generative AI Use

During the preparation of this manuscript, the author used OpenAI ChatGPT (GPT-5.6) and Gemini 3.1 Pro to assist with language refinement, editing, restructuring, summarization, and clarification of author-provided manuscript text, including refinement of the abstract and presentation of the manuscript. The use of ChatGPT and Gemini was intended to improve clarity, readability, consistency, and conciseness.

The author reviewed, edited, and verified all AI-assisted content and confirms that the originality and accuracy of the manuscript have been checked. ChatGPT was not used as an author and did not replace the author's responsibility for research design, data, analysis, interpretation, or conclusions. The author takes full responsibility for the integrity and accuracy of the entire manuscript, including all references and cited sources. The author has also reviewed the applicable terms of use for the AI tool and confirms that its use is suitable for publication in accordance with the policy.

Abbreviations

AI	Artificial Intelligence
AST	Assisted Sprint Training
EMG	Electromyography
FAT	Fully Automatic Timing
FPS	Frames Per Second
GRF	Gated Recurrent Force
GRU	Ground Reaction Units
HSI	Hamstring Strain Injuries
IMU	Inertial Measurement Unit
RST	Resisted Sprint Training
SEA	Southeast Asian
TCN	Temporal Convolutional Networks

Author Contributions

Edgar Jeevan Danaraj: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing

Data Availability Statement

The datasets generated and analyzed during the current study, including the wind-normalization computational outputs and the comprehensive performance rankings, are available from the corresponding author upon reasonable request and in accordance with the data-sharing guidelines of the publisher.

Conflicts of Interest

The author declares no conflicts of interest.

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