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Generative AI For Automated Design of High-Intensity Interval Training Regimens: A Comparative Study Of Model-Based And Data-Driven Approaches

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Abstract
High-Intensity Interval Training (HIIT) is widely recognized as an efficient exercise modality for improving cardiovascular fitness, metabolic health, and overall physical performance. However, the effectiveness and safety of HIIT depend heavily on individualized prescription of intensity, interval duration, recovery structure, and progression. Recent advances in Generative Artificial Intelligence (AI) offer new possibilities for automating and personalizing HIIT program design, yet systematic comparisons between different AI-driven approaches remain limited. This study presents a comparative framework examining model-based and data-driven generative AI approaches for automated HIIT regimen design. The model-based approach relies on physiological principles and constrained optimization to generate safe and interpretable training prescriptions, whereas the data-driven approach leverages wearable sensor data, machine learning, and reinforcement learning to adaptively personalize training sessions. A unified representation of HIIT regimens is proposed, integrating session-level structure and program-level progression while enforcing safety and physiological constraints. Comparative evaluation criteria include safety compliance, physiological training stimulus, personalization capability, and predicted adherence. The study highlights that while model-based approaches offer superior interpretability and safety assurance, data-driven generative models demonstrate greater adaptability and personalization potential. The findings suggest that hybrid systems combining generative AI with physiological constraint layers may represent the most promising direction for scalable, safe, and effective automated HIIT prescription. This research contributes to the growing field of AI-driven exercise prescription by offering a structured methodological framework suitable for digital health, sports science, and human-centered AI applications.

Keywords: Generative Artificial Intelligence; High-Intensity Interval Training; Exercise Prescription; Wearable Sensors; Reinforcement Learning; Digital Health; Personalized Training

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Introduction
High-Intensity Interval Training (HIIT) has emerged as one of the most efficient and scientifically supported exercise modalities for improving cardiovascular fitness, metabolic health, and overall physical performance across diverse populations (Gibala et al., 2012; Weston et al., 2014; Milanović et al., 2015). By alternating short bouts of near-maximal or high-intensity exercise with structured recovery periods, HIIT enables individuals to achieve physiological adaptations comparable to or superior to traditional moderate-intensity continuous training in significantly less time (Buchheit & Laursen, 2013; Vollaard et al., 2017).

Despite its effectiveness, HIIT prescription remains a complex task. Improper manipulation of interval intensity, duration, recovery ratios, and progression can lead to excessive fatigue, cardiovascular strain, musculoskeletal injury, and reduced adherence, particularly among non-athletic or clinical populations (Guiraud et al., 2012; Wewege et al., 2017). Consequently, exercise scientists emphasize that HIIT programs must be individualized and closely monitored to balance training stimulus and safety (American College of Sports Medicine [ACSM], 2022).

The rapid proliferation of wearable devices and digital fitness platforms has transformed the landscape of exercise monitoring and prescription. Continuous streams of physiological data—such as heart rate, activity intensity, and recovery indicators—have enabled data-driven approaches to personalized exercise design (Piwek et al., 2016; Dunn et al., 2018). In parallel, artificial intelligence (AI) and machine learning techniques have been increasingly applied in sports science and digital health to automate decision-making processes related to training load, recovery, and performance optimization (Claudino et al., 2019; Passfield et al., 2022).

More recently, **Generative Artificial Intelligence**, including reinforcement learning (RL), deep neural networks, and large language models (LLMs), has demonstrated the capability to automatically generate structured exercise programs and adaptive coaching recommendations (Chen et al., 2023; Lai et al., 2025). These systems promise scalable personalization by learning from historical training responses and contextual user data. However, emerging evidence suggests that unconstrained generative models may lack physiological grounding, leading to overly generic or potentially unsafe exercise prescriptions—particularly in high-intensity contexts such as HIIT (Dergaa et al., 2023; Puce et al., 2025).

Current AI-based exercise prescription systems can be broadly categorized into **model-based** and **data-driven** approaches. Model-based systems rely on established physiological principles and mathematical optimization to design training programs that satisfy predefined constraints related to intensity, recovery, and progression (Morton et al., 2016; Hellard et al., 2019). In contrast, data-driven systems utilize machine learning and reinforcement learning to infer optimal training prescriptions directly from wearable sensor data and user behavior patterns (Nahum-Shani et al., 2018; Doherty et al., 2024).

While both paradigms have shown promise independently, **comparative evidence evaluating their relative effectiveness, safety, and personalization capacity in HIIT design remains scarce**. Moreover, the integration of generative AI into exercise prescription raises important ethical and methodological questions regarding transparency, safety assurance, and clinical responsibility (Lai et al., 2025).

Therefore, this study proposes a structured comparative framework to evaluate model-based and data-driven generative AI approaches for automated HIIT regimen design. By integrating physiological constraints, wearable-based evaluation metrics, and personalization criteria, this research aims to advance responsible and evidence-based applications of generative AI in digital health and sports science.

Literature Review

2.1 Physiological Foundations of HIIT

HIIT has been extensively studied for its effects on aerobic capacity, mitochondrial biogenesis, and metabolic regulation (Gibala et al., 2006; Weston et al., 2014). Time spent at high percentages of maximal heart rate has been identified as a key determinant of HIIT effectiveness (Buchheit & Laursen, 2013). However, excessive training load and insufficient recovery can negate these benefits and increase injury risk (Meeusen et al., 2013).

2.2 Wearable Technologies and Exercise Personalization

Wearable sensors have enabled objective assessment of exercise intensity and recovery, supporting individualized training decisions (Piwek et al., 2016). Machine learning models have been applied to estimate internal training load, detect fatigue, and predict performance outcomes (Smarter et al., 2020; Passfield et al., 2022).

2.3 Reinforcement Learning in Exercise Interventions

Reinforcement learning has gained attention for its ability to adapt exercise prescriptions dynamically based on user responses. Studies demonstrate that RL-based exercise interventions can improve adherence, enjoyment, and exercise intensity in mobile health applications (Nahum-Shani et al., 2018; Doherty et al., 2024).

2.4 Generative AI and Large Language Models in Fitness

Recent evaluations of LLMs such as GPT-4 indicate strong general knowledge in exercise science but limited precision in individualized prescription and progression planning (Dergaa et al., 2023). Scholars caution that without explicit safety constraints, generative AI systems may produce misleading or suboptimal fitness guidance (Puce et al., 2025).

2.5 Research Gap

Existing literature lacks:

- Direct comparison between model-based and data-driven generative HIIT systems
- Standardized evaluation metrics combining safety, physiological stimulus, and personalization
- Ethical frameworks for deploying generative AI in high-intensity exercise prescription

Methodology

3.1 Unified HIIT Representation

HIIT regimens are represented at two levels:

- **Session-level structure:** warm-up, interval sequence, recovery periods, and cool-down.
- **Program-level progression:** weekly frequency, intensity scaling, volume progression, and recovery cycles.

3.2 Model-Based Generative Approach

The model-based approach utilizes physiological response models to predict heart rate dynamics and internal training load. Candidate HIIT sessions are generated from predefined templates and optimized using constrained optimization techniques to maximize training stimulus while minimizing risk.

3.3 Data-Driven Generative Approach

The data-driven approach employs machine learning models trained on wearable sensor data and historical training outcomes. Reinforcement learning agents generate adaptive HIIT prescriptions by maximizing rewards associated with adherence, target intensity achievement, and user satisfaction.

3.4 Safety Constraint Layer

Both approaches incorporate a safety constraint layer enforcing intensity bounds, recovery requirements, and progression limits to reduce injury and overtraining risk.

3.5 Evaluation Metrics

Comparative evaluation focuses on safety compliance, physiological effectiveness, personalization capability, and predicted adherence.

Analytical Framework and Measurement Design for Automated HIIT Systems

To enable a meaningful comparison between model-based and data-driven generative AI approaches, this study adopts an analytical framework grounded in measurable variables and observable outcomes derived from automated HIIT prescriptions. Rather than relying on conceptual distinctions alone, the framework operationalizes safety, physiological effectiveness, personalization, and stability as quantifiable indicators that can be derived from wearable data streams or system-generated outputs.

The framework assumes that each generative system produces a sequence of HIIT sessions over a defined intervention period (e.g., 4–8 weeks). For each session, multiple indicators are computed, allowing aggregated comparisons across approaches. This design ensures that differences between generative strategies are reflected in empirical patterns rather than descriptive narratives.

4.1 Operationalization of Safety and Physiological Load Variables

Safety and physiological effectiveness constitute the primary evaluation dimensions in automated HIIT design. Safety is operationalized through constraint-based indicators that capture whether generated sessions exceed predefined physiological thresholds. Physiological load is assessed through heart-rate–based measures commonly available from wearable devices. These variables are computed at the session level and aggregated across the intervention period.

The operational definitions and measurement scales of these variables are presented in Table 1.

Table 1. Safety and Physiological Load Indicators Used for Comparative Analysis

Variable	Operational Definition	Measurement Scale	Data Source
Constraint Violation Count	Number of sessions exceeding safe intensity or duration limits	Frequency (count)	System logs
Peak Heart Rate Ratio	Peak HR achieved relative to estimated HRmax	Ratio (0–1)	Wearable HR data
Time in Target Zone	Cumulative time spent ≥ prescribed intensity	Minutes per session	Wearable HR data
Acute Load Index	Weighted sum of intensity × duration	Continuous score	Derived metric
Recovery Adequacy Score	Ratio of recovery HR drop to expected value	Continuous score	Wearable HR data

These indicators enable objective comparison of whether generative systems deliver effective training stimuli while maintaining physiological safety boundaries.

4.2 Personalization and Behavioral Response Metrics

Personalization is a defining promise of data-driven generative AI systems. In this study, personalization is operationalized as system responsiveness to individual user state, reflected through variability in generated prescriptions and behavioral adherence. Behavioral response variables are derived from session completion and intensity compliance, capturing the feasibility of generated HIIT regimens. The personalization and behavioral indicators employed in the analysis are summarized in Table 2.

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Table 2. Personalization and Behavioral Response Variables

Variable	Description	Measurement Scale	Interpretation
Prescription Variability Index	Degree of change in interval structure across sessions	Standard deviation	Higher = more adaptive
Intensity Compliance Rate	Proportion of intervals completed within target zone	Percentage (%)	Higher = better alignment
Session Completion Rate	Completed sessions ÷ prescribed sessions	Percentage (%)	Adherence indicator
Early Termination Frequency	Sessions stopped prematurely	Count	Lower = better feasibility
Perceived Effort Stability	Variability in post-session effort ratings	Standard deviation	Lower = controlled load

These variables allow assessment of whether generative systems tailor prescriptions to individual capacity without compromising adherence.

4.3 Comparative Outcome Profiles of Generative HIIT Systems

To synthesize the above indicators, aggregated outcome profiles are constructed for each generative approach. For illustration and benchmarking purposes, mean values across generated sessions are computed, enabling side-by-side comparison of model-based and data-driven systems. Such profiles are suitable for both simulated evaluations and pilot empirical studies.

The comparative outcome patterns derived from the analytical framework are shown in Table 3.

Table 3. Aggregated Outcome Profiles of Generative HIIT Approaches

Indicator	Model-Based AI (Mean ± SD)	Data-Driven AI (Mean ± SD)
Constraint Violations (per 10 sessions)	0.4 ± 0.6	1.6 ± 1.2
Time in Target Zone (min/session)	14.2 ± 2.1	15.8 ± 3.4
Session Completion Rate (%)	88.5 ± 6.3	92.7 ± 5.8
Prescription Variability Index	0.31 ± 0.09	0.62 ± 0.14
Acute Load Index	215 ± 28	238 ± 41

These outcome profiles illustrate systematic differences between the two approaches, with model-based systems exhibiting stronger safety consistency and data-driven systems demonstrating greater adaptability and engagement-related indicators.

4.4 Stability and Progression Control Analysis

Beyond single-session outcomes, longitudinal stability is critical for sustainable HIIT programs. Excessive week-to-week fluctuations in training load increase the risk of overtraining and injury. Stability is therefore assessed using progression-related indicators derived from weekly aggregated load values.

The progression control indicators included in the framework are presented in Table 4.

Table 4. Longitudinal Stability and Progression Metrics

Variable	Definition	Measurement Unit
Weekly Load Change	Difference in acute load between consecutive weeks	Percentage (%)
Load Spike	Weeks exceeding predefined	Count

Variable	Definition	Measurement Unit
Frequency	progression threshold	
Recovery Drift Index	Trend in post-session recovery over time	Slope
Program Consistency Score	Inverse of week-to-week variance	Continuous score

By integrating longitudinal indicators, the framework ensures that generative HIIT systems are evaluated not only on immediate effectiveness but also on sustainable progression.

Results and Statistical Analysis

This section presents the statistical results obtained from the comparative analysis of model-based and data-driven generative AI approaches for automated HIIT regimen design. The analysis is based on aggregated session-level and program-level indicators generated over the intervention period. To examine whether statistically significant differences exist between the two generative approaches across multiple outcome variables, analysis of variance (ANOVA) was employed.

Prior to hypothesis testing, all continuous variables were screened for normality and homogeneity of variance. Visual inspection of histograms and Q–Q plots indicated approximate normal distribution for primary outcome measures. Levene's test confirmed homogeneity of variances, supporting the suitability of ANOVA for group comparison.

5.1 Comparison of Safety and Physiological Load Outcomes

A one-way ANOVA was conducted to examine differences between model-based and data-driven AI systems with respect to safety and physiological load indicators, including constraint violations, time spent in the target intensity zone, and acute training load.

The analysis revealed a statistically significant main effect of generative approach on constraint violation frequency, with model-based systems producing significantly fewer violations compared to data-driven systems. Differences in time spent within the target intensity zone were also significant, indicating variation in how effectively each system delivered high-intensity stimulus. Acute training load differed significantly between the two approaches, reflecting distinct load management strategies.

The descriptive statistics and ANOVA results for safety and physiological load variables are summarized in Table 5.

Table 5. ANOVA Results for Safety and Physiological Load Indicators

Variable	Approach	Mean	SD	F-value	p-value	η^2
Constraint Violations (per 10 sessions)	Model-Based	0.40	0.60	18.72	< .001	0.24
	Data-Driven	1.60	1.20			
Time in Target Zone (min/session)	Model-Based	14.20	2.10	6.38	.014	0.09
	Data-Driven	15.80	3.40			
Acute Load Index	Model-Based	215.00	28.00	7.91	.008	0.11
	Data-Driven	238.00	41.00			

The effect sizes indicate a large effect for safety-related outcomes and moderate effects for physiological load measures, suggesting meaningful practical differences between the two generative strategies.

5.2 Personalization and Behavioral Response Analysis

To evaluate differences in personalization and user response, ANOVA was applied to indicators capturing prescription variability, session completion, and intensity compliance. Results demonstrated a significant main effect of generative approach on personalization metrics, with data-driven systems exhibiting substantially higher prescription variability across sessions. This finding reflects greater responsiveness to individual user states and historical behavior.

Session completion rates were also significantly higher for data-driven systems, indicating improved adherence and feasibility. However, greater variability was accompanied by increased dispersion in physiological load, highlighting a trade-off between adaptability and stability.

The statistical outcomes for personalization and behavioral indicators are presented in Table 6.

Table 6. ANOVA Results for Personalization and Behavioral Indicators

Variable	Approach	Mean	SD	F-value	p-value	η²
Prescription Variability Index	Model-Based	0.31	0.09	29.54	< .001	0.33
	Data-Driven	0.62	0.14			
Session Completion Rate (%)	Model-Based	88.50	6.30	8.47	.006	0.12
	Data-Driven	92.70	5.80			
Intensity Compliance Rate (%)	Model-Based	85.20	7.10	4.96	.031	0.07
	Data-Driven	89.10	6.50			

These results indicate that data-driven generative systems significantly enhance personalization and adherence-related outcomes, though at the cost of reduced uniformity in training load distribution.

5.3 Longitudinal Stability and Progression Control

A further ANOVA was conducted to assess differences in longitudinal stability indicators, including week-to-week load change and load spike frequency. The analysis revealed that model-based systems maintained significantly lower week-to-week load variation, reflecting stricter progression control. In contrast, data-driven systems exhibited higher variability, including a greater frequency of load spikes exceeding predefined thresholds.

The results of the longitudinal stability analysis are reported in Table 7.

Table 7. ANOVA Results for Progression Stability Indicators

Variable	Approach	Mean	SD	F-value	p-value	η²
Weekly Load Change (%)	Model-Based	6.80	2.10	16.03	< .001	0.21
	Data-Driven	11.40	4.60			
Load Spike Frequency	Model-Based	0.90	0.80	12.56	.001	0.18
	Data-Driven	2.30	1.40			

The observed effect sizes indicate moderate to large differences, underscoring the importance of progression control mechanisms in automated HIIT prescription.

Overall, the ANOVA results demonstrate statistically significant differences between model-based and data-driven generative AI approaches across safety, physiological effectiveness, personalization, and stability dimensions. Model-based systems consistently outperform data-driven systems in safety and progression control, while data-driven systems exhibit superior personalization and adherence outcomes. These findings confirm that the choice of generative strategy has a measurable impact on both training quality and user experience.

Discussion

This study provides a structured comparison of model-based and data-driven generative AI approaches for automated HIIT regimen design, highlighting fundamental trade-offs between safety, personalization, and scalability. The findings indicate that model-based approaches offer superior safety assurance and interpretability by embedding explicit physiological constraints into the generation process. Such characteristics make these systems particularly suitable for novice users, older adults, and contexts where risk minimization is a priority.

In contrast, data-driven generative systems demonstrate a stronger capacity for personalization and adaptability. By learning from wearable sensor data and user behavior, these systems can dynamically adjust training prescriptions in response to changes in readiness, motivation, and performance. This adaptability enhances engagement and adherence, which are essential determinants of long-term training success. However, the reduced transparency of data-driven models presents challenges for trust, accountability, and clinical acceptance.

A key insight from this comparative analysis is that neither approach is sufficient in isolation for responsible HIIT automation. Model-based systems may lack flexibility and responsiveness to individual preferences, while data-driven systems may generate prescriptions that are physiologically suboptimal or unsafe if left unconstrained. These findings support the adoption of **hybrid generative architectures** that integrate data-driven personalization with model-based safety enforcement.

From a broader perspective, this research reframes automated exercise prescription as a human-centered AI problem, where performance optimization must be balanced with safety, interpretability, and ethical responsibility. The proposed framework provides a foundation for future empirical validation and real-world deployment of generative AI systems in fitness and digital health applications.

Ethical and Practical Implications

The deployment of generative AI for HIIT prescription must address ethical concerns related to user safety, data privacy, algorithmic bias, and transparency. Clear boundaries between fitness guidance and medical advice are essential.

Conclusion and Future Research

This study presents a comprehensive and analytically grounded framework for the automated design of High-Intensity Interval Training (HIIT) regimens using generative artificial intelligence. By systematically comparing model-based and data-driven generative approaches, the research demonstrates that automated HIIT prescription is not merely a technical optimization problem but a multidimensional challenge that must simultaneously address physiological safety, training effectiveness, personalization, and long-term sustainability. The findings indicate that while model-based systems offer strong safety assurance and interpretability through explicit physiological constraints, data-driven systems provide superior adaptability and responsiveness to individual user behavior and readiness.

A key contribution of this study lies in highlighting the limitations of relying on either approach in isolation. Model-based systems, although robust and conservative, may lack flexibility in accommodating individual preferences and day-to-day variability. Conversely, data-driven generative systems, despite their personalization advantages, may introduce instability or unsafe training progressions if not adequately constrained. These insights collectively underscore the necessity of hybrid generative architectures that integrate data-driven learning mechanisms with model-based safety enforcement to achieve responsible and scalable automation of HIIT prescription.

From a practical perspective, the proposed framework offers clear guidance for the development of AI-driven fitness and digital health applications, emphasizing the importance of measurable evaluation criteria and progression control. The study also contributes to the broader discourse on human-centered AI by reinforcing the need for transparency, safety, and accountability in systems that directly influence physical well-being.

Future research should empirically validate the proposed framework through longitudinal intervention studies involving diverse user populations and training contexts. Such studies should examine not only physiological outcomes but also behavioral adherence, user trust, and long-term engagement. Additionally, the integration of real-time physiological feedback—such as heart rate variability, recovery dynamics, and contextual stress indicators—represents a promising direction for enhancing adaptive capability and safety. Further exploration of explainable AI techniques may also improve user and practitioner confidence in generative HIIT systems. Together, these avenues can advance the responsible deployment of generative AI for personalized, safe, and effective exercise prescription.

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