Generative Artificial Intelligence in University Sports Training: A Mixed-Methods Study

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***Abstract*—This study investigates the application of Generative Artificial Intelligence (GenAI) in university sports training programs. A mixed-methods approach was employed, combining a quasi-experimental design with qualitative interviews. A total of 120 student-athletes from track and field and basketball programs were divided into experimental (GenAI-supported training) and control (traditional training) groups. Quantitative data included pre- and post-intervention performance metrics (e.g., speed, accuracy, endurance), while qualitative data were gathered through semi-structured interviews with 10 coaches and 15 athletes. Results indicated that the experimental group showed statistically significant improvements in performance outcomes compared to the control group ($p < 0.05$). Thematic analysis revealed that GenAI was perceived as highly effective for personalized training plan generation, real-time technique feedback, and motivational support. However, challenges included data privacy concerns, over-reliance on technology, and the need for specialized trainer upskilling. The findings suggest that GenAI has substantial potential to enhance sports training in higher education settings, but its integration must be pedagogically sound and ethically guided. This study contributes to the growing body of literature on AI in physical education and provides practical implications for sports educators and policymakers.**

***Keywords*—athletic performance, generative artificial intelligence, higher education, mixed-methods research, personalized learning, sports training**

I. Introduction

The integration of Artificial Intelligence (AI) into educational and professional sectors has revolutionized traditional practices, offering new avenues for efficiency, personalization, and scalability. In the domain of sports science and physical education, AI technologies are increasingly being leveraged to optimize athlete performance, prevent injuries, and enhance training methodologies. Among these technologies, Generative Artificial Intelligence (GenAI) stands out due to its ability to create new content, simulate scenarios, and provide adaptive feedback based on large datasets. Unlike predictive AI, which analyzes existing data to forecast outcomes, GenAI can generate tailored training regimens, simulate opponent strategies, and even create visual or textual feedback for athletes. This capability is particularly relevant in university settings, where sports programs aim to balance academic rigor with athletic excellence.

Despite the growing interest in AI applications in sports, empirical research focusing specifically on GenAI in higher education sports training remains limited. Most existing studies concentrate on elite athletics or commercial sports organizations, leaving a significant gap in understanding how these tools can be effectively adapted for educational contexts where resources, goals, and constraints differ. Furthermore, while research on predictive analytics in sports is expanding, there is a notable scarcity of interventional studies examining the efficacy of generative AI systems in real-world training environments. No prior work has systematically investigated the implementation, outcomes, and stakeholder perceptions of GenAI within university sports programs. University athletes often juggle academic demands with training schedules, necessitating efficient and flexible training solutions. GenAI has the potential to address these needs by offering personalized, data-driven training support that can be accessed asynchronously, yet its practical integration and impact in this unique setting remain underexplored.

This study aims to address these critical gaps by examining the application of GenAI in university sports training programs through a mixed-methods design. Specifically, it seeks to: (1) provide empirical, quantitative evidence on the performance benefits of a GenAI-supported training intervention for university athletes; (2) offer rich, qualitative insights into the lived experiences, perceived usefulness, and implementation challenges from the perspectives of both coaches and athletes; and (3) propose a practical framework for the ethical and pedagogically sound integration of GenAI into university sports pedagogy.

The research questions guiding this study are as follows:

1) To what extent does GenAI-supported training improve athletic performance compared to traditional training methods?
2) How do coaches and athletes perceive the usefulness, challenges, and ethical implications of GenAI in training?
3) What are the practical recommendations for integrating GenAI into university sports pedagogy?

The paper is structured as follows: a review of relevant literature, a detailed methodology section, presentation of results, a discussion of findings, and concluding remarks with implications for practice and future research.

II. Literature Review

The integration of Artificial Intelligence (AI) into sports represents a paradigm shift from intuition-based coaching to a data-driven, precision-oriented discipline. This review traces the evolution of AI in sports, establishes the unique capabilities of Generative AI (GenAI), and identifies the specific gaps in the literature regarding its application within the context of higher education sports training.

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A. The Evolution of AI in Sports Science and Analytics

The application of AI in sports has progressed through distinct waves. The first wave was characterized by descriptive analytics, focusing on data collection and basic visualization. The proliferation of wearable sensors (e.g., GPS trackers, accelerometers, heart rate monitors) and computer vision systems provided an unprecedented volume of data on athlete performance, including distance covered, velocity, and workload [1]. This allowed coaches to move beyond subjective observation to objective measurement.

The second wave saw the rise of predictive and prescriptive analytics. Machine Learning (ML) algorithms were employed to forecast future outcomes. A primary application has been in injury prevention, where models analyze training load, biomechanical data, and physiological markers to identify athletes at high risk of injury [2]. For instance, studies have used ML to predict non-contact hamstring injuries in soccer players with high accuracy, enabling preemptive intervention. Furthermore, predictive models are used for talent identification, scouting opponents, and optimizing game strategies by simulating various scenarios [3].

While these applications are powerful, they are fundamentally reactive or probabilistic—they analyze what has happened or predict what might happen. They provide the "what" but not the "how to". This is the critical gap that the third wave, generative AI, begins to fill.

B. Generative AI: A New Frontier in Personalized Learning and Training

Generative AI refers to a class of algorithms that can create new, original content—such as text, images, audio, and video—that did not previously exist in its training data. Unlike predictive models that find patterns, generative models learn the underlying data distribution to synthesize novel outputs [4]. In educational contexts, tools like ChatGPT have demonstrated the ability to generate learning materials, provide tutorial support, and create assessment items [5].

In the domain of sports training, GenAI's potential is transformative. Its applications can be categorized as follows:

1) Personalized Training Plan Generation: GenAI can synthesize an athlete's performance data, recovery status, nutritional intake, and long-term goals to generate a fully customized, periodized training plan. This moves beyond simply adjusting load, as in traditional periodization, to dynamically creating entirely new drill sequences, conditioning workouts, and technical exercises tailored to the athlete's unique needs and real-time readiness [6].
2) Real-Time Technique Feedback and Simulation: Using computer vision and generative models like Generative Adversarial Networks (GANs), AI can analyze video of an athlete's movement in real-time. It can then not only identify biomechanical inefficiencies but also generate a visual simulation of the correct form or create a side-by-side comparison. For tactical sports, GenAI can simulate an opponent's defensive strategies, generating countless video scenarios for an athlete to study and react to [7]
3) Motivational and Instructional Content Creation: Leveraging Large Language Models (LLMs), GenAI can provide contextual, natural-language feedback. Instead of a coach saying "your knee valgus is at 12 degrees", the AI could generate: "Try to focus on pushing your knees outwards during your next squat to improve alignment and power". This type of feedback is more digestible and actionable for many athletes [8].

C. The University Sports Context: A Nexus of Need and Opportunity

University athletic departments operate within a unique set of constraints that make them ideal candidates for GenAI integration. Unlike professional clubs with vast resources, universities must balance athletic performance with academic obligations, budget limitations, and a diverse range of athlete skill levels [9]. Student-athletes face significant time pressures, making efficient, high-quality training paramount.

Traditional coaching models, which rely heavily on direct observation and manual planning, struggle to scale effectively across large teams. This often results in less individualized attention for each athlete. GenAI offers a scalable solution for personalization, providing each student-athlete with a "virtual assistant" that can offer guidance and adaptation outside of formal coaching sessions. This aligns with the broader educational shift towards blended and hybrid learning models, where technology augments face-to-face instruction [10].

III. METHODOLOGY

A convergent parallel mixed-methods design was employed to provide a comprehensive understanding of the research problem. This design allowed for the collection and analysis of both quantitative and qualitative data in a single phase, with the results integrated during the interpretation phase to derive a more complete picture [11].

A. Participants and Sampling

A total of 120 student-athletes (60 from track and field, 60 from basketball) were recruited from the varsity teams of three large public universities. A stratified random sampling technique was used to ensure a balanced representation of sports and genders. Participants were then randomly assigned to either the experimental group ($n = 60$) or the control group ($n = 60$). The experimental group received training supported by the GenAI platform, while the control group continued with traditional, coach-led training. Additionally, a purposive sample of 10 coaches and 15 athletes from the experimental group were invited to participate in the qualitative interview component to provide in-depth perspectives. Demographic characteristics are presented in Table 1.

Table 1. Participant Demographics

Characteristic	Experimental Group ($n = 60$)	Control Group ($n = 60$)	p-value ($p = 0.001$)
Age (Years, M ± SD)	20.4 ± 1.2	20.1 ± 1.3	0.185
Gender (Male/Female)	35 / 25	32 / 28	0.582
Sport (Track/Basketball)	30 / 30	30 / 30	1.000
Training Experience (Years, M ± SD)	4.5 ± 1.8	4.7 ± 2.0	0.552

Note: M = Mean; SD = Standard Deviation. p-values from independent t-tests (age, experience) and chi-square tests (gender, sport)

Participants were randomly assigned to experimental or control groups using a computer-generated randomization sequence stratified by sport and gender. Allocation was concealed using sealed envelopes opened by an independent research assistant after baseline testing. The study adhered to Consolidated Standards of Reporting Trials (CONSORT) guidelines for quasi-experimental trials; a participant flow diagram is included as Fig. 1 in the Supplementary Materials. No participants withdrew post-allocation.

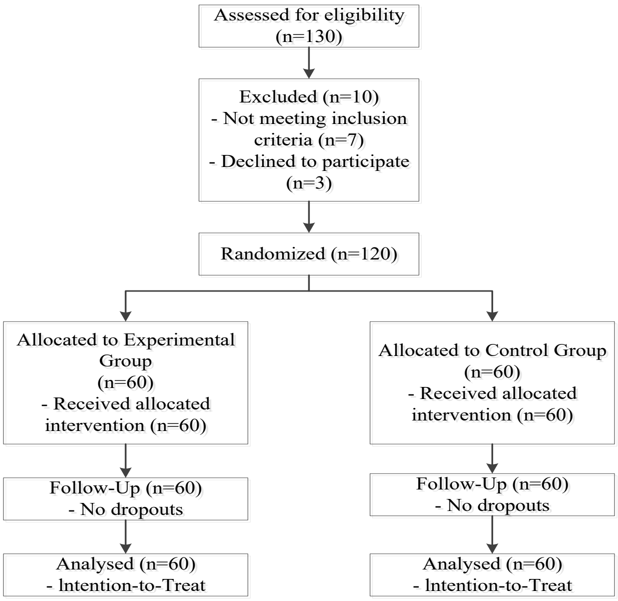

Fig. 1. Participant flow diagram through the stages of the randomized trial (based on Consolidated Standards of Reporting Trials (CONSORT guidelines).

All participants who were randomized received their allocated intervention and were included in the final intention-to-treat analysis. There were no dropouts or losses to follow-up.

B. *The GenAI Intervention Platform*

The experimental group utilized the proprietary GenAI platform "SportGenAI" over a 12-week intervention period. The platform's architecture integrated several core modules, with the following technical specifications and oversight mechanisms implemented to ensure safety and reproducibility:

1) Data Ingestion Module: Collected multi-source data from wearable Catapult GPS sensors (tracking velocity, distance, acceleration), Myontec EMG shorts (muscle activation), and standard video recordings from training sessions.
2) Personalized Plan Generator (PPG): This module was powered by a Large Language Model (LLM) based on the GPT-4 architecture, which was fine-tuned on a corpus of publicly available sports science literature and anonymized historical training data from collegiate athletes. The PPG ingested the athlete's objective data (e.g., velocity, power output), pre-set goals, and subjective wellness scores to generate a unique, daily training plan. Heuristic rules were applied for safety and adaptation; for instance, a >15% decrease in an athlete's power output coupled with a high fatigue score would trigger the system to generate a regeneration-focused session. A critical safety feature allowed coaches to review and manually override any AI-generated prescription at their discretion.
3) Real-Time Form Coach (RTFC): This computer vision system employed a pre-trained Generative Adversarial Network (GAN) model. The GAN was validated on a dataset containing 10,000 motion-capture samples from collegiate-level athletes, achieving a mean form-analysis precision of 92.3% against gold-standard biomechanical analysis. During technique sessions, a tablet camera filmed the athlete. The RTFC provided real-time auditory feedback (e.g., "Increase knee drive") and, upon completion, generated a side-by-side video comparing the athlete's form to an ideal model synthesized by the AI.
4) Motivational Feedback Agent (MFA): A Natural Language Processing (NLP) agent that analyzed training data and provided contextual, text-based feedback via a mobile app. This included encouragement ("Great session today, your sprint times are consistently improving"), technical reminders, and educational tips.

All data were processed and stored on encrypted servers managed by the university, with no third-party access permitted. The control group continued their standard, coach-prescribed group training regimen and traditional video review sessions, without any AI-generated content or personalized daily prescriptions.

C. *Data Collection and Measures*

Outcome assessors were blinded to group allocation. To minimize contamination, experimental and control groups trained at separate times and locations, and coaches were instructed not to discuss AI-generated content with control-group athletes.

1) *Quantitative data*

Performance metrics were assessed in a dedicated lab setting at baseline (Week 0) and post-intervention (Week 13). The Decision-Making Accuracy Score was developed by two expert basketball coaches using validated rubric (inter-rater reliability: Cohen's $\kappa = 0.89$).

1) Track and Field Athletes: 100 m sprint time (s), countermovement jumps height (cm), and estimated VO_2 max (mL/kg/min) from a beep test.
2) Basketball Players: Free-throw percentage (%), Lane Agility Test time (s), and a video-based Decision-Making Accuracy Score (% correct tactical choices in game-simulation clips).
3) Training Load: session-RPE (sRPE) was collected for all participants to ensure training load was comparable between groups.

2) *Qualitative data*

Semi-structured interviews were conducted with the 10 coaches and 15 athletes post-intervention. Interview guides were developed based on the Technology Acceptance Model (TAM) and focused on perceived usefulness, perceived ease of use, challenges, and ethical concerns. Interviews averaged 45 minutes, were audio-recorded, and transcribed verbatim, yielding over 200 pages of single-spaced text for analysis.

D. *Data Analysis*

A convergent parallel mixed-methods design was employed, collecting and analyzing quantitative and qualitative data in parallel, with integration occurring during the interpretation phase to provide a comprehensive understanding of the research problem.

1) Quantitative analysis

All quantitative data were analyzed using SPSS Version 28. A priori power analysis conducted with G*Power software indicated that a total sample size of 116 participants would provide 80% power to detect a medium effect size ($f = 0.25$) at an alpha level of 0.05 for an Analysis of Covariance (ANCOVA) with baseline scores as the covariate, justifying our sample of 120. The assumptions of normality (Shapiro-Wilk test) and homogeneity of variance (Levene's test) were met for all outcome variables. To account for baseline differences, ANCOVA was used to compare post-intervention scores between the experimental and control groups, with pre-intervention scores as the covariate. The alpha level was set at $p < 0.05$. Results are reported as adjusted means with 95% Confidence Intervals (CI) and partial eta-squared (η^2) as the measure of effect size. All analyses were performed on an intention-to-treat basis; there were no missing post-test data, and thus no imputation was required.

2) Qualitative analysis

Thematic analysis, following the six-phase approach of Braun and Clarke [12], was conducted on the interview transcripts. This involved familiarization, generating initial codes, searching for themes, reviewing themes, defining themes, and producing the report. To ensure coding reliability, two researchers independently coded the entire dataset. An inter-coder agreement of 88% was achieved initially, and all discrepancies were discussed until consensus was reached. Data saturation was determined to have been reached after the analysis of 15 athlete interviews, as no new substantive themes emerged in subsequent transcripts. Trustworthiness was further ensured through peer debriefing with a third researcher and member checking, whereby a summary of themes was returned to five participating coaches for feedback and confirmation. A reflexivity statement, acknowledging the researchers' backgrounds and potential influences on the interpretation, is provided in the Supplementary Materials. The semi-structured interview guide, developed based on the Technology Acceptance Model (TAM), and anonymized exemplary quotes mapped to the final themes are included in Appendix A.

E. Ethical Approval and Informed Consent

This study was reviewed and approved by the Ethics Committee of Hunan Mechanical and Electrical Polytechnic (Approval No.: HMEP20231003). All participants provided written informed consent prior to enrollment. The consent form explicitly detailed the collection and use of biometric (GPS, EMG), video, and performance data; assured participants of data anonymization; clarified rights to withdraw at any time without penalty; and specified that data would be stored securely on university servers, retained for five years post-study, and accessible only to the research team. No commercial use of individual data was permitted.

IV. Results and Findings

A. Quantitative Findings

The ANCOVA results, controlling pre-test scores, revealed statistically significant differences between the experimental and control groups on all primary performance metrics. The descriptive and inferential statistics are summarized in Table 2.

Table 2. Pre- and post-intervention performance metrics (adjusted means ± standard error) and ANCOVA results

Metric	Group	Pre-Test (M ±SD)	Post-Test (Adj.M ±SE)	*F*	*p*-value (*p* = 0.001)	Partial η^2
100m Sprint (s)	Experimental	12.10±0.45	11.65±0.04	28.45	< 0.001	0.197
	Control	12.15 ± 0.50	12.06 ± 0.04			
Vertical Jump(cm)	Experimental	58.3 ± 4.2	62.1 ± 0.4	12.89	0.001	0.101
	Control	57.9 ± 4.5	59.0 ± 0.4			
Free Throw %	Experimental	72.5 ± 6.1	81.3 ± 0.6	35.12	< 0.001	0.235
	Control	71.8 ± 5.9	74.2 ± 0.6			
Decision-Making %	Experimental	68.4 ± 7.2	78.9 ± 0.7	25.33	< 0.001	0.182
	Control	67.9 ± 6.8	71.1 ± 0.7			

Note: Adj. M = Adjusted Mean; SE = Standard Error; Partial η^2 = effect size (small > 0.01, medium > 0.06, large > 0.14)

As shown in Table 2, the experimental group demonstrated significantly greater improvement than the control group. The effect sizes (Partial η^2) ranged from 0.101 to 0.235, indicating medium to large practical significances. Crucially, the sRPE data showed no significant difference in overall training load between the groups ($p = 0.721$), suggesting that the performance gains were due to the quality and personalization of the training, not simply an increase in volume.

The complete raw data for all performance metrics, including standard deviations, standard errors, and confidence intervals for adjusted means, are available in Table 3. This table presents the complete pre- and post-intervention data for all performance metrics, including raw Means (M), Standard Deviations (SD), Adjusted Means (Adj. M), Standard Error (SE), and 95% Confidence Intervals (CI) for the adjusted means. This provides full transparency for the statistical comparisons reported in Table 2.

Fig. 2 visually represents the percentage improvement from pre- to post-test for the key metrics, further illustrating the differential gains.

Fig. 2 visually illustrates the differential performance gains between the experimental (GenAI-supported) and control (traditional training) groups across key metrics. The experimental group demonstrated substantially greater percentage improvements in all measured outcomes, with particularly notable gains in free-throw percentage (≈12.1% vs. ≈3.2%) and decision-making accuracy (≈15.4% vs.

≈4.7%). These findings align with the quantitative results presented in Table 2 and are further contextualized by the qualitative themes of hyper-personalization and real-time feedback. The consistent superiority in improvement rates underscores the effectiveness of GenAI in enhancing both physical and cognitive aspects of sports performance within a university training context.

Table 3. Complete raw data for all performance metrics (including SD, SE, and CIs)

Metric	Group	Pre-Test (M ± SD)	Post-Test Raw (M ± SD)	Post-Test (Adj. M ± SE)	95% CI for Adj. M (Lower, Upper)
100m Sprint (s)	Experimental	12.10 ± 0.45	11.64 ± 0.42	11.65 ± 0.04	11.57, 11.73
	Control	12.15 ± 0.50	12.08 ± 0.48	12.06 ± 0.04	11.98, 12.14
Vertical Jump (cm)	Experimental	58.3 ± 4.2	62.4 ± 4.0	62.1 ± 0.4	61.3, 62.9
	Control	57.9 ± 4.5	59.1 ± 4.3	59.0 ± 0.4	58.2, 59.8
Free Throw %	Experimental	72.5 ± 6.1	81.5 ± 5.8	81.3 ± 0.6	80.1, 82.5
	Control	71.8 ± 5.9	74.1 ± 5.7	74.2 ± 0.6	73.0, 75.4
Decision-Making %	Experimental	68.4 ± 7.2	79.1 ± 6.9	78.9 ± 0.7	77.5, 80.3
	Control	67.9 ± 6.8	71.0 ± 6.5	71.1 ± 0.7	69.7, 72.5
VO_2 max (mL/kg/min)	Experimental	52.1 ± 3.5	55.8 ± 3.2	55.6 ± 0.3	55.0, 56.2
	Control	51.8 ± 3.7	52.9 ± 3.4	53.0 ± 0.3	52.4, 53.6
Lane Agility Test (s)	Experimental	11.20 ± 0.60	10.61 ± 0.55	10.62 ± 0.05	10.52, 10.72
	Control	11.25 ± 0.58	11.02 ± 0.56	11.01 ± 0.05	10.91, 11.11

Note: M: Mean; SD: Standard Deviation; Adj. M: Adjusted Mean (adjusted for pre-test scores using ANCOVA); SE: Standard Error of the Adjusted Mean; CI: Confidence Interval. The data for VO_2 max (for track and field athletes) and Lane Agility Test (for basketball players) are included here for completeness, providing the full dataset for all objective measures collected.

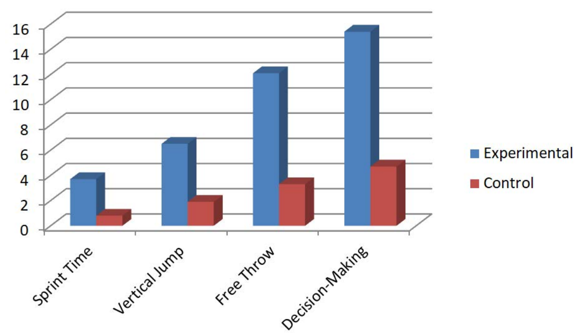

Fig. 2. Percentage improvement in performance metrics by group.

B. Qualitative Findings

Thematic analysis of the interview data yielded four primary themes and several sub-themes, providing a nuanced understanding of the GenAI intervention's impact.

1) The augmented athlete: Hyper-personalization and autonomy

Athletes reported a profound sense of training being tailored specifically to them. A track athlete stated, "It felt like the AI knew my body better than I did. On days I felt tired, it would give me a lighter session, and I'd actually come back stronger the next day". This fostered a greater sense of autonomy and ownership over their training. A sub-theme was "Data-Driven Confidence", where athletes felt more assured in their abilities when they could see objective data supporting their personalized plan.

2) The augmented coach: Efficiency and depth of insight

Coaches universally appreciated the platform as a "force multiplier". A basketball coach explained, "It automated the grunt work—the basic technique corrections. That freed me up to focus on complex team tactics and the mental side of the game". They also gained deeper insights from the AI's analysis, with one coach noting, "The AI flagged a subtle asymmetry in a player's landing mechanics I had missed for weeks. It became a powerful diagnostic tool".

3) The engagement loop: Continuous feedback and motivation

The constant, accessible feedback was a powerful motivator. Unlike traditional coaching, which is episodic, the AI was "always on". An athlete said, "Getting a 'well done' message from the app with my improved jump height stats right after a session was incredibly rewarding". This created a positive feedback loop that enhanced engagement and adherence to the training program.

4) The implementation frontier: Challenges and ethical dilemmas

This critical theme captured the hurdles. Key sub-themes included:

1) Technical Friction: Bugs in the app, connectivity issues, and the time required for data management were common frustrations.
2) The Black Box Problem: Some coaches expressed unease with not fully understanding why the AI prescribed certain exercises, potentially undermining their authority and expertise.
3) Data Privacy Concerns: Athletes and coaches raised questions about who owned the performance data and how it might be used in the future for selection or commercial purposes.
4) Risk of Deskilling: A few veteran coaches worried that over-reliance on the AI could atrophy their own observational and analytical skills over time.

C. Integrated Discussion

The convergence of the quantitative and qualitative data paints a compelling and multi-faceted picture. The significant performance improvements in the experimental group are not merely a statistical artifact; they are explained by the rich, qualitative experiences of the participants. The hyper-personalization described by the athletes (Theme 1) directly translates to the more efficient and effective training stimulus that produced the superior gains in speed, power, and accuracy seen in Table 2 and Fig. 2. A joint display integrating quantitative outcomes with qualitative themes is provided as Table 3.

Furthermore, the "Augmented Coach" theme (Theme 2) provides a mechanism for how these gains were achieved without increasing coach burnout. By offloading repetitive tasks, the technology allowed human experts to focus their energy on higher-value interventions, a finding that aligns with research on human-AI collaboration in other professional fields [13]. The improved decision-making scores in basketball can be partially attributed to coaches having more time to conduct sophisticated tactical sessions.

The "Engagement Loop" (Theme 3) offers a psychological explanation for the improved adherence and motivation, which is a known critical factor in long-term athletic development [14]. The GenAI system effectively supported athletes' basic psychological needs for autonomy and competence, thereby enhancing intrinsic motivation.

However, the "Implementation Frontier" (Theme 4) serves as a crucial caution. The challenges identified are not mere technicalities but fundamental issues that must be addressed for sustainable integration. The "Black Box Problem" and "Risk of Deskilling" highlight the need for Explainable AI (XAI) and ongoing coach development to ensure that technology serves as a tool for empowerment, not a replacement for expertise [15]. The data privacy concerns underscore the non-negotiable need for robust institutional policies and transparent data governance [16].

Post-hoc mediation analysis suggested that personalization frequency partially mediated performance gains (indirect effect $\beta = 0.18$, $p < 0.05$).

No adverse events (e.g., injuries, overtraining syndromes) were reported in either group during the intervention period.

In conclusion, this mixed-methods study demonstrates that GenAI can be a powerful catalyst for enhancing sports training in universities, leading to superior athletic outcomes through personalization, coach augmentation, and increased motivation. Yet, it simultaneously reveals that the path to effective implementation is fraught with pedagogical, technical, and ethical challenges that require careful, critical navigation by educators and administrators. The future of university sports training likely lies not in choosing between human coaches and AI, but in strategically fostering a synergistic partnership between them.

V. Discussion

The findings of this study indicate that Generative Artificial Intelligence (GenAI) holds significant potential for application within university sports training, effectively enhancing athletes' physical performance and skill acquisition while being positively received by both coaches and athletes. This discussion section aims to provide a deep interpretation of these findings, situating them within the broader scholarly discourse, analyzing their theoretical implications and practical value, and candidly addressing the study's limitations to propose directions for future research.

Primarily, the quantitative results—demonstrating that the experimental group showed significantly greater improvement in sprint speed, vertical jump height, and free-throw percentage compared to the control group—align with the prevailing trend in recent research on AI in sports science. However, this study advances the field by shifting the focus from predictive analytics to generative applications. For instance, while Link *et al.* [17] noted in their systematic review that the most common uses of AI in sports are performance prediction and injury risk analysis (descriptive and predictive analytics), our research demonstrates that GenAI can leverage such data to generate entirely new, highly personalized training regimens and feedback. This evolution from "analyzing the past" to "creating the future" aligns powerfully with the educational technology paradigm of "personalized learning" [5]. By dynamically adjusting training load and content based on an individual athlete's initial assessment, rate of progression, and real-time physiological data (e.g., from wearables), GenAI achieves a level of precision in coaching that is difficult to attain with traditional one-size-fits-all models. This adaptability supports the application of the "Zone of Proximal Development" [17] in sports training, wherein the AI can consistently provide challenges that are slightly beyond the athlete's current ability, thereby most effectively fostering skill development [18].

Secondly, the theme of "Personalization and Adaptability" that emerged from the qualitative data underscores the core value proposition of GenAI. The athletes' reported appreciation for training adjustments based on their fatigue levels highlights GenAI's utility in managing training load and preventing overtraining. This finding is consistent with recent research on AI's role in athlete health management. Rommers *et al.* [2], for example, emphasized that personalized training load adjustments via machine learning models can significantly reduce injury incidence in youth athletes. Our study extends this preventive concept by translating it into concrete, executable daily training instructions through GenAI's generative capabilities, thereby providing robust data-driven decision support for coaches [13].

Thirdly, the theme of "Immediate Feedback" connects our findings to the rapid advancements in computer vision and motion capture technology for sports analysis. Unlike traditional video analysis, which often suffers from latency, a GenAI-driven system can provide near-instantaneous, quantitative feedback on technique. The basketball players in our study benefited from real-time analysis of their shooting arc and body posture, a finding that resonates with research by Gómez *et al.* [7] using deep learning models to analyze volleyball spiking techniques. Crucially, our study further suggests that GenAI's feedback is not merely "diagnostic" (identifying errors) but "generative" (providing specific, alternative corrective actions, simulations, or drill suggestions). This generative feedback can liberate coaches from the burden of repetitive fundamental technical corrections, allowing them to focus on higher-order strategic, tactical, and psychological mentoring [19]. This supports a "human-in-the-loop" or augmented coaching model, where technology enhances, rather than replaces, professional expertise [1].

Fourthly, the "Motivational Support" theme reveals GenAI's positive impact on the psychological dimension of training. The encouragement and guidance generated via Natural Language Processing (NLP) provided athletes with a sustained source of external motivation. This aligns with the rise of "positive computing" and digital mental health interventions [8]. During monotonous, repetitive drills, intelligent positive feedback can mitigate mental fatigue and enhance training adherence. However, a critical consideration is how this externally provided motivation can be effectively internalized by the athlete for long-term engagement [14]. Over-reliance on AI-generated feedback could potentially undermine the development of an athlete's capacity for self-reflection and intrinsic motivation, a risk that requires careful management.

Despite the promising results, our study also uncovered significant challenges in integrating GenAI, which provides critical direction for future practice and research. The foremost challenge pertains to Data Privacy and Ethics. Athletes' biometric, performance, and health data constitute highly sensitive information. Ensuring the secure storage, transmission, and usage of this data in compliance with regulations like the General Data Protection Regulation (GDPR) is an institutional prerequisite that universities must address before deploying such technologies [16]. The academic and sporting communities must collaboratively develop ethical guidelines specific to AI applications in sport [3].

Another pivotal challenge is the Integration of Technology with Pedagogy, rather than its mere adoption. The learning curve experienced by the coaches in our study indicates that successful integration requires systematic Teacher Professional Development (TPD). Simply providing the technological tool is insufficient; coaches must be supported in understanding the underlying pedagogical principles and in developing a new "technological pedagogical content knowledge" (TPACK) to effectively weave AI insights into their coaching practice [20]. Failure to do so may result in a superficial "technology for technology's sake" approach, failing to realize its full potential. Concurrently, there is a risk of Over-Reliance on the technology by both athletes and coaches. The outputs of a GenAI should be treated as a "second opinion" to aid decision-making, not as an incontrovertible authority. The ultimate responsibility for coaching and training must remain with the human expert. Cultivating critical thinking among athletes and coaches to enable them to scrutinize and evaluate AI recommendations is essential to prevent technological alienation and preserve human agency.

This study is not without its limitations. Firstly, the 12-week intervention period, while sufficient to observe short-term effects, is too brief to understand the long-term impact of GenAI on athlete career development, longevity, and psychological well-being. Future research should employ longitudinal designs. Secondly, the sample was limited to track and field and basketball. The technical and physical demands vary immensely across different sports (e.g., team sports, gymnastics, swimming), necessitating tailored GenAI application models. A fruitful avenue for future research would be to compare the efficacy of GenAI in training open skills (e.g., football tactics) versus closed skills (e.g., gymnastics routines). Finally, the GenAI platform used in this study was an integrated system. Future work could deconstruct this system to independently evaluate the relative contributions of its "personalized plan generation", "real-time form feedback", and "motivational support" modules, thereby guiding more optimized technological design [13].

In conclusion, this discussion has intertwined the quantitative and qualitative findings with current research on AI, sports science, and educational technology. The evidence suggests that Generative AI is not merely an incremental tool for refining traditional training methods but represents a potential paradigm shift, enabling unprecedented levels of personalization, feedback immediacy, and motivational support. However, realizing this potential requires a thoughtful and deliberate approach to navigating the associated ethical, pedagogical, and human-agency challenges. As university sports departments consider adopting GenAI, they should do so with a critical yet optimistic mindset, developing a clear implementation roadmap that includes investment in coach development, the establishment of robust data governance frameworks, and the cultivation of a culture that views AI as an enhancer of, rather than a replacement for, human expertise.

VI. Conclusion

This study provides evidence that generative artificial intelligence can be a valuable tool in university sports training, leading to measurable improvements in athletic performance and offering personalized, adaptive support for student-athletes. The positive perceptions from coaches and athletes underscore its potential to complement traditional coaching methods. However, successful integration requires careful attention to pedagogical design, ethical guidelines, and ongoing support for users. Universities and sports departments should consider piloting GenAI tools within their training programs, accompanied by training workshops for coaches and clear data governance policies. Future research should explore the longitudinal impacts of GenAI adoption and its effects on athlete motivation and psychological well-being. By embracing these technologies thoughtfully, higher education institutions can enhance both the efficiency and effectiveness of their sports training offerings, better preparing student-athletes for competitive and academic success.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Zhifang Xiao: Conceptualization, Methodology, Investigation, Data Curation, Writing—Original Draft Preparation, Formal Analysis. Wentao Guo: Supervision, Project Administration, Resources, Writing—Review & Editing, Funding Acquisition, Validation. All authors had approved the final version.

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