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PERSPECTIVE OPEN ACCESS

Evidence for the Effectiveness of the Performance Passport Within an Intelligence-Based Weightlifting Anti-Doping Programme

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ABSTRACT

Anti-doping organisations are tasked with detecting, deterring and preventing doping in sport, and because biological testing consumes a large share of budgets, efficient resource allocation is essential. Enhancing effectiveness requires better insight into how well current methods identify athletes at risk. The International Testing Agency (ITA) recently introduced the Athlete Performance Passport (APP), which uses competition performance data to flag at-risk weightlifters for targeted testing. This study evaluates the APP alongside established approaches, including Athlete Passport Management Unit (APMU) recommendations and atypical findings from the steroidal module of the Athlete Biological Passport (ABP). Data from 1960 male and 1583 female athletes were analysed, identifying 175 individuals (109 male and 66 female) who committed an Article 2.1 Anti-Doping Rule Violation (ADRV) between December 2009 and April 2025. The study assessed how effectively each method identified these athletes. Overall, the APP detected 34% of athletes who committed ADRVs during this period. Focusing on data since the steroidal passport's introduction in 2014, the APP identified 30% of ADRVs, outperforming APMU suspicious reports (17%) and atypical ABP steroidal profiles (10%). When combined, these methods identified 38% of ADRVs. These findings indicate that performance-based monitoring can strengthen anti-doping risk assessment and improve targeted testing strategies, particularly in sports with comprehensive competition data.

1 | Introduction

The World Anti-Doping Agency (WADA) mandates anti-doping organisations (ADOs) to provide a comprehensive anti-doping programme through the World Anti-Doping Code [1] via education, detection, deterrence and finally results management. Despite this increasingly multidisciplinary approach, the collection and analysis of biological samples from athletes remains the core activity of ADOs accounting for around 50% of the annual budget for anti-doping [2]. In this regard, testing figures from the latest WADA report [3] suggest there are increases in the financial resources being allocated to testing as indicated by

greater numbers of biological samples being analysed (288,865 in 2023 to 297,965 in 2024; +3.2%). However, the incidence of Adverse Analytical Findings (AAFs, positive tests) remains low at less than 1% [3]. Consequently, for ADOs to optimise their current anti-doping testing strategies, a better understanding of the efficiency and effectiveness of current approaches is needed.

From a doping control perspective, the International Standard for Testing and Investigation [4] requires that an ADO develops a proportionate Test Distribution Plan (TDP) based upon a risk assessment for sports and the respective disciplines under their jurisdiction. The level of risk identified and the budget

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at disposal in turn dictate the number of doping controls conducted for specific athletes and at what points during the year. The risk assessment will include an analysis of the physiological requirements of the sport, the substances or methods most likely to enhance performance, rewards and/or potential incentives for doping, history of doping of an athlete or in a sport, nation or event, including patterns within a sporting season, statistical findings on doping trends and information received/intelligence developed. Following guidelines set out by WADA [5], ADOs also rely on indirect detection methods via the Athlete Biological Passport (ABP; Sottas et al. [6]) and the review of Athlete Passport Management Unit's (APMU; Schobinger et al. [7]) to provide useable information to guide decision making on test allocation and timing based upon an analysis of patterns within key biomarkers from blood and urine testing. Increasingly, intelligence and investigation (I&I) teams have widely been implemented into ADOs as an extrasurveillance strategy to compile information consistent with doping and assist in directing anti-doping samples to be collected around suspicious time periods.

The steroidal module of the ABP comprises two matrixes. It was first introduced in 2014 in urine and in 2023 in blood serum sample types. An atypical passport finding is triggered from a result generated by the Adaptive Module in ADAMS, which identifies either (a) a primary marker(s) value(s) as being outside the athlete's intraindividual range or (b) a longitudinal profile consisting of (up to) the last five valid primary marker values as deviating from expected ranges, assuming a normal physiological condition. An atypical passport finding will lead to an APMU report being produced and a status submitted reflective of the perceived risk of doping from the ABP profile and sample values. Thereafter further analytical testing can be requested or refined target testing recommendations of an athlete.

One additional source of information available to ADOs, but not systematically considered in determining testing strategy, is when the performance of an athlete is statistically better than expected in (i) comparison to age-matched counterparts and (ii) comparison to personal historical competition results. As the primary reason for doping is for the athlete to improve their performance, longitudinal monitoring of an individual's competition results may be used to reveal suspicious performance improvements. Indeed, there is a growing body of evidence to demonstrate that athlete performance is sensitive to the emergence of new drugs or methods available to athletes and by which to identify the effectiveness of new anti-doping measures [8–11]. Moreover, due to the low within-subject variability of performance in elite athletes [12], longitudinal mathematical models have been shown to discriminate between performances of athletes with and without previous anti-doping rule violations (ADRVs) [13–15]. To date, the feasibility of using performance markers for anti-doping is best described in centimetre, gramme or second measured sports, whereby the athlete's performance potential is predominantly determined by their specific physiological characteristics that are potentially modifiable by doping agents. In this regard, previous research has demonstrated the efficacy of applying longitudinal Bayesian mathematical modelling to sprint and middle distance running to compare the yearly rate of change

in sanctioned (via an ADRV) athlete's performances across their careers to quantiles of performance in their age-matched peers from the wider population of unsanctioned athletes within the discipline [14]. The model demonstrated an ability to discriminate between athletes with and without recorded ADRVs based on the rate of change in their running performance, with area under the ROC curve values ranging from 0.78 to 0.80 across age groups.

2 | Use of Performance Monitoring in Anti-Doping

The International Testing Agency (ITA) has been supporting the International Weightlifting Federation (IWF) with the delivery of its anti-doping programme since 2019 including risk assessment, test distribution planning, intelligence and investigations, results management delegation, in-competition and out-of-competition testing, as well as ABP administration. Until now, weightlifting is a sport with one of the highest percentages of AAF's within Olympic sports [3] over the last decade. Possible reasons for the high incidence of doping in weightlifting are due to the potential potency of doping agents on muscle hypertrophy and strength (e.g., androgenic anabolic steroids), directly impacting the competition result, which is determined by the sum weight lifted within the best attempts of snatch and clean and jerk lifts. The sport is conducted indoors, with minimal influence from external or environmental factors and relatively few technological or rule-based changes over time, thereby simplifying the modelling of longitudinal performance. Indeed, Bayesian modelling using performance change as a function of age [15] has shown tight-fitting individual performance trajectories that are appropriate for the assessment of athletic performance changes over time. Due to the relative simplicity of modelling longitudinal athlete performance, it is a sport that lends itself to applying performance monitoring for doping control purposes.

The performance model was built on weightlifting data comprised of competition results from male and female weightlifters who had a least four competition results to establish a baseline. The best results for snatch and clean and jerk for each lifter are combined into a total lift score, which are then transformed into the Sinclair Total to allow for differences in the levels of lift scores across weight categories [16]. The Sinclair total allows for the consideration of results across weight categories without adjusting for weight category in the model. Subsequently, the data are analysed using a flexible Bayesian model as described in Griffin et al. [15], with two key risk metrics derived, namely, *excess performance* (represents individual performances adjusted for the average performance of athletes within the population at the same age as well as any confounders) and *delta excess performance* (the change in excess performance for an athlete over a fixed period, e.g., 1 year). The magnitude of *delta excess performance* compared to population estimates was subsequently used to risk stratify weightlifters for 'abnormal' changes in their performance on the probability of their delta excess performance exceeding the 75th percentile for the metric established from the wider population [14]. A probability of ≥ 0.8 was deemed to be 'high risk', and a probability of 0.5–0.8 was deemed to be 'medium risk'. Figure 1 shows the Athlete Performance Passport (APP) of a male weightlifter who is deemed to be high-risk from their career trajectory.

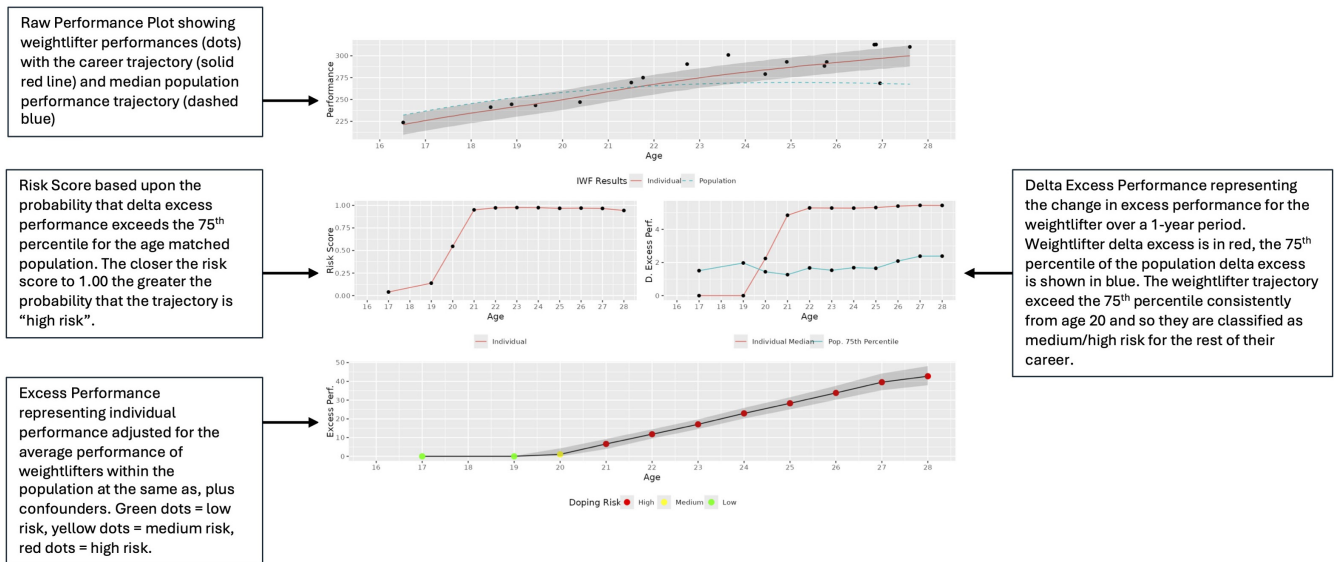


FIGURE 1 | Athlete Performance Passport (APP) for a male weightlifter. Note that the weightlifter is low risk in the early stages of their career as their performance is below the median population performance trajectory and evolves at a similar rate (low delta excess performance). From the age of 21.5 years, their performance starts to exceed the population performance trajectory and continues to evolve to a greater magnitude than the age-matched population, shown by a greater delta excess performance, and therefore high level of risk.

3 | Evaluation

Performance monitoring was first introduced to the ITA's routine anti-doping programme for weightlifting in 2020 with risk ratings used to inform both in- and out-of-competition testing, long-term storage of samples, laboratory retrospective analysis and within risk assessment outcomes for Registered Testing Pool allocation. Weightlifters calculated to contain a high-risk rating were subject to be tested both (i) during the primary preparatory out-of-competition phase before major competitions, and/or (ii) tested in-competition immediately following the completion of their final lift before exiting the competition venue.

Under the ABP service agreement, the APMU reviewed all atypical and abnormal steroidal ABP profiles for weightlifters whose passports were under the custodianship of the IWF. Following review, the APMU provided an assessment and, where appropriate, recommended follow-up actions. The reviewed cohort also included athletes whose passports were held by other custodians but for whom the ITA had been delegated access. Cases predating the introduction of the steroidal module in 2014 were also included where relevant. However, cases for which the ITA assumed results management only after a sanction had already been imposed were not eligible for ABP review.

To evaluate the use of an APP derived risk assessment in identifying weightlifters that subsequently test positive for a banned substance through both in- and out-of-competition testing, a retrospective analysis was conducted of sanction data. The APP contained the performance results of 1960 male (total of 18,874 results) and 1583 female (total of 15,968 results) weightlifters who had at least four result observations between 24 April 1998 and 7 April 2025. Within the APP, weightlifters were classified

for their doping 'risk' using the delta excess performance criteria explained above.

Sanction data were obtained from all samples collected by the ITA from 18 December 2019 to 7 April 2025 as well as Article 2.1 delegated ADRVs as part of the IWF anti-doping programme since 2009. Within the total population, 175 (109 males and 66 females) were found to have a known 2.1 ADRVs as of 7 April 2025. As the APP requires four competitions in order to establish a baseline from which to compare, 65 (of the 175) athletes were excluded from the analysis due to insufficient performance information being available, resulting in 110 athletes with 2.1 ADRVs identified by the performance model and resultantly included within the analysed database. Athletes were then subcategorised into low, medium and high risk on the basis of their delta excess performance. Table 1 presents the prohibited list substance category which led to the 2.1 ADRV for weightlifters categorised in medium- and high-risk groups ($n=60$). Interestingly, not all substances, which have led to an ADRV, are known performance enhancing for weightlifting [17].

Prohibited substances categorised within the S1 (Anabolic agents) classification have long been researched for their performance enhancing capabilities in weightlifting and other strength and power based sports [18]. Studies have demonstrated increases in lean muscle mass, muscle fibre size and strength, characteristics that confer a substantial advantage in weightlifting [19, 20]. Therefore the APP and other risk stratification tools were evaluated in how effectively they retrospectively identified weightlifters who served an ADRV for a S1 category sanction since the ABP steroidal module was first introduced in 2014. There were 126 ADRVs from 2014 to 2025, of which 79 were from a S1 category violation. As shown in Figure 2, within this population of 79 S1 sanctioned

TABLE 1 | Anti-doping rule violations by prohibited substance group for 60 weightlifters identified as medium- or high-risk by the APP during the period 2009 to 2025. The total number of ADRVs within the athlete population is shown subdivided by sex. Analytical ADRVs are divided into substance groups: S1 Anabolic agents, S2 Peptide hormones, growth factors, S3 Beta-2 agonists, S4 Hormone and metabolic modulators, S5 Diuretics and masking agents, S6 Stimulants, S7 Narcotics, S8 Cannabinoids, S9 Glucocorticoids according to the WADA Prohibited List as well as ADRVs where the substance/class is listed as 'unknown'.

	Total identified ADRVs (% of total population)	Number of ADRVs per substance category									
		S1	S2	S3	S4	S5	S6	S7	S8	S9	Unknown
Male	42 (70%)	26	4	2	2	0	4	0	1	0	3
Female	18 (30%)	9	0	0	0	2	2	0	1	0	4

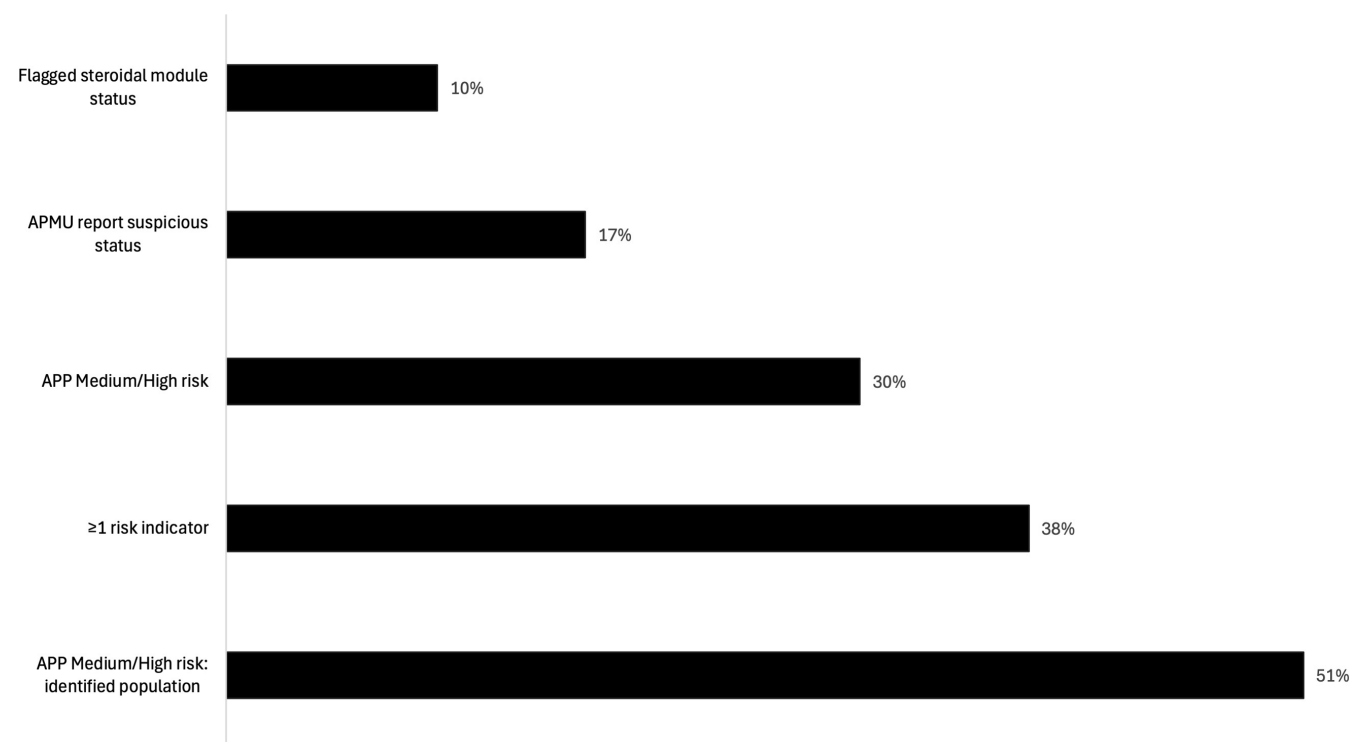


FIGURE 2 | Success rates for identifying S1 category anti-doping rule violations (ADRVs) since 2014 using various risk stratification methods of ABP steroidal profile, APMU reports and APP. The dataset comprised a total population of 79 weightlifters with S1 ADRVs between 2014 and 2025. Of these 47 were identified as having sufficient competitive results to construct an APP (identified population). The figure also shows the proportion of athletes in the total population identified through the combination of one or more risk indicators (APP, ABP and APMU).

weightlifters, the APP flagged 24 (30%) as being medium/high risk, compared to 13 (17%) as being APMU suspicious and 8 (10%) as being flagged atypical by the steroidal module ABP passport status. Forty-seven of the 79 S1 sanctioned weightlifters had sufficient competitive results to construct an APP, with 51% subsequently being flagged as having a medium-/high-risk performance trajectory.

The use of doping convictions in the form of 2.1 ADRVs provides an ability to categorise weightlifter performance into either an incidence of confirmed doping or not. As we have demonstrated previously [14], misclassification of doping status (i.e., athletes who are presumed clean due to being unsanctioned but who are doping) will materially affect the ability to evaluate the efficacy of the APP to identify weightlifters who are at high risk of doping. Misclassification is likely to occur due to factors such as the presence of false negatives at the testing stage, variation in

doping regimes, time between doping and anti-doping test and variations in testing times. As a consequence, it is important to note that identifying the size of the athlete population subgroup who are doping but do not have an ADRV is challenging.

4 | Perspectives

As shown by previous research there is little evidence that simply increasing the numbers of anti-doping samples collected leads to more ADRVs [21, 22]. Indeed, sophisticated doping practices, short detection windows and low test sensitivity for some prohibited substances have led to criticism of current anti-doping practices due to the low success rate of detection compared to the assumed true prevalence of doping [22–24]. Therefore, anti-doping organisations should aim to improve risk assessment processes using an intelligence-based approach incorporating

multiple sources of information for better targeted testing. Indeed, as demonstrated in Figure 2, analysing data since the introduction of the steroidal module (2014–2025), the APP identified more weightlifters with S1 ADRVs (30%) than APMU recommendations (17%) or ABP steroidal profiles being flagged as atypical (10%). More importantly, by combining these sources of information, 38% of S1 ADRVs were correctly identified. The results for the APP improved substantially (30% vs. 51% correctly identified) when weightlifters had sufficient data to construct APP profiles since the introduction of the Steroidal ABP.

The data presented provide strong evidence that performance monitoring in weightlifting is a valuable tool for detecting abnormal performance patterns indicative of doping. This demonstrates that incorporating an athlete's performance risk score can serve as a credible supplementary tool within a comprehensive risk assessment framework for weightlifting. Although improving performance is a primary goal for athletes, declines in performance may also be relevant when developing a test distribution plan. Athletes experiencing a reduction in performance, for example, due to injury or other factors, may be motivated to use prohibited substances or methods in an attempt to regain or maintain their previous level of performance.

The APP supports the ITA and other ADOs in using evidence of abnormal performance trajectories as a rationale for implementing targeted investigative measures. These measures include prioritising anti-doping test collections during periods of elevated doping risk associated with peak competitive performance and conducting retrospective analyses of stored samples. Indeed, a recent study from the Norwegian Anti-Doping Agency suggested that between 2015 and 2019 52% of all ADRVs were informed by intelligence gathering supporting the implementation of I&I teams [19]. This raises the question of whether performance monitoring could also be an appropriate tool for integration into other sports where environmental factors minimally confound performance outcomes.

It must be recognised that the APP encompasses a complete dataset of an athlete's competition results, thereby presenting a comprehensive overview of the athlete's career. Similar to the ABP programme, the APP is only identified once a baseline profile has been established. This breadth of data enables the identification of potentially suspicious periods of performance and can capture the cumulative effect of doping, which may be difficult with biological analytical testing. In contrast, the ABP relies on collecting samples at critical time points to indirectly detect doping-related patterns. It should be recognised that one of the limitations of the steroidal module of the ABP programme is that it is primarily designed to detect profile abnormalities associated with substances within the S1 category. By comparison, the APP and other complementary anti-doping strategies offer broader opportunities to detect the use of other prohibited substance classes and methods of doping. Consequently, direct comparisons between the two approaches present inherent challenges when drawing parallel conclusions. Separately, the deterrent effect of sample collection by ADOs should not be overlooked, although it remains difficult to quantify. One of the principal advantages of developing an APP is that its associated mathematical modelling

incurs relatively low costs compared with the substantial expenses linked to ABP implementation, I&I activities and sample collection and analysis.

The 'real-world' data analysed above is prone to risks of bias and the effects of confounding factors; a correlation between an athlete with a 2.1 ADRV and a high-risk score on their APP does not prove a causal association between the two. However, the controlled nature of the environment within which weightlifting performances take place, coupled with minimal technological and training-related advances over the period, as well as the model accounting for age and seasonality differences in performance [15], reduces the likely impact of confounding factors. Incorporating performance monitoring into other sports may be more challenging where confounding factors, such as variable environmental conditions, are present. These factors inevitably reduce the statistical confidence of conclusions drawn from performance models across different sporting disciplines. Depending on the sport, such challenges may be difficult, or even impossible, to mitigate, particularly due to the rules and dynamics, especially in team sports.

5 | Conclusions

This manuscript argues for the use of an APP as a practical and reliable anti-doping tool to support robust risk assessment and to inform targeted testing and broader investigative strategies. The evidence supporting this position is derived from an analysis of historical ADRVs involving weightlifters sanctioned under Article 2.1, based on IWF/ITA records from 2019 onwards. These cases were evaluated against APP outcomes and ABP indicators of suspiciousness, including both APMU report status and steroidal profile abnormalities. The APP alone classified 51% of the ADRV S1 category population as presenting a 'medium' or 'high' risk, limited to athletes with an established performance baseline of at least four competition results. When combined with ABP findings, 38% of these S1 sanctioned athletes were flagged by one or more anti-doping monitoring approaches. Based on these findings, the manuscript recommends that ADOs incorporate performance monitoring into their risk assessment frameworks where competition data are robust and external confounding factors are minimal.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Research data are not shared.

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