DOPING TRENDS IN PROFESSIONAL SPORTS

A WADA ANALYSIS (2014–2022)

ABSTRACT

This report analyzes doping patterns in professional sport using World Anti-Doping Agency (WADA) data from 2014 to 2022. It combines exploratory analysis, clustering, and dimensionality reduction to identify substance use trends, high-risk sports, and evolving doping behaviors. The study highlights consistent use of anabolic agents in strength-based disciplines and identifies Cannabinoids, Stimulants, and Beta-2 Agonists as key substances shaping sport-specific doping profiles. Findings reveal structural and temporal patterns that can support more targeted, risk-based anti-doping strategies for policymakers and sporting bodies.

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Contents

1. Introduction 4
2. Data Description 4
   Data sources 4
   Data extraction and preprocessing 5
   Data Quality and Limitations 5
3. Exploratory Data Analysis 6
   Anti-Doping Patterns Across Sports 6
      A Correlation-Based Classification of Anti-Doping Behavior (2014–2022) 11
      Analysis of Doping Profiles in Competitive Sports 16
      Summary: Exploratory Data Analysis 23
4. Clustering of Doping Profiles Across Sports (2014–2022) 23
      Methodological Framework 23
5. Conclusions and Outlook 29
6. Glossary of Terms and Abbreviations 32
7. Substance Groups and WADA Identifiers 33
8. Acknowledgements 34
9. References 35
10. Appendix: 37

Tables

Table 1: Summary of testing volume and AAF Risk by Sport (2014–2022) 7

Figures

Figure 1: Sanctioned AAF rates per 1,000 samples by sport in 2014. Outliers (Z ≥ 2) are highlighted in red. 8
Figure 2: Sanctioned AAF rates per 1,000 samples by sport in 2020. Outliers (Z ≥ 2) are highlighted in red. 8
Figure 3: Sanctioned AAF rates per 1,000 samples by sport in 2022. Outliers (Z ≥ 2) are highlighted in red. 9
Figure 4: Total AAFs per sport in 2014 (regardless of sanction outcome), based on substance detection counts. 9
Figure 5: Total AAFs per sport in 2020 (regardless of sanction outcome), based on substance detection counts. 10
Figure 6: Total AAFs per sport in 2022 (regardless of sanction outcome), based on substance detection counts. 10
Figure 7: AAF Rate Z-Score (Relative to All Sports in the Same Year) 12
Figure 8: Sport-Year Doping Behavior Patterns (Relative to Sport's Own History) 13
Figure 9: Doping Substance Profiles ("Fingerprints") for Body-building, 2014-2022 17
Figure 10: Doping Substance Profiles ("Fingerprints") for Cycling, 2014-2022 18
Figure 11: Pairwise Distance Between Sport Doping Profiles (Overall). 19
Figure 12: Stable substance profile Example, American Football 21
Figure 13: Recovered Stability substance profile Example, Tennis 21
Figure 14: Moderate volitility substance profile Example, Skiing 22
Figure 15: High volatile/chaotic substance profile Example, Golf 23
Figure 16: Cluster Plot: PCA (10a) and UMAP (10b) Projection of Sports Based on Substance Use 24
Figure 17: Cluster Membership Over Time (Hierarchical Clustering on PCA Projection) 25
Figure 18: Cluster Membership Over Time (Hierarchical Clustering on UMAP Projection) 25
Figure 19: Clustering of Sports by Substance Group: (a) Anabolic Agents (S1), (b) Cannabinoids (S8) 26
Figure 20: Feature Importance for Cluster Prediction — K-Means Clustering (PCA Projection) 27
Figure 21: Feature Importance for Cluster Prediction — Hierarchical Clustering (PCA Projection) 28
Figure 22: Sanctioned AAF rates per 1,000 samples by sport in 2015. Outliers (Z ≥ 2) are highlighted in red. 37
Figure 23: Sanctioned AAF rates per 1,000 samples by sport in 2016. Outliers (Z ≥ 2) are highlighted in red. 37
Figure 24: Sanctioned AAF rates per 1,000 samples by sport in 2017. Outliers (Z ≥ 2) are highlighted in red. 37
Figure 25: Sanctioned AAF rates per 1,000 samples by sport in 2018. Outliers (Z ≥ 2) are highlighted in red. 38
Figure 26: Sanctioned AAF rates per 1,000 samples by sport in 2019. Outliers (Z ≥ 2) are highlighted in red. 38

Figure 27:Sanctioned AAF rates per 1,000 samples by sport in 2021. Outliers (Z ≥ 2) are highlighted in red. 38
Figure 28: Total AAFs per sport in 2015 (regardless of sanction outcome), based on substance detection counts. 39
Figure 29: Total AAFs per sport in 2016 (regardless of sanction outcome), based on substance detection counts. 40
Figure 30: Total AAFs per sport in 2017 (regardless of sanction outcome), based on substance detection counts. 40
Figure 31: Total AAFs per sport in 2018 (regardless of sanction outcome), based on substance detection counts. 41
Figure 32: Total AAFs per sport in 2019 (regardless of sanction outcome), based on substance detection counts. 41
Figure 33: Total AAFs per sport in 2021 (regardless of sanction outcome), based on substance detection counts. 42
Figure 34: Raw AAF Rates per 1,000 Samples (Capped at 50) 43
Figure 35: Z-Score of AAFs (Own history) 44
Figure 36: AAF Rate Z-Score (Relative to All Sports in the same Year) 45
Figure 37: AAF Rate Z-Score (Relative to All Sports in All Years) 46
Figure 38: Sport-Year Doping Behavior Patterns (Relative to All Sports in the Same Year) .47
Figure 39: Sport-Year Doping Behavior Patterns (Relative to All Sports in All Years) 48

1. Introduction

Doping remains a significant challenge in elite sport, impacting athlete health, fair competition, and the integrity of sport worldwide. Despite rigorous testing and policy interventions by the World Anti-Doping Agency (WADA), doping continues across various sports.

Historically, anti-doping efforts have centered on the detection of prohibited substances; however, there is increasing recognition that patterns of doping differ markedly across sports. These differences are influenced not only by the physiological demands specific to each discipline—such as strength, endurance, or agility—but also broader socio-cultural influences such as team norms, perceived peer behavior, and the rationalization of rule violations (Backhouse, Griffiths and McKenna, 2013; Engelberg, Moston and Skinner, 2015). Consequently, particular classes of substances—such as anabolic agents, stimulants, and diuretics—are more prevalent within certain sport categories, highlighting the necessity of sport-specific anti-doping strategies.

This issue has attracted growing academic and policy interest. An important contribution was made by Aguilar-Navarro et al. (2020), who conducted an analysis of WADA doping control data spanning 2014 to 2017. Their study identified clear associations between specific substances and particular sports, thereby reinforcing the importance of tailored anti-doping interventions. Nevertheless, the timeframe of their research was limited, and it did not account for the effects of regulatory changes, the emergence of novel substances, or external disruptions such as the COVID-19 pandemic.

The present study aims to build upon and extend this earlier work by analyzing WADA's doping control data over a longer timeframe, from 2014 to 2022. The aim is to provide insights for policymakers, regulators, and sports organizations to target and strengthen anti-doping measures.

2. Data Description

Data sources

Two datasets from the World Anti-Doping Agency's (WADA) annual Testing Figures reports were used for this study, covering the period from 2014 through to 2022 (World Anti-Doping Agency, 2015–2023).

The first dataset, "Total AAFs per Drug Class as Reported in Sports," records the number of Adverse Analytical Findings (AAFs) categorised by substance class, limited only to disciplines in which AAFs were reported. Blood and/or urine samples from athletes were analysed by laboratories accredited within the Anti-Doping Administration and Management System (ADAMS). In 2021 and 2022, dried blood spots (DBS) were also analyzed.

The second dataset, "Total Samples Analysed," provides comprehensive data of the total number of doping control tests conducted per discipline, including cases where no AAFs were detected. The number of AAFs in this dataset, unlike the first dataset correspond to adjudicated Anti-Doping Rule Violations (ADRVs), therefore they are not just flagged as AAFs but also confirmed violations. The details regarding the detection method - blood, urine or DBS - is detailed in this dataset although they were not used during the following analysis.

Data extraction and preprocessing

Initially, attempts were made to extract data directly from PDF files using various libraries such as tabula-py and camelot, followed by exporting the data to Excel. However, these methods proved unreliable due to significant formatting issues in the WADA PDF. Consequently, a semi-manual extraction approach was adopted using Adobe software (Adobe Inc 2025). Relevant tables were converted into an Adobe-compatible format and then exported into Excel files, with separate worksheets created for each year.

The first dataset "Total AAFs per Drug Class as Reported in Sports," comprises seven tables per year. The second dataset consists of eight tables annually.

Following extraction, the data underwent thorough cleaning and standardisation processes to ensure consistency across years, sports, and substance categories. This involved correcting typographical errors, removing unnecessary columns, consolidating related categories, addressing missing values, and standardising sport and substance labels. This consistent structure facilitated longitudinal and comparative analyses across the 2014–2022 timeframe.

Data Quality and Limitations

The datasets used in this study are robust but possess inherent limitations, including:

- Absence of detailed athlete-level demographic information such as gender, age, country, and exposure data.
- Incomplete data coverage for certain sports across the full nine-year period.
- Potential discrepancies between reported AAFs and confirmed doping violations, limiting direct comparison or interchangeability of the two datasets.

As previously mentioned, the number of AAFs recorded in the first dataset does not directly correspond to adjudicated Anti-Doping Rule Violations (ADRVs), leading to potential discrepancies between the two datasets.In short, this study used two WADA datasets from 2014–2022: one showing drug test results with Adverse Analytical Findings (AAFs) by substance, and another showing total doping tests per sport. Automated data extraction from PDFs failed due to formatting issues, so a semi-manual method using Adobe software was used instead. The data were then cleaned and standardized for consistency. Limitations include missing athlete details, incomplete sport coverage, and the fact that AAFs don’t always indicate confirmed doping violations.

3. Exploratory Data Analysis

Sports disciplines in both the "Total AAFs per Drug Class as Reported in Sports" and "Total Samples Analyzed" datasets were refined to include only those present in every year from 2014 to 2022. The intersection of sport lists across all years resulted in a core group of 46 sports consistently represented in both datasets throughout the study period. This strategy enables robust, year-on-year comparisons and minimizes bias related to inconsistent data coverage, establishing a reliable foundation for subsequent trend and comparative analyses.

Anti-Doping Patterns Across Sports

Error! Reference source not found. provides a summary of testing volume and AAF rate by sport (2014-2022). This shows a comparison across sports in terms of which are high risk for doping and/or under-reporting.

The AAF rate represents the percentage of positive findings out of all tests conducted in a given sport, serving as a proxy for potential doping prevalence or risk.

To enhance interpretability, AAF rates are classified into three tiers:

- **High AAF Rate (≥ 2.0%)** – Indicates a strong signal of potential systemic doping issues. Sports in this category show elevated detection rates that may point to high-risk doping environments or insufficient deterrence.
- **Moderate AAF Rate (1.0%–1.99%)** – Suggests intermediate doping risk, warranting continued monitoring. This may reflect specific subpopulations or disciplines with irregularities, or sports with developing control systems.
- **Low AAF Rate (< 1.0%)** – Implies lower apparent doping prevalence, potentially reflecting more effective deterrence, lower biological risk, or insufficient detection.

Table 1: Summary of testing volume and AAF Risk by Sport (2014–2022)

SPORT	TOTAL TESTS (2014–2022)	TOTAL AAFS	AAF RATE (%)	RISK
BODYBUILDING	12316	2023	16.43	High
ARM WRESTLING	1899	167	8.79	High
KICKBOXING	4838	231	4.77	High
POWERLIFTING	31061	1323	4.26	High
MUAYTHAI	2789	117	4.20	High
KABADDI	2032	83	4.08	High
AMERICAN FOOTBALL	9188	299	3.25	High
GOALBALL	1164	37	3.18	High
BOULES SPORTS	1078	33	3.06	High
SAMBO	3379	88	2.60	High
POWERBOATING	987	18	1.82	Moderate
WUSHU	3303	56	1.70	Moderate
BOXING	41455	660	1.59	Moderate
WEIGHTLIFTING	95980	1501	1.56	Moderate
EQUESTRIAN	6294	92	1.46	Moderate
WRESTLING	50369	679	1.35	Moderate
UNDERWATER SPORTS	4107	51	1.24	Moderate
GOLF	4852	51	1.05	Moderate
ARCHERY	9514	99	1.04	Moderate
CYCLING	206409	2073	1.00	Moderate
JUDO	41267	368	0.89	Low
ROLLER SPORTS	7248	64	0.88	Low
SQUASH	2806	24	0.86	Low
ATHLETICS	278214	2359	0.85	Low
TAEKWONDO	19895	164	0.82	Low
KARATE	11253	92	0.82	Low
ICE HOCKEY	33157	258	0.78	Low
BASKETBALL	51760	395	0.76	Low
SHOOTING	18498	139	0.75	Low
TRIATHLON	42292	318	0.75	Low
FLOORBALL	3445	22	0.64	Low
HANDBALL	34736	195	0.56	Low
ROWING	45274	248	0.55	Low
FIELD HOCKEY	13753	73	0.53	Low
VOLLEYBALL	37756	201	0.53	Low
AQUATICS	133661	697	0.52	Low
TENNIS	51303	253	0.49	Low
TABLE TENNIS	10805	51	0.47	Low
GYMNASTICS	24356	108	0.44	Low
FENCING	16323	70	0.43	Low
FOOTBALL (SOCCER)	301567	1148	0.38	Low
CRICKET	11262	34	0.30	Low
SKATING	37662	100	0.27	Low
BADMINTON	15378	42	0.27	Low
SKIING	60467	143	0.24	Low
BIATHLON	22818	51	0.22	Low

This classification allows for clear cross-sport comparisons of doping risk regardless of absolute testing volume. For instance, sports like Bodybuilding, Arm Wrestling, and Kickboxing fall into the high-risk category, while global sports with substantial testing (e.g., Football (Soccer), Athletics, Cycling) show consistently low AAF rates despite their large scale.

These findings highlight both known doping challenges and potential blind spots, informing future test allocation and risk-based targeting.

Figure 1, Figure 2, and Figure 3 shown below for illustrative purposes and Figure 22 to Figure 27 in the appendix present bar charts of the sanctioned *AAF Rate per 1,000 Samples by Sport*, highlight statistical outliers across all sports (Z-score across all sports ≥ 2) in red.

While general trends remain consistent, some sports stand out. *Bodybuilding* is a persistent outlier across all years. *Arm Wrestling* also appears frequently, except in 2015 (borderline) and 2020. *Muaythai* emerges in 2015, and *Powerboating* in 2020. Despite their elevated sanctioned AAF rates, these sports represent less than 2% of all testing samples. This suggests that high detection rates may stem from relatively low testing volumes—possibly reflecting constrained resources, niche participation, or a higher targeted suspicion per test conducted. Testing trends and sanctioned AAF rate are strongly aligned for cycling — indicating proactive testing based on perceived doping risks. This reinforces historical scrutiny and continued vigilance.

The three charts below were selected—2014, 2020, and 2022—to provide a concise but meaningful overview. 2014 offers a baseline at the start of the study period, 2020 captures the major disruption caused by COVID-19, and 2022 reflects the most recent data, showing whether testing levels have recovered. This approach highlights key trends without unnecessary repetition.

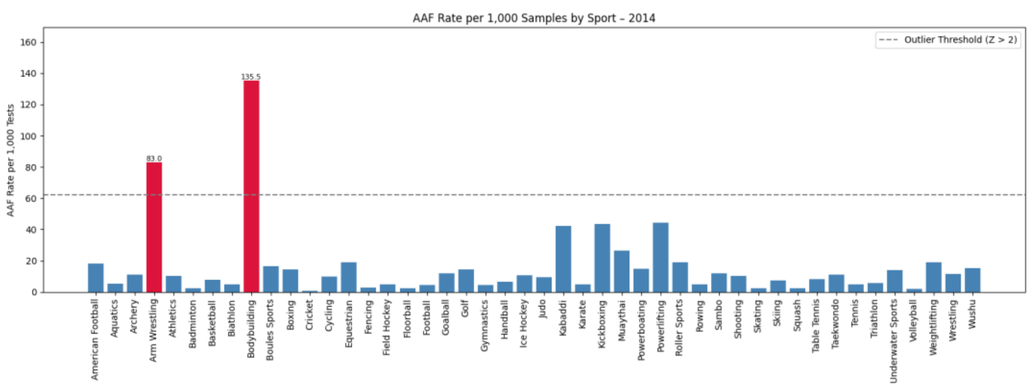


Figure 1: Sanctioned AAF rates per 1,000 samples by sport in 2014. Outliers (Z ≥ 2) are highlighted in red.

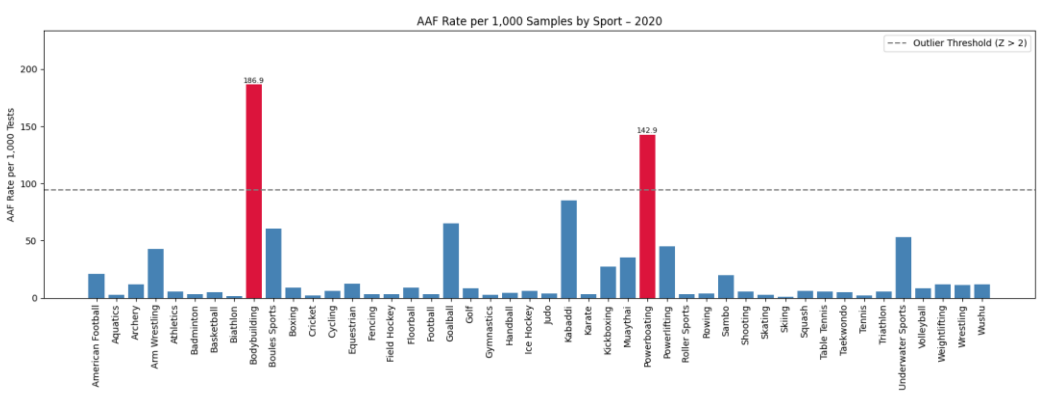


Figure 2: Sanctioned AAF rates per 1,000 samples by sport in 2020. Outliers (Z ≥ 2) are highlighted in red.

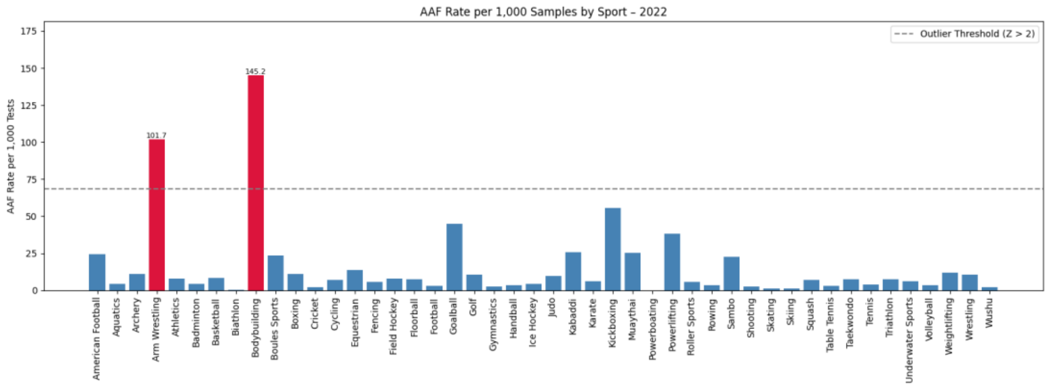


Figure 3: Sanctioned AAF rates per 1,000 samples by sport in 2022. Outliers (Z ≥ 2) are highlighted in red.

Error! Reference source not found., **Error! Reference source not found.** and **Error! Reference source not found.** shown below for illustrative purposes and Figure 28 to Figure 33 in the appendix, based on the *"Total AAFs per Drug Class as Reported in Sports"* dataset, depict the absolute number of AAFs reported per sport annually from 2014 to 2022 whether or not they led to sanctions.

Three of these charts are shown below for illustrative purposes. This set of charts follows the same selection logic used earlier: focusing on the years 2014, 2020, and 2022. These years were chosen to highlight key moments in the dataset—the starting point, the major disruption during the pandemic, and the most recent snapshot.

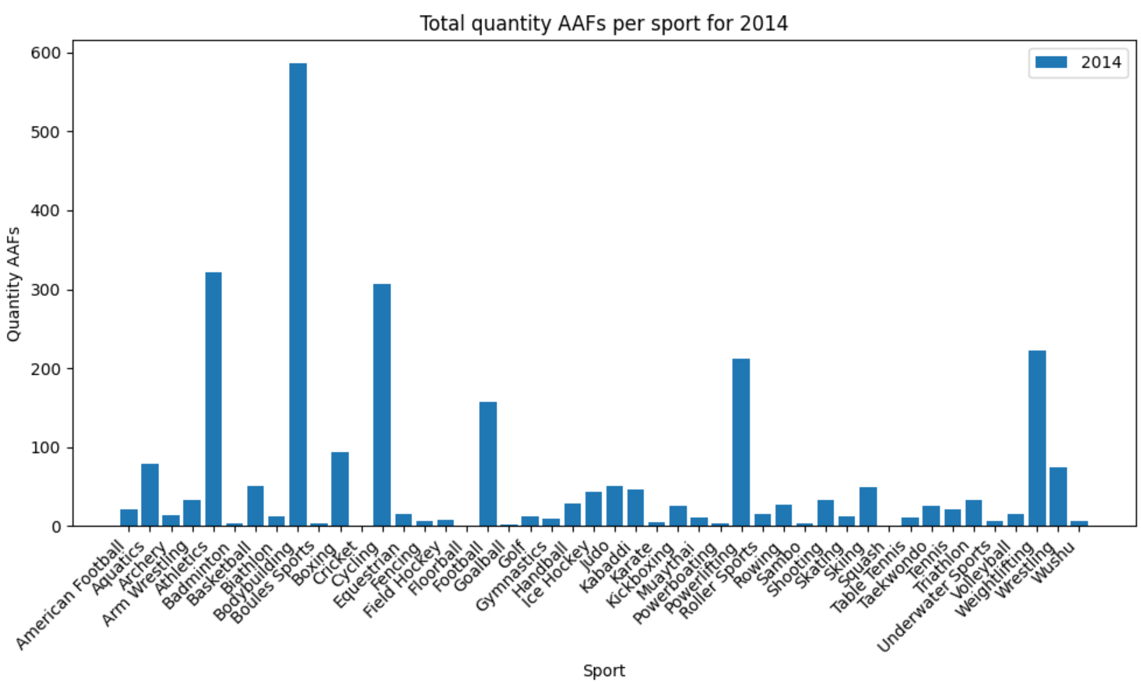


Figure 4: Total AAFs per sport in 2014 (regardless of sanction outcome), based on substance detection counts.

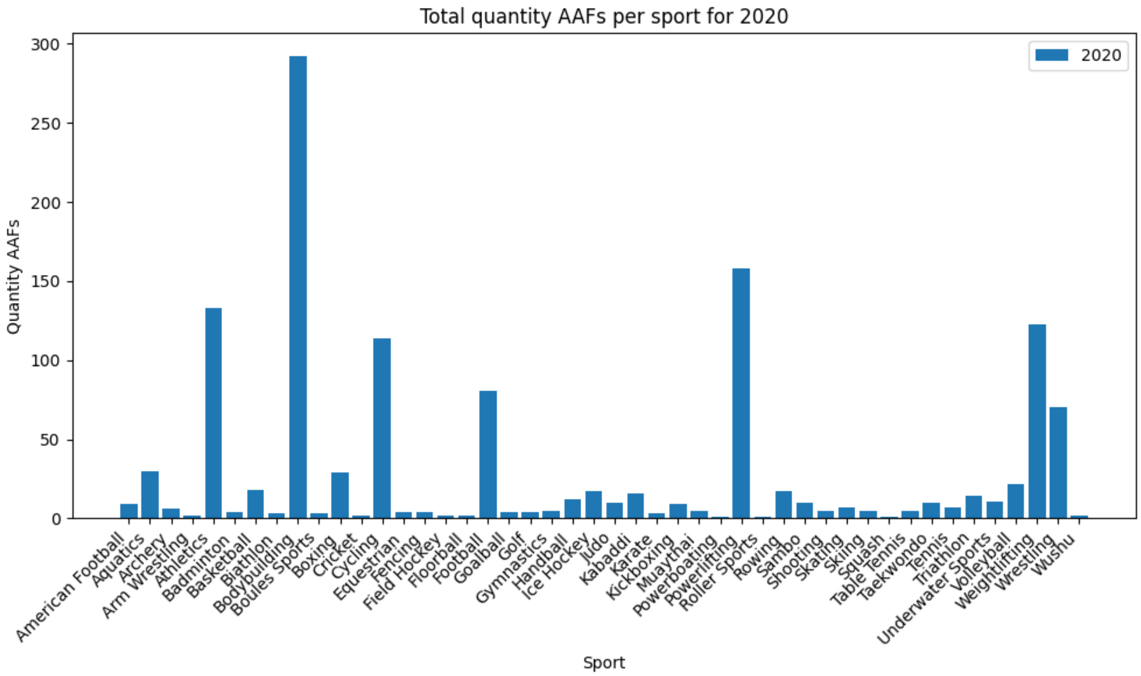


Figure 5: Total AAFs per sport in 2020 (regardless of sanction outcome), based on substance detection counts.

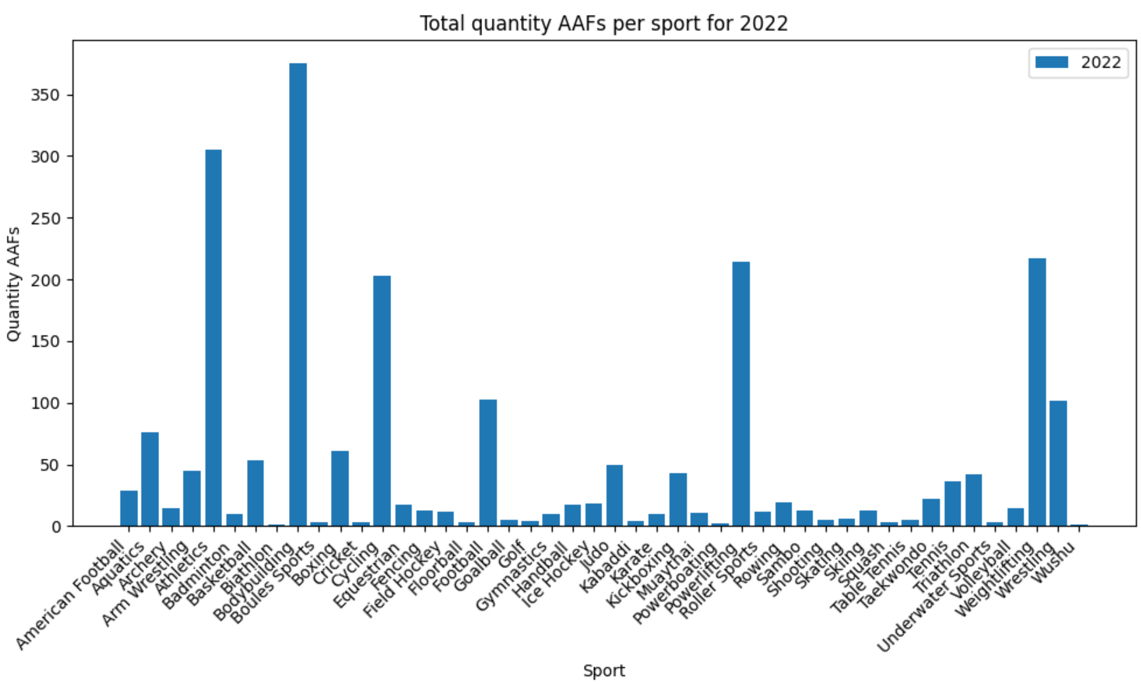


Figure 6: Total AAFs per sport in 2022 (regardless of sanction outcome), based on substance detection counts.

The data show persistent AAF concentrations in *Bodybuilding, Cycling, Athletics, Powerlifting,* and *Weightlifting*. This reinforces prior findings for *Bodybuilding*, which also has a high rate of sanctioned AAFs.

By contrast, *Arm Wrestling, Muaythai,* and *Powerboating*—though they have high rates of sanctioned AAFs —do not show significant absolute AAF counts. Their elevated rate of sanctioned AAFs is therefore likely driven by low testing frequency rather than widespread doping. Additionally, it is possible that some AAFs in these sports are flagged but later dismissed or not pursued to sanction, highlighting the importance of distinguishing between raw AAFs and sanctioned AAFs by the ADRVs

A Correlation-Based Classification of Anti-Doping Behavior (2014–2022)

This analysis focuses on how testing intensity and time trends relate to sanctioned anomalous Adverse Analytical Findings (AAFs) across disciplines. Figure 7 and Figure 8 shown below as well as 28 to 35 in the appendix are heatmaps visualising:

- Raw AAF Rates per 1,000 Samples (Capped at 50)
- AAF Rate Z-Score (Relative to All Sports in the same Year)
- AAF Rate Z-Score (Relative to All Sports in All Years)
- Z-Score of AAFs (Own history)
- Sport-Year Doping Behavior Patterns (Relative to Sport's Own History)
- Sport-Year Doping Performance Patterns (Relative to All Sports in the Same Year)
- Sport-Year Doping Behavior Patterns (Relative to All Sports in All Years

Two of these figures are shown below. The first shows AAF rate Z-scores relative to all sports in the same year, helping identify which sports stand out as high-risk at any given time. The second shows sport-year behavior patterns relative to each sport's own history, highlighting unusual changes that may warrant further investigation. Together, these charts balance cross-sport comparison with within-sport trend detection.

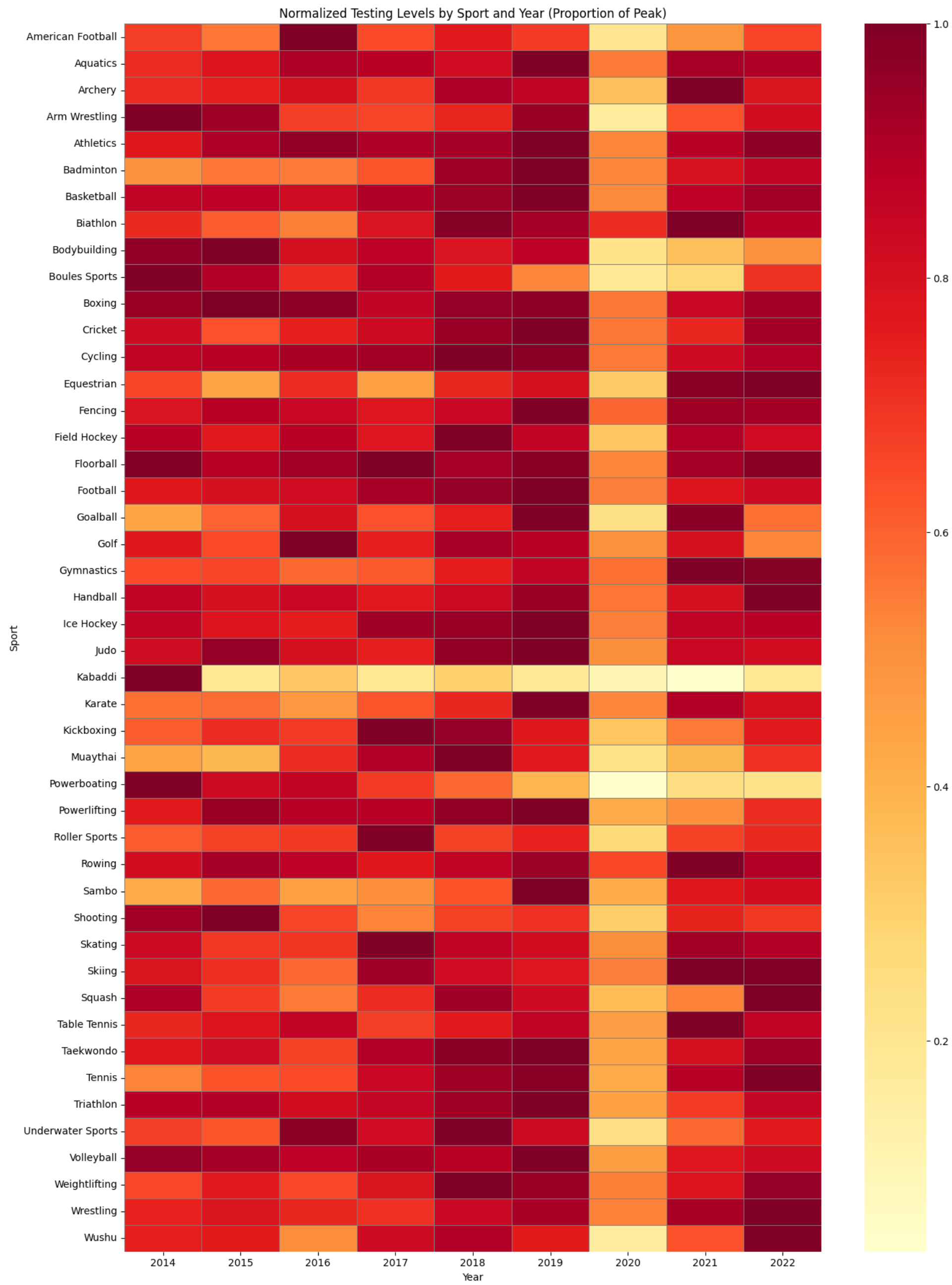


Figure 7: AAF Rate Z-Score (Relative to All Sports in the Same Year)

This chart highlights sports that are statistical outliers in terms of Adverse Analytical Finding (AAF) rates each year. Controlling for year-to-year variations in overall testing intensity and AAF rates, enables the identification of sport-specific doping behaviors within a consistent annual context. Notably, it clearly illustrates the impact of COVID-19 on testing and AAF patterns.

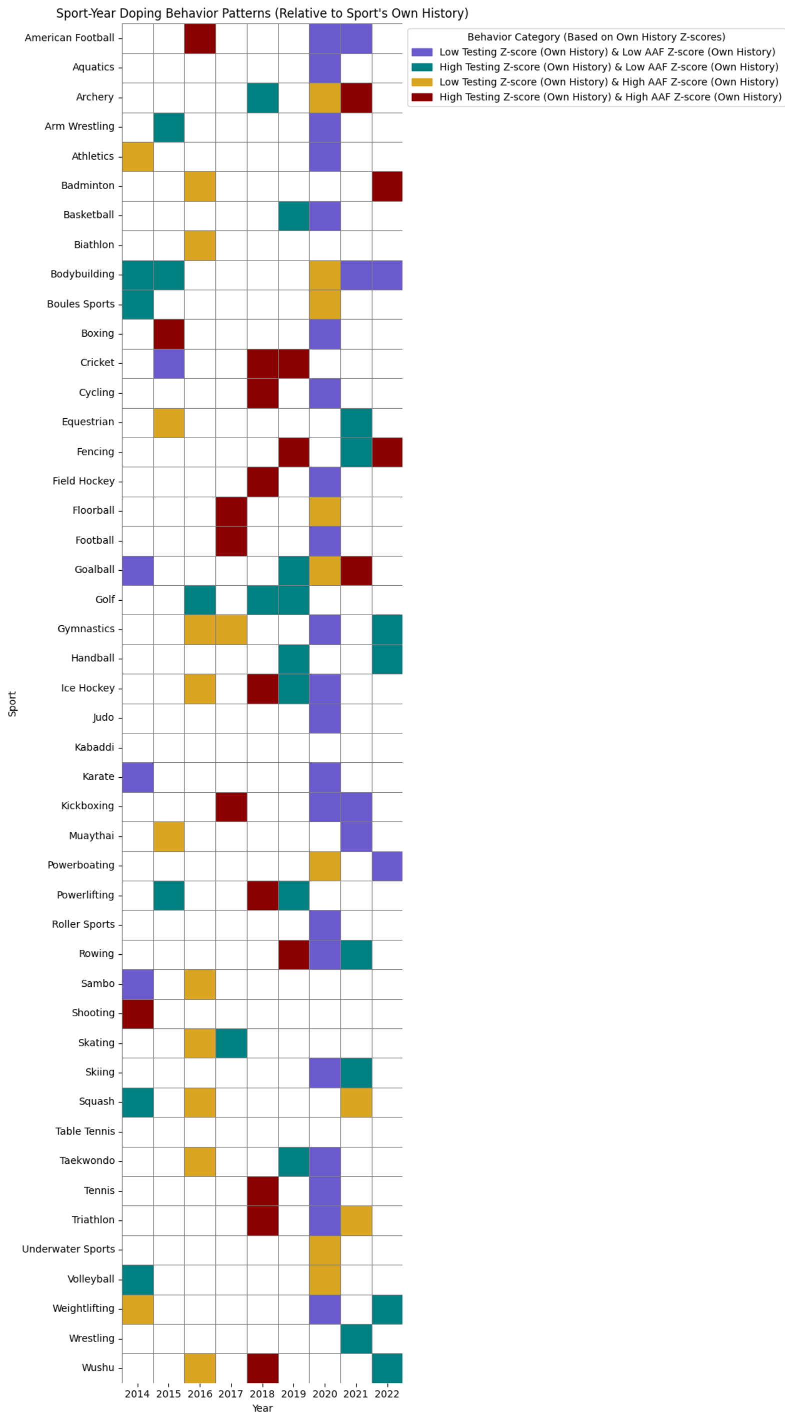


Figure 8: Sport-Year Doping Behavior Patterns (Relative to Sport's Own History)

This chart identifies whether a sport's doping behavior in a given year deviates from its own historical baseline. It highlights internal anomalies such as sudden spikes in AAFs for sports that are not typically flagged. This makes it particularly effective at uncovering unexpected doping patterns in usually low-profile sports.

The two selected heatmaps (Figure 7 and Figure 8) — *AAF Rate Z-Score (Relative to All Sports in the Same Year)* and *Sport-Year Doping Behavior Patterns (Relative to Sport's Own History)* — were chosen for their complementary strengths in analyzing doping trends over time.

The *AAF Rate Z-Score (Relative to All Sports in the Same Year)* controls for year-to-year variations in overall testing intensity and doping rates. This makes it ideal for identifying sports that are statistical outliers within any given year, providing a clear view of which sports stand out against their peers during that time frame. It also highlights the impact of external factors such as COVID-19 on doping detection rates.

In contrast, the *Sport-Year Doping Behavior Patterns (Relative to Sport's Own History)* heatmap focuses on deviations within each sport's own historical doping profile. This internal comparison is crucial for spotting unexpected anomalies, such as sudden spikes in adverse findings in sports that typically have low doping rates. This allows for the detection of unusual doping behaviors that might be overlooked in cross-sport comparisons.

Together, these charts provide a balanced and nuanced analysis of doping behavior, capturing both inter-sport comparisons and intra-sport temporal changes.

Z-Score (Own History) ↔ % Peak Testing

Assesses whether increased testing intensity within a sport corresponds to a greater deviation in doping rates compared to its own historical norm.

Strong Alignment Between Testing and sanctioned AAFs

Criteria: Z-Score (Own History) ↔ % Peak Testing ≥ 0.7

Sports: Cycling, Arm Wrestling, American Football, Boxing

Interpretation:
These sports exhibit a strong positive relationship between testing volume and sanctioned AAF deviations. This likely reflects targeted testing in response to perceived risk, with elevated testing coinciding with periods of heightened suspicion or known doping risk.

Note: Bodybuilding displays a high correlation for Z-Score (All Sports) (0.753), as previously mentioned, but a very weak correlation for Z-Score (Own History) (–0.036). This suggests that while its doping trends mirror global patterns, the sport's internal year-to-year testing intensity does not track closely with its own doping anomalies—implying that testing strategies may not be adaptively targeted to risk.

Weak or No Correlation Between Testing and sanctioned AAFs

Criteria: –0.4 < Z-Score (Own History) ↔ % Peak Testing < 0.4

Sports: Judo, Basketball, Athletics, Tennis, Wrestling, Karate, Shooting, Archery, Badminton, Skating, Gymnastics

Interpretation:
In these predominantly Olympic and traditional sports, testing levels appear disconnected from doping deviations. This may reflect routine, quota-driven testing, rather than intelligence-led strategies, potentially missing shifts in actual doping activity.

Negative Correlation — More Testing, Fewer sanctioned AAFs

Criteria: Z-Score (Own History) ↔ % Peak Testing ≤ –0.4

Sports: Underwater Sports, Squash, Powerboating, Biathlon, Boules Sports, Volleyball, Weightlifting, Table Tennis, Gymnastics

Interpretation:
These sports demonstrate a negative relationship between testing and AAF anomalies. This could indicate either an effective deterrence, where increased testing reduces violations, or a testing misalignment, where resources are focused on low-risk times/athletes, inadvertently suppressing detection rates.

Year ↔ Z-Score (Own History)

Evaluates temporal trends in doping anomalies: are they increasing or decreasing over time within a sport?

Several sports show strong negative temporal correlations, suggesting a decline in doping anomalies over time. Strongest declines observed in: Ice Hockey, Football (Soccer), Athletics, Table Tennis and Weightlifting.

Interpretation:
This may reflect greater compliance, more sophisticated doping avoidance strategies, or diminishing detection effectiveness.

Athletics and Weightlifting consistently report high absolute numbers of AAFs, confirming their status as high-risk sports. However, both show a strong decline in sanctioned AAF rates over time (negative Year ↔ Z-Score correlations). This suggests a shift toward greater compliance, more discreet doping practices, or diminishing detection effectiveness, reflecting both persistent exposure and adaptive response to anti-doping measures.

Football (Soccer) and Athletics have consistently ranked among the most heavily tested sports, reflecting their global prominence, large athlete bases, and perceived doping risks. This sustained testing intensity signals stable, resource-intensive anti-doping policies. At the same time, both sports show a strong decline in doping anomalies over time (negative

Year ↔ Z-Score correlations), indicating possible trends toward greater compliance, evolved evasion tactics, or less effective anomaly detection. Together, these patterns highlight a combination of robust anti-doping commitment and shifting doping dynamics under persistent regulatory pressure.

Z-Score (Own History) ↔ Z-Score (All Sports)

Measures how closely a sport's doping behaviour aligns with global doping trends across all sports.

There is the strongest Global Synchronization of Doping Behaviour observed in: Powerboating, Kabaddi, Karate, Muaythai, Golf

Interpretation:
These sports' doping behavior patterns are highly synchronized with broader global trends, suggesting common external influences (e.g., WADA enforcement shifts), shared anti-doping policies or resource structures, or reactive testing responses influenced by international developments.

Both Powerboating and Muaythai are niche sports with relatively few tests, yet they consistently exhibit statistically high rates of sanctioned AAFs. This pattern likely reflects targeted testing, where a higher proportion of tests yield violations despite low overall volumes.
Both sports also show strong alignment with global doping trends (Z-Score (Own History) ↔ Z-Score (All Sports)), indicating that their anti-doping patterns are shaped more by international enforcement cycles or regulatory harmonization (e.g., WADA directives) than by internal, sport-specific risk assessments.
The infrequent and concentrated nature of testing likely amplifies sanction rates, revealing a reactive, campaign-style testing approach—globally synchronized, but not necessarily continuous or intelligence-led within the sport itself.

Analysis of Doping Profiles in Competitive Sports

A review of substance profiles across sports reveals consistent, sport-specific patterns. Among detected substances, anabolic agents are the most prominent, followed by stimulants and diuretics/masking agents. These three categories often constitute the largest proportions in most sports over multiple years, highlighting their central role in performance enhancement or concealment.

Temporal Trends

From 2014 to 2019, there was a notable increase in the detection of stimulants, anabolic agents, cannabinoids, and diuretics/masking agents. In contrast, 2020 saw a sharp decline across nearly all substance categories, likely due to the COVID-19 pandemic's disruption of sporting events and anti-doping efforts. Beta-blockers, however, remained relatively stable, less affected by pandemic-related changes.

Since 2020, detection levels have gradually risen again, though by 2022, only cannabinoids had returned to pre-pandemic levels. Glucocorticoids and beta-2 agonists remain below earlier frequencies, while narcotics and peptide hormones/growth factors stabilised post-2020, with narcotics peaking previously in 2016–2017.

Substances like chemical and physical manipulation and oxygen transfer enhancers frequently recorded zero adverse analytical findings (AAFs), but their extremely low annual counts (typically <4) suggest statistical insignificance rather than meaningful trends. Some substances remain consistently absent or appear only sporadically, likely reflecting limited relevance or detection/reporting limitations.

Each sport shows a distinct doping fingerprint—some dominated by a single substance class, others exhibiting mixed profiles shaped by physiological demands, strategic considerations, and regulatory oversight.

This doping fingerprint is illustrated below for body-building and cycling, which have stable profiles from year to year. These charts show the distribution of adverse analytical findings (AAFs) by substance class for bodybuilding and cycling over the period 2014–2022. Anabolic agents make up over half of the detected substances in bodybuilding, while they account for about one-third in cycling. Bodybuilding also shows a higher relative use of diuretics and masking agents. In contrast, cycling exhibits a greater proportional use of stimulants, including beta-blockers, peptide hormones, and glucocortico-steroids. A complete set of doping fingerprints for all 46 sports is available in the Colab code.

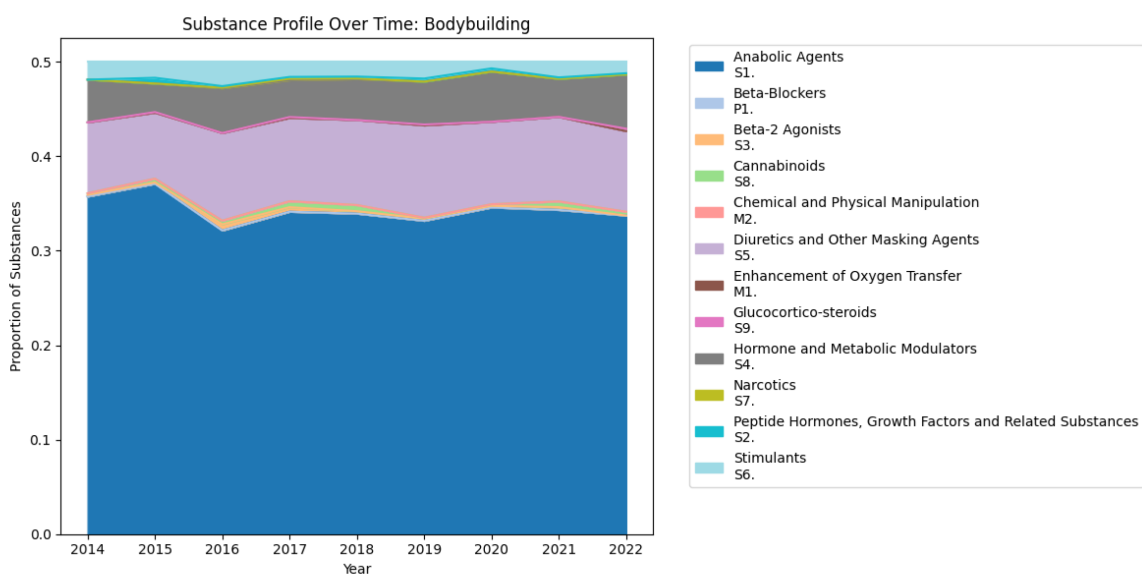


Figure 9: Doping Substance Profiles ("Fingerprints") for Body-building, 2014-2022

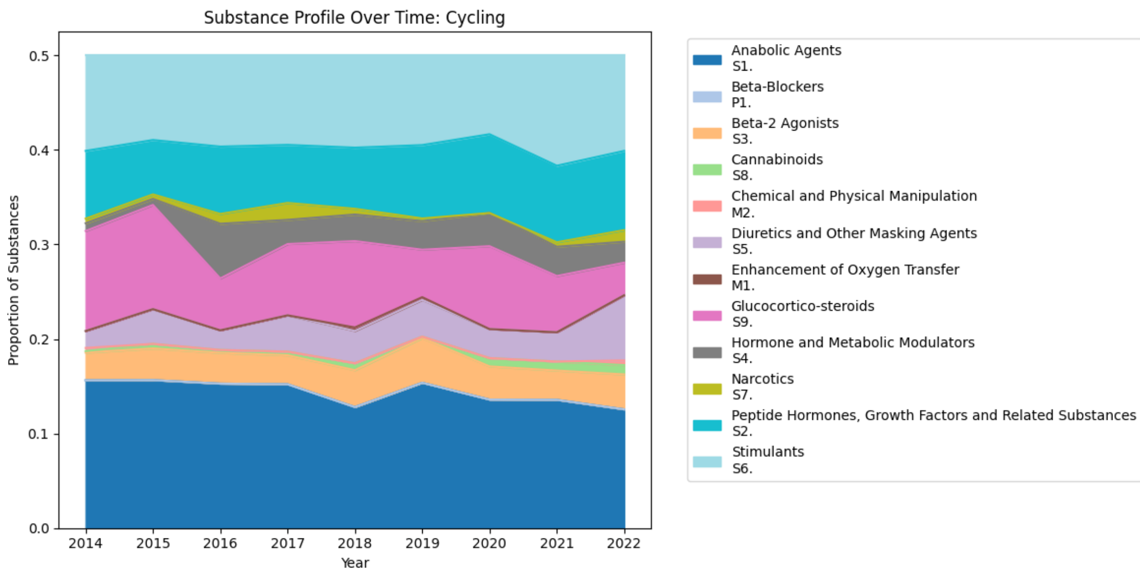


Figure 10: Doping Substance Profiles ("Fingerprints") for Cycling, 2014-2022

Comparative Clustering of Sports

Substance usage trends often align across sports, hinting at broader factors such as new detection technologies, regulatory changes, or shifts in athlete medical practices. These converging influences suggest that substance prevalence is not solely driven by the intrinsic demands of each sport, but also by evolving anti-doping ecosystems.

Building on this, the analysis of pairwise Euclidean distances between doping profiles reveals distinct clusters of similarity. The distance matrix and heatmap highlight affinities between sports that share physical demands, competition structures, or testing intensities.

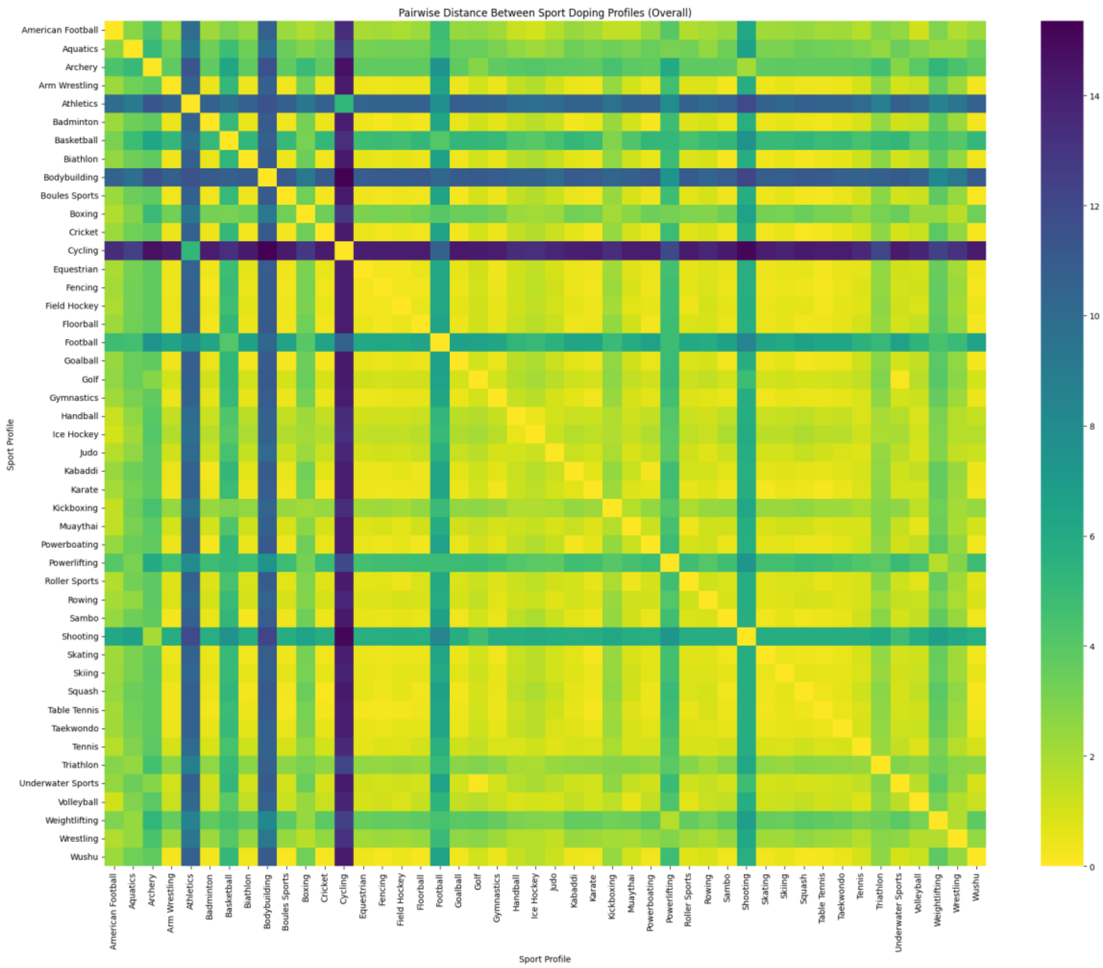


Figure 11: Pairwise Distance Between Sport Doping Profiles (Overall).

This heatmap visualizes the overall similarity between sports based on their doping profiles. Darker shades indicate greater similarity (i.e., smaller Euclidean distances), highlighting sports that share comparable patterns of adverse analytical findings across substance classes.

Sports with lower physical contact and greater emphasis on precision—Boules Sports, Wushu, Fencing, Table Tennis, Squash—tend to group closely, likely reflecting similar doping risk profiles marked by fewer anabolic agents and more stimulants or coordination-enhancing substances.

Wushu frequently emerges as a central node, often aligning with Cricket, Squash, and Fencing, suggesting a common reliance on neuromotor-enhancing substances. Likewise, Boules Sports and Fencing repeatedly appear together, indicating a stable, shared doping pattern.

Some proximity pairings, like Golf and Underwater Sports, likely reflect low testing intensity or low AAF incidence, rather than genuine biochemical similarity.

However, while some sports cluster together in terms of overall substance profiles, they may still differ in temporal stability. For instance, Golf, Fencing, and Squash, though occasionally grouped with other precision-oriented sports, exhibit high year-to-year volatility in their doping profiles.

This suggests that while their overall substance use patterns may resemble one another or other technical sports, the consistency of those patterns over time diverges sharply—potentially due to inconsistent enforcement, evolving doping strategies, or shifts in athlete demographics.

Dominant Substance Categories

Across the dataset:

- Anabolic agents (S1) dominate in 25 of the 46 white-listed sports, especially strength-based ones like Bodybuilding, Weightlifting, Wrestling, Boxing. Interestingly, sports like Football (Soccer), Fencing and Triathlon also show notable use, likely due to recovery and endurance benefits.
- Stimulants (S6) lead in 8 sports, such as Basketball, Ice Hockey, Gymnastics, Aquatics, where cognitive sharpness and rapid reactions are key.
- Diuretics and masking agents (S5) are the dominant substances in 8 sports, including Archery, Badminton, Taekwondo, and Rowing, where rapid weight adjustment or concealment of other banned substances offers a strategic or regulatory edge.
- Glucocorticoids (S9) and beta-agonists/blockers dominate fewer sports but serve specific roles—for example in Cricket and Skiing glucocorticoids are likely to be used for managing inflammation and pain after injury.

Temporal Stability and Volatility of Substance Use Profiles

Sports are grouped into four categories based on the stability of their doping profiles (2014–2022, excluding 2020), as measured by cosine similarity trends.

1) **Stable** - High and consistent cosine similarity over time (avg. > 0.90)

Sports:
Bodybuilding, Powerlifting, Weightlifting, Cycling, Boxing, Football (Soccer), Volleyball, Basketball, Athletics, Goalball, American Football, Wrestling, Arm Wrestling, Taekwondo

Interpretation:
This category reflects well-established anti-doping frameworks, consistent regulatory oversight, or persistent cultural norms leading to high year-to-year profile similarity.

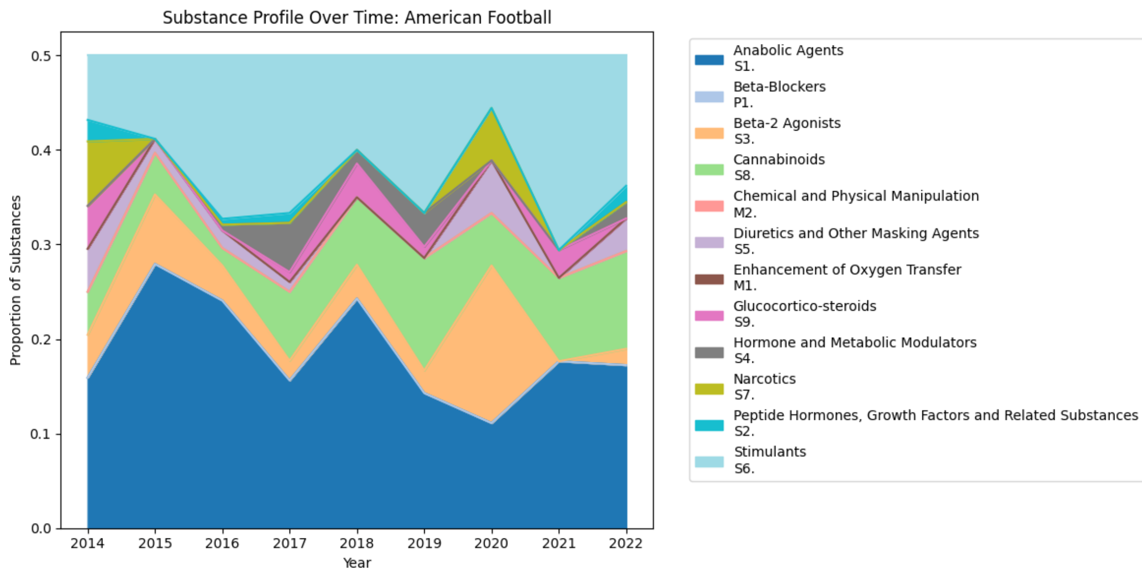


Figure 12: Stable substance profile Example, American Football

2) **Recovered Stability** - Cosine similarity has improved after prior volatility, signalling stabilisation in doping profiles over time.

Sports:
Tennis, Kabaddi, Aquatics, Kickboxing, Triathlon, Shooting, Judo

Interpretation:
Indicates maturing enforcement, reforms, or recovery from earlier inconsistencies.

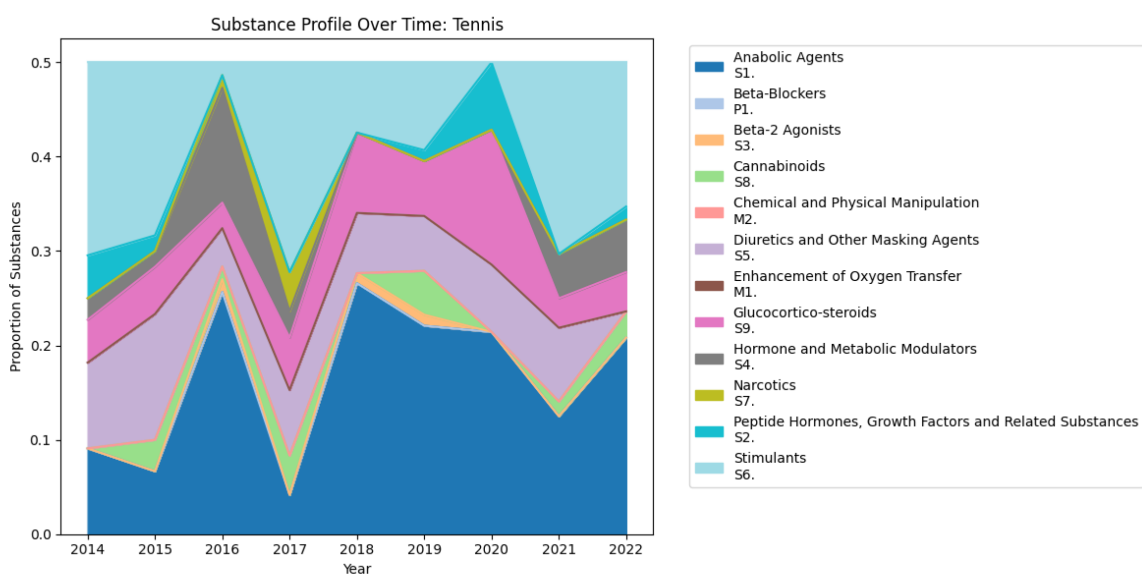


Figure 13: Recovered Stability substance profile Example, Tennis

3) **Moderate Volatility** - Moderate profile fluctuations suggesting some instability or evolving doping practices.

Sports:
Rowing, Gymnastics, Skiing, Wushu, Sambo, Kabaddi, Field Hockey, Boules Sports, Archery, Ice Hockey, Handball

Interpretation:
These patterns may reflect changing testing intensities, sport-specific evolution, or geopolitical influences.

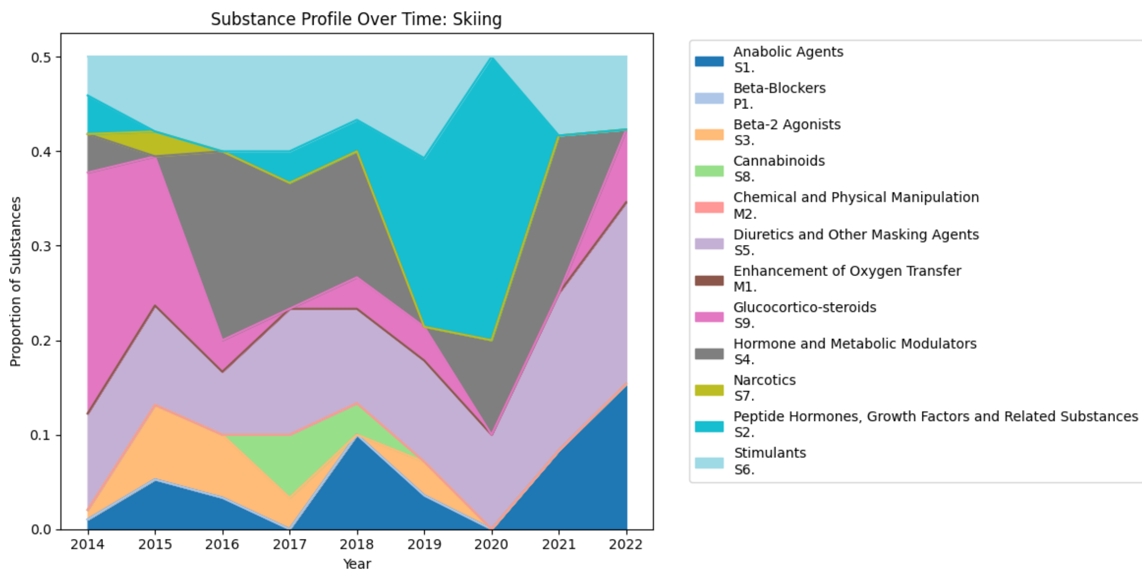


Figure 14: Moderate volitility substance profile Example, Skiing

4) **Highly Volatile / Chaotic** - Low or erratic cosine similarity (avg. often < 0.6), with some years showing near-zero similarity.

Sports:
Fencing, Golf, Powerboating, Badminton, Floorball, Cricket, Table Tennis, Biathlon, Karate, Underwater Sports, Muaythai, Equestrian, Skating, Roller Sports, Squash.

Interpretation:
Suggests inconsistent enforcement, sporadic testing regimes, or the emergence of new or unpredictable doping strategies.

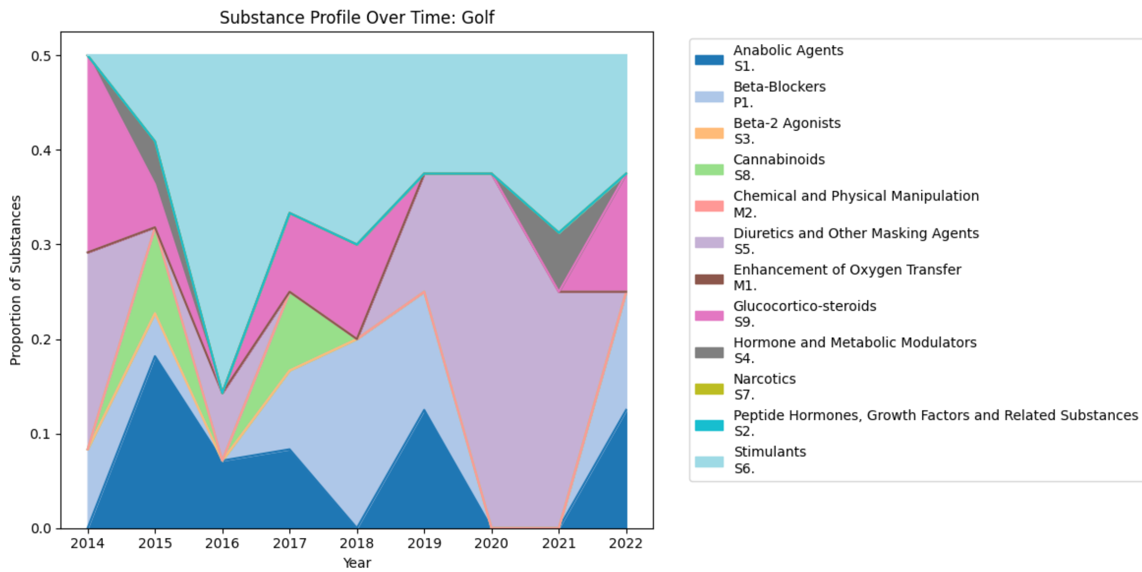


Figure 15: High volatile/chaotic substance profile Example, Golf

Summary: Exploratory Data Analysis

In short, doping patterns are very different across sports, influenced by things like the physical demands of the sport, how strictly it's regulated, and how much testing is done. Strength sports tend to show more use of anabolic agents, while sports that require alertness or weight control often involve stimulants and diuretics. Detections dropped sharply during COVID-19 and hadn't fully recovered by 2022. While some sports show consistent doping patterns over time, others change from year to year. The findings from correlation and clustering analyses suggest that both long-term systems and short-term behavior shape how doping shows up in sport.

4. Clustering of Doping Profiles Across Sports (2014–2022)

To explore structural patterns in anti-doping data across sports, a comprehensive unsupervised clustering framework was applied. This section summarises the methodologies, insights, and comparative patterns extracted from clustering analyses using both dimensionality reduction and substance-specific approaches.

Methodological Framework

Each sport's annual doping profile was represented as a vector of substance-specific adverse analytical findings (AAF proportions). These profiles were pre-processed via standard scaling and, when required, normalised to enable meaningful comparison.

Three distinct dimensionality reduction techniques were implemented in order to reduce the number of variables in the datasets while retaining essential information:

1. **PCA** (Principal Component Analysis)
2. **UMAP** (Uniform Manifold Approximation and Projection)
3. **t-SNE** (used for visualization only, not clustering)

Clustering was conducted using both:

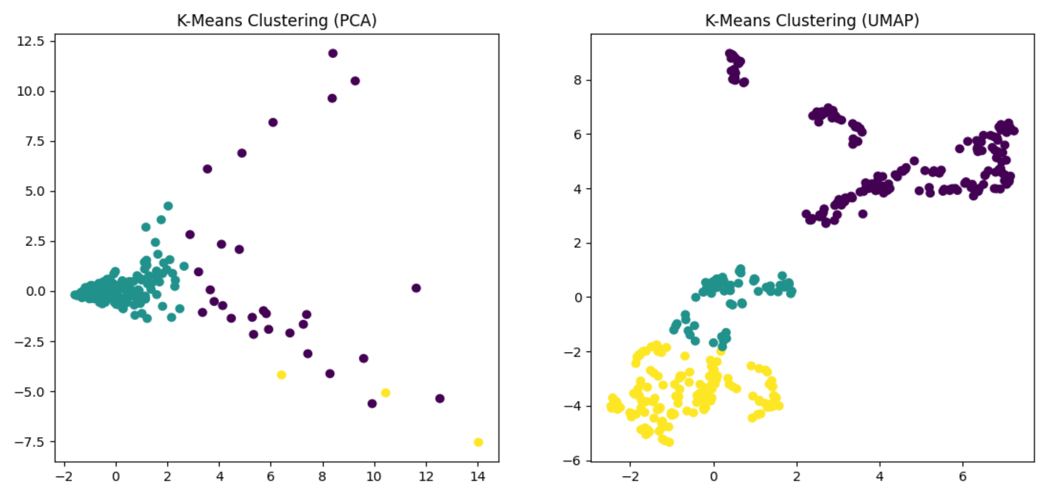
- **K-Means**: emphasizing centroid-based segmentation
- **Agglomerative Hierarchical Clustering**: capturing nested group structures

Silhouette scores and inertia-based elbow plots informed cluster quantity choices (k=3 or k=4).

General Clustering Results

Both PCA and UMAP projections revealed clusters of sports with similar substance profiles, often preserving temporal consistency. Hierarchical clustering provided interpretable dendrogram-style divisions, while K-Means yielded tighter, compact clusters in reduced-dimensional space.

PCA-based clustering exhibited higher silhouette scores (≥0.83 for K-Means), suggesting cleaner separation of doping behaviours among sport-year profiles. UMAP revealed nuanced patterns not captured in PCA but with moderately lower silhouette scores.



Each data point in these charts represents a sport, with colors indicating cluster membership.

Figure 16: Cluster Plot: PCA (10a) and UMAP (10b) Projection of Sports Based on Substance Use

This chart shows how sports group together based on their doping profiles and supports the results of the unsupervised clustering analysis.

Cluster Dynamics and Migration

Longitudinal tracking of cluster assignments across the 2014–2022 timeline highlighted "migrating sports" – disciplines whose profiles evolved significantly enough to shift between clusters. Migration was quantified for both PCA and UMAP projections using hierarchical clustering.

Sports such as *American Football*, *Bodybuilding*, *Handball*, *Kickboxing*, *Rowing*, *Skiing*, and *Tennis* demonstrated multiple cluster transitions, indicative of shifting substance prevalence or changing testing strategies.

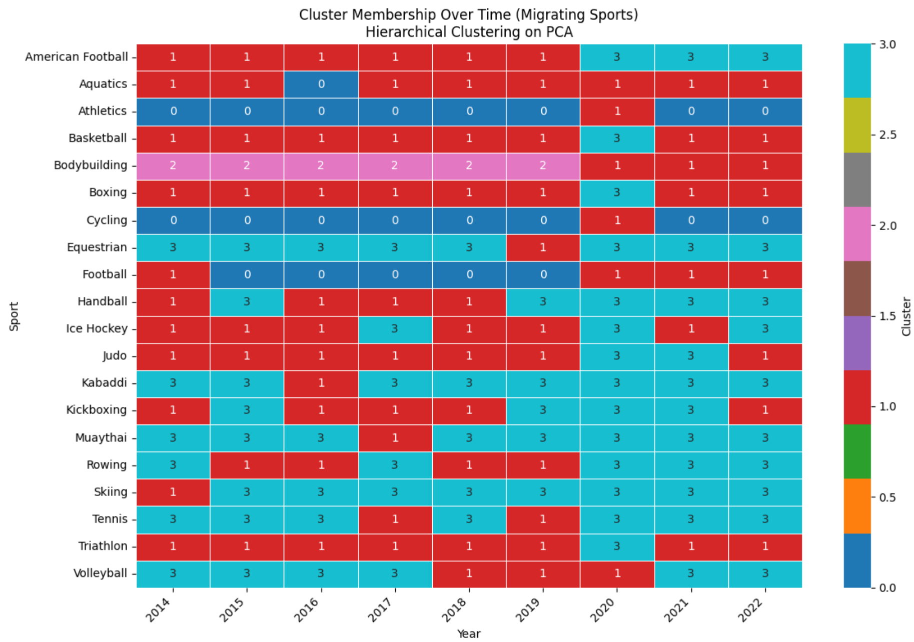


Figure 17: Cluster Membership Over Time (Hierarchical Clustering on PCA Projection)

This heatmap displays annual cluster assignments for each sport from 2014 to 2022 using hierarchical clustering on PCA-reduced features. Each color denotes a distinct cluster. Shifts in color across years indicate "migrating sports" — disciplines whose doping profiles evolved significantly over time, such as American Football, Bodybuilding, and Kickboxing. These transitions suggest changes in testing strategies, substance prevalence, or doping behavior patterns.

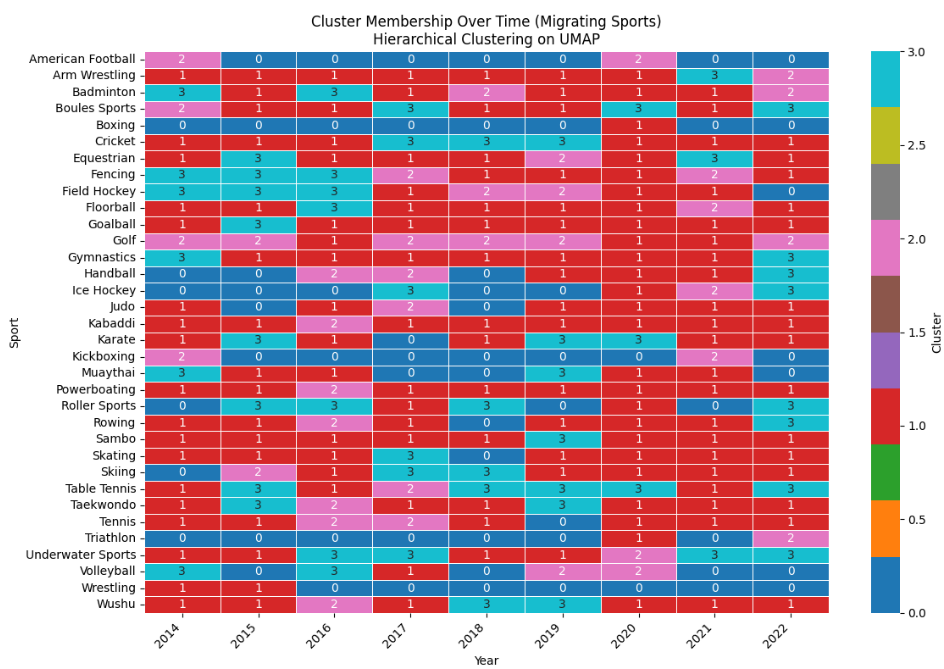


Figure 18: Cluster Membership Over Time (Hierarchical Clustering on UMAP Projection)

This heatmap shows cluster membership dynamics across sports and years using hierarchical clustering on UMAP-reduced features. The chart complements the PCA-based analysis and confirms migration trends through an alternative dimensionality reduction method. Consistent transitions across both projections strengthen the evidence of temporal shifts in doping profiles for several sports.

Substance-wise Hierarchical Clustering

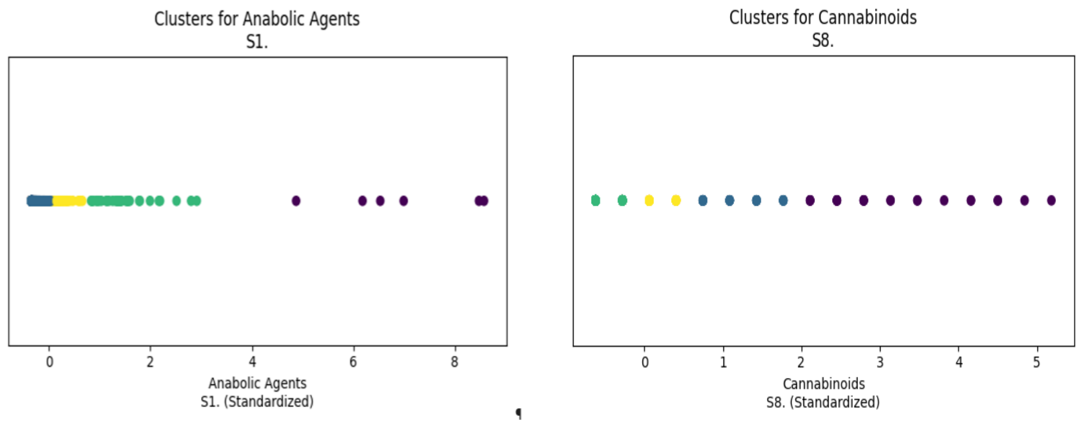


Figure 19: Clustering of Sports by Substance Group: (a) Anabolic Agents (S1), (b) Cannabinoids (S8)

Beyond global profiles, per-substance clustering isolated behaviours specific to doping classes (e.g., S1: Anabolic Agents, S8: Cannabinoids). For each category, hierarchical clustering was applied to isolate sports with anomalously high or shared patterns of use. This highlighted specialisation in certain substances among specific sports (e.g., Cannabinoids in combat and recreational sports).

These cluster plots illustrate sport-level patterns in Adverse Analytical Findings (AAFs) specific to two major substance groups: (a) Anabolic Agents (S1) and (b) Cannabinoids (S8). Hierarchical clustering was applied based on AAF prevalence profiles across sports. In (a), sports such as Bodybuilding and Weightlifting form distinct clusters, indicating elevated and consistent use of anabolic agents. In (b), Cannabinoid-related AAFs cluster strongly within combat and recreational sports, suggesting differentiated substance use patterns linked to cultural or contextual factors. These clusters highlight substance-specific doping behaviors that are masked in aggregate analyses.

Feature Importance Analysis

Permutation-based feature importance scores were computed to determine which substances most influenced clustering structure under different configurations.

To keep the report clear and concise, feature importance is shown only for the two PCA clustering models (K-means and Hierarchical). This simplifies the presentation while still highlighting the main substances that drive the clusters.

- Under **K-Means (PCA)**, the primary discriminants were:
    - Stimulants (S6)
    - Anabolic Agents (S1)
    - Peptide Hormones and Related Substances (S2)
    - Cannabinoids (S8)

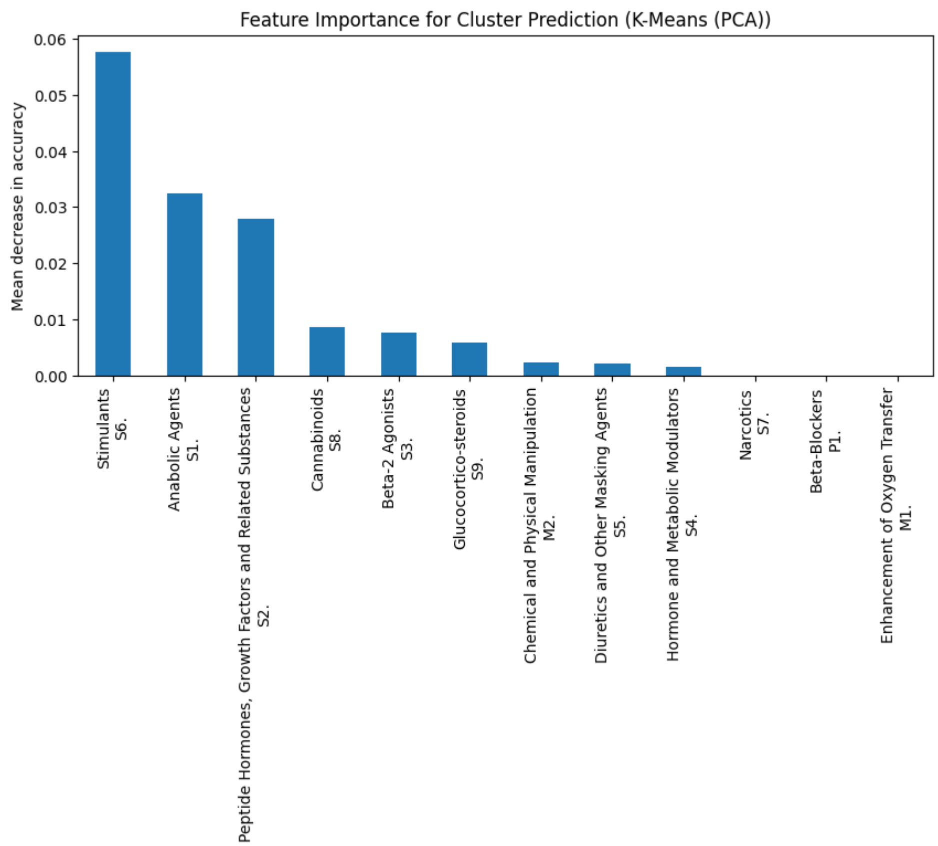


Figure 20: Feature Importance for Cluster Prediction — K-Means Clustering (PCA Projection)

This bar chart displays permutation-based feature importance scores for substance groups in predicting cluster membership using K-means clustering on PCA-reduced data. Higher bars indicate greater influence on the resulting clustering structure. Substances such as Stimulants (S6), Anabolic Agents (S1).

- Under **K-Means (UMAP)**, the highest impact features were:
    - Cannabinoids (S8)
    - Narcotics (S7)
    - Beta-Blockers (P1)
    - Beta-2 Agonists (S3)

- Under **Hierarchical (PCA)**, clusters were strongly separated by:
    - Stimulants (S6)
    - Beta-2 Agonists (S3)
    - Cannabinoids (S8)
    - Glucocortico-steroids (S9)
    - Anabolic Agents (S1)

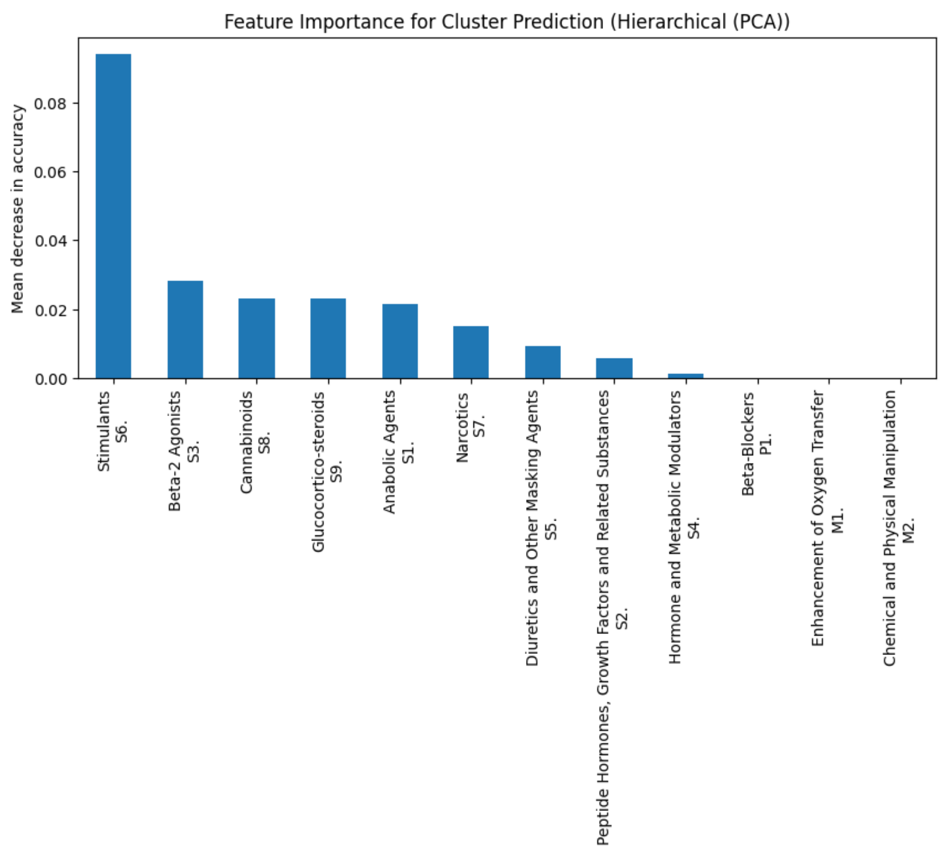


Figure 21: Feature Importance for Cluster Prediction — Hierarchical Clustering (PCA Projection)

This bar chart illustrates the permutation-based importance of different substance groups in determining cluster assignments using hierarchical clustering on PCA-reduced data. Notably, Stimulants (S6), Beta-2 Agonists (S3), Cannabinoids (S8), Glucocorticoid-Steroids (S9), and Anabolic Agents (S1) are identified as the most influential features. This supports the analysis highlighting these substances as key discriminants under the Hierarchical (PCA) clustering method.

- Under **Hierarchical (UMAP)**, the dominant contributors remained:
    - Cannabinoids (S8)
    - Narcotics (S7)
    - Beta-Blockers (P1)

Feature contributions varied by method. However, Cannabinoids (S8), Stimulants (S6), and Beta-2 Agonists (S3) consistently emerged as strong determinants across models.

Interpretive Implications

Clustering elucidated latent structure in doping practices. Certain sports consistently co-clustered due to similar substance preferences, likely reflecting physiological demands, cultural norms, or strategic doping choices. Migratory behaviours point toward evolving doping patterns or detection improvements.

Feature importance reinforced the prominence of certain substances in differentiating doping profiles. This highlights focal points for surveillance and substance-specific policy adjustments.

Summary: Clustering of doping profiles

In short, unsupervised clustering was used to analyze doping patterns from 2014 to 2022. It applies techniques to simplify the data (PCA and UMAP) and grouping methods (K-Means and Hierarchical) based on drug test results for specific substances. The best results came from combining PCA with K-Means, which created clear groups, while UMAP helped find more subtle trends. Tracking how groups changed over time showed shifting doping behaviors in some sports like Bodybuilding and Tennis. Analysis also highlighted certain drug types—Cannabinoids, Stimulants, and Beta-2 Agonists—as important for distinguishing patterns. Overall, this approach revealed meaningful trends in doping that can help guide targeted testing and policy decisions in different sports.

5. Conclusions and Outlook

This analysis of WADA anti-doping data from 2014 to 2022 shows that doping varies a lot between sports. Factors like the physical demands of the sport, how testing is done, and the focus of regulations all play a role. Big sports like Football (Soccer) and Cycling get tested a lot, while others like Bodybuilding and Muaythai have high positive rates even with less testing. This means it is important to look at both the rate of positives and the actual number of cases to get a full picture.

Using exploratory and clustering analyses, this study showed clear patterns in which substances are used. Anabolic agents are common in strength sports, while Cannabinoids, Stimulants, and Beta-2 Agonists stand out as important in distinguishing different sports' doping profiles. Some sports, like Bodybuilding, Tennis, and Handball, showed changes over time in their doping patterns, suggesting shifts in behavior or testing approaches. This highlights the need for flexible testing policies.

Extension of Previous Work

This study builds directly on the work of Aguilar-Navarro et al. (2020), who analyzed WADA doping control data from 2014 to 2017 to highlight sport-specific patterns in the use of banned substances. Their findings showed that the prevalence of certain drug classes—such as anabolic agents and stimulants—varied across sports, supporting the argument for sport-specific anti-doping strategies.

The present study extends this research in several meaningful ways. First, it broadens the temporal scope to include data from 2014 to 2022, allowing for the analysis of longitudinal trends, including the observable impact of COVID-19 on testing and detection rates. Second, it applies a more advanced analytical framework, incorporating dimensionality reduction techniques (PCA, UMAP) and unsupervised clustering algorithms (K-Means, Hierarchical). These methods enable the identification of latent structure in the data, revealing clusters of sports with similar doping profiles and capturing temporal shifts in substance use patterns that are not easily detected through descriptive statistics alone.

A further contribution of the present study lies in the distinction between absolute case counts and relative detection rates. By accounting for variation in testing volume—particularly in low-sample sports—it reduces the risk of misinterpretation and provides a more robust basis for evaluating doping prevalence. Additionally, the analysis identifies specific drug classes (e.g. cannabinoids, stimulants, beta-2 agonists) as key discriminatory features in clustering models, offering practical value for risk-based testing strategies.

In summary, while Aguilar-Navarro et al. established the need for differentiated anti-doping approaches, the present study builds on that foundation by integrating more recent data, applying data-driven exploratory methods, and producing insights with greater temporal and structural resolution. These enhancements align with the broader goals of applied data science: leveraging computational techniques to inform evidence-based policy and decision-making

Strengths and weaknesses

The study's strengths include using multiple methods for reducing data complexity and grouping sports, which helps confirm the patterns that were found. Looking at both overall doping profiles and specific substances gave more detailed insights and helped identify which substances deserve more focus in anti-doping efforts.

There are some limitations. The analysis relies on reported positive cases, which can be affected by differences in testing strategies, how many tests are done, and detection methods in different countries and years. Sports with fewer tests can show high positive rates simply because of small sample sizes. Also, the unsupervised methods used find patterns but cannot prove cause and effect, and results can vary depending on data processing choices.

Relevance and Impact

This work offers useful information for different interest groups.

- Policymakers and anti-doping authorities can use these results to better target testing resources and adjust strategies as doping patterns change.
- Sporting organizations get a clearer view of the doping risks specific to their sport, helping them create better education and compliance programs.

- For researchers in data science, this study shows how techniques like clustering and dimensionality reduction can be applied to real-world sports data to uncover hidden patterns.

Outlook

Future research could incorporate additional contextual variables—such as geographic data, athlete backgrounds, or relevant social factors—to deepen understanding and enhance the policy relevance of findings. The methods applied here could also be extended to related areas such as injury prevention, performance analysis, and the monitoring of broader sports integrity issues. Overall, this work illustrates the value of data science in advancing fairness, safety, and transparency in elite sport.

One particularly promising direction is forecasting, which offers the potential to anticipate future doping trends. Predictive modeling can support more proactive, risk-based anti-doping strategies by identifying emerging high-risk sports and patterns of substance use before they escalate.

Although a comprehensive forecasting analysis lies beyond the scope of this report, I implemented and tested four established models—XGBoost, Holt-Winters, LSTM, and LightGBM—using Python, applying them individually to each sport in the WADA dataset. This sport-specific approach helps avoid conflating trends across disciplines with different doping risks, testing volumes, and competition structures.

Preliminary results and full code are available in my GitHub repository. Due to space constraints, the models and their comparative performance are not discussed in detail here. However, early results demonstrate the potential of data-driven methods for forecasting doping patterns in a nuanced, sport-specific manner.

While initial findings are promising, future research could further optimize model selection by sport, integrate broader variables (e.g., rule changes, testing intensity, athlete turnover), and test predictive accuracy against newly emerging data.

Such a targeted and adaptive forecasting framework could support anti-doping agencies in developing dynamic, evidence-based interventions tailored to the evolving risk landscape of elite sport.

Overall, this project demonstrates how historical doping data, when combined with modern data science tools, can generate actionable insights for policy and prevention.

6. Glossary of Terms and Abbreviations

AAFs
Adverse Analytical Findings — Positive test results indicating the presence of prohibited substances or methods.

ADRVs
Anti-Doping Rule Violations — Breaches of anti-doping regulations, typically resulting from confirmed AAFs.

ADAMS
Anti-Doping Administration and Management System — A secure online platform managed by WADA for data entry, storage, and sharing of doping control information among relevant stakeholders.

COVID-19
Coronavirus Disease 2019 — The global pandemic impacting sports testing schedules and procedures.

DBS
Dried blood spots — A method of collecting small blood samples on filter paper for easy transport and testing. Used in anti-doping to detect prohibited substances with minimal invasiveness.

Elbow plot
A graphical method used to determine the optimal number of clusters in K-Means clustering. It shows the relationship between the number of clusters and the total within-cluster variance; the "elbow" point suggests the best number of clusters to use.

Holt-Winters
A simple method for forecasting time series with trends and seasonality

K-Means Clustering
A machine learning method used to partition data points into clusters based on similarity.

LightGBM
A fast tree-based model that works well with large datasets but needs extra features for time series tasks.

LSTM
A neural network model designed to handle patterns in sequential or time-based data.

PCA
Principal Component Analysis — A dimensionality reduction technique that transforms variables into principal components.

t-SNE
t-distributed Stochastic Neighbor Embedding — A technique for visualizing high-dimensional data by reducing dimensions.

UMAP
Uniform Manifold Approximation and Projection — A dimensionality reduction method emphasizing the preservation of data structure.

WADA
World Anti-Doping Agency — The global organization responsible for promoting, coordinating, and monitoring the fight against doping in sports.

XGBoost
A fast, accurate model that uses boosted decision trees for prediction, especially good with structured data.

Z-Score
A statistical measure that describes a value's relationship to the mean of a group of values, expressed in standard deviations.

7. Substance Groups and WADA Identifiers

S1: Anabolic Agents
Substances that promote muscle growth and increase strength, often used to enhance physical performance (e.g., anabolic steroids).

S2: Peptide Hormones, Growth Factors, and Related Substances
Hormones that stimulate the body's production of red blood cells, muscle growth, or tissue repair (e.g., Erythropoietin (EPO), Human Growth Hormone (HGH)).

S3: Beta-2 Agonists
Drugs that relax airway muscles and are used to treat asthma but can also have muscle-building or fat-reducing effects when misused.

S4: Hormone and Metabolic Modulators
Substances that alter hormone levels or metabolism to boost performance or counteract side effects of other doping agents (e.g., anti-estrogens, insulin modulators).

S5: Diuretics and Other Masking Agents
Compounds that increase urine production to dilute doping substances or mask their presence in drug tests.

S6: Stimulants
Drugs that increase alertness, energy, and endurance by stimulating the central nervous system (e.g., amphetamines, ephedrine).

S7: Narcotics

Strong painkillers that can mask injury or pain, allowing athletes to perform beyond safe physical limits (e.g., morphine, fentanyl).

S8: Cannabinoids
Substances derived from cannabis that can impair performance, concentration, and reaction time, and are banned in competition.

S9: Glucocorticoids
Anti-inflammatory drugs that can reduce pain and swelling, potentially allowing injured athletes to compete when they shouldn't.

P1: Beta-Blockers (Prohibited in particular sports)
Drugs that lower heart rate and reduce anxiety, giving an advantage in precision sports like shooting or archery.

M1: Enhancement of Oxygen Transfer
Techniques or substances that increase the blood's oxygen-carrying capacity to boost endurance (e.g., blood doping**,** Erythropoietin (EPO))**.**

M2: Chemical and Physical Manipulation
Methods used to tamper with samples or interfere with drug detection, including intravenous infusions or sample substitution.

8. Acknowledgements

I am grateful to the World Anti-Doping Agency (WADA) for their commitment to transparency and anti-doping efforts, which made this investigation possible. The availability of statistical data from accredited anti-doping laboratories has been essential to this work. I also appreciate the broader role WADA plays in promoting clean sport through its policies and initiatives. Additionally, I thank the staff of the CAS program at the Mathematical Institute, University of Bern for their expert instruction and feedback during the Certificate of Advanced Studies (CAS) in Applied Data Science, as well as my peers for their collaborative support and insightful discussions.

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10.Appendix:

AAF rate per 1000 samples by sport

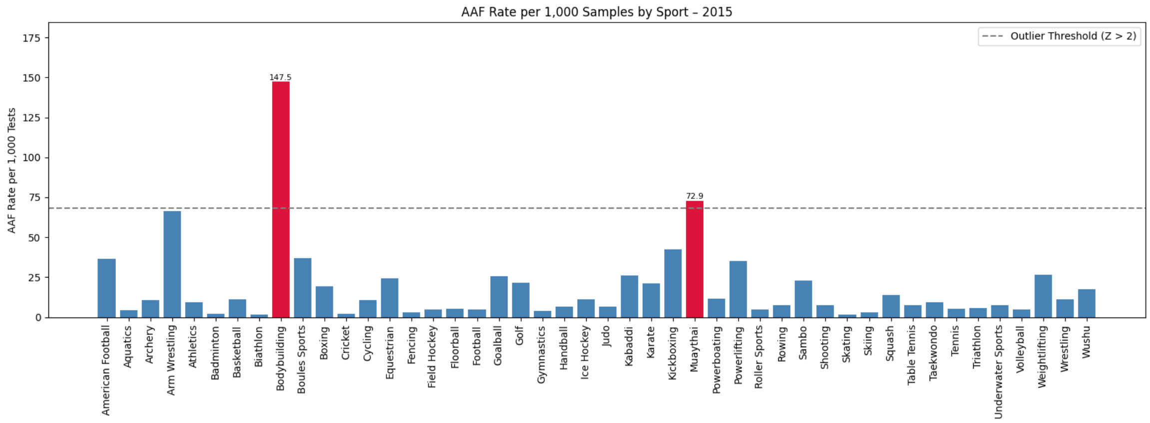

Figure 22: Sanctioned AAF rates per 1,000 samples by sport in 2015. Outliers (Z ≥ 2) are highlighted in red.

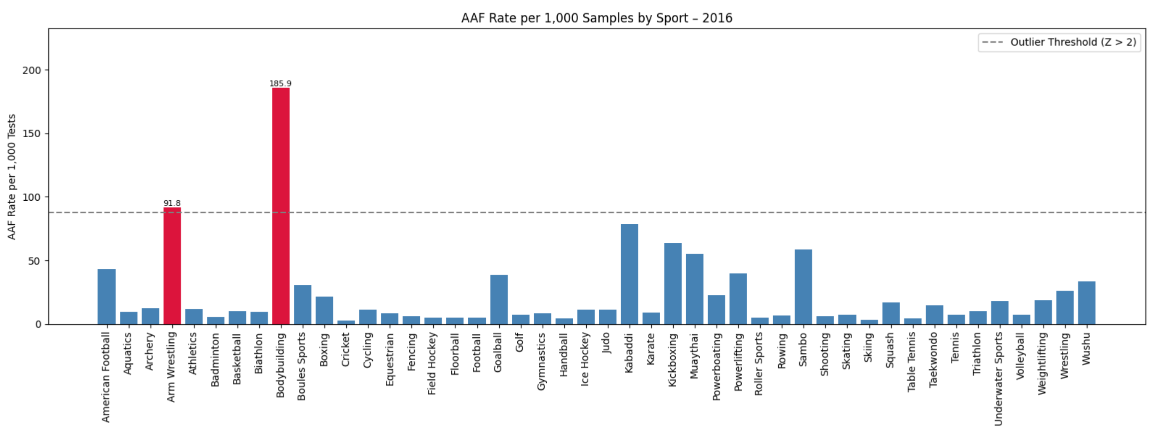

Figure 23: Sanctioned AAF rates per 1,000 samples by sport in 2016. Outliers (Z ≥ 2) are highlighted in red.

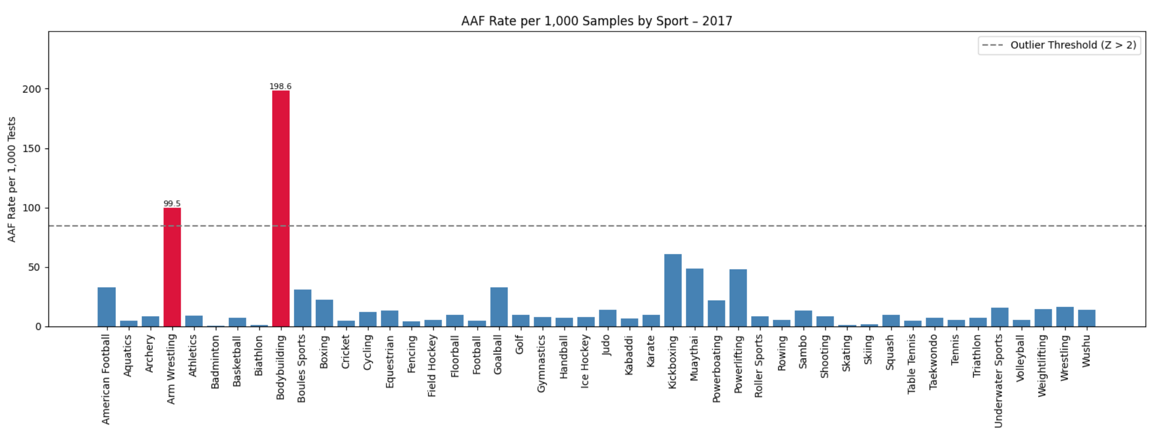

Figure 24: Sanctioned AAF rates per 1,000 samples by sport in 2017. Outliers (Z ≥ 2) are highlighted in red.

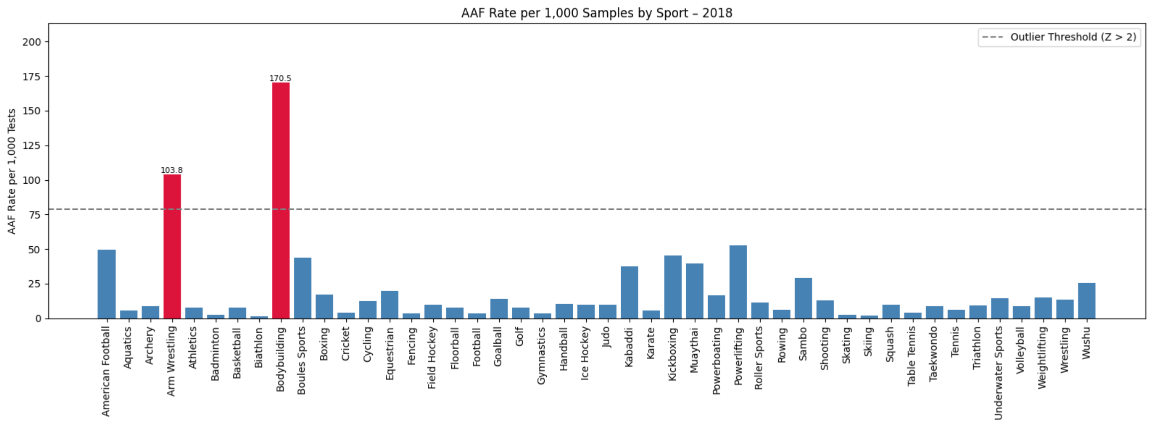

Figure 25: Sanctioned AAF rates per 1,000 samples by sport in 2018. Outliers (Z ≥ 2) are highlighted in red.

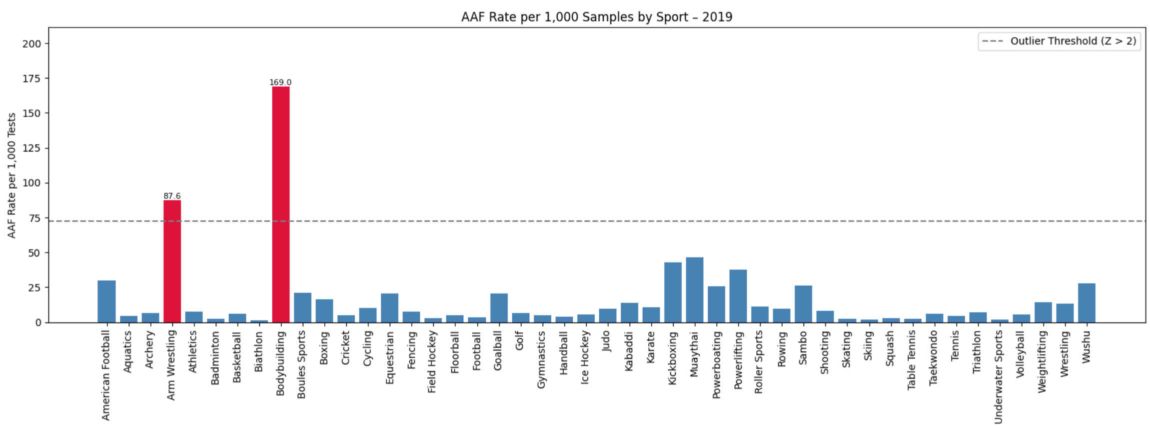

Figure 26: Sanctioned AAF rates per 1,000 samples by sport in 2019. Outliers (Z ≥ 2) are highlighted in red.

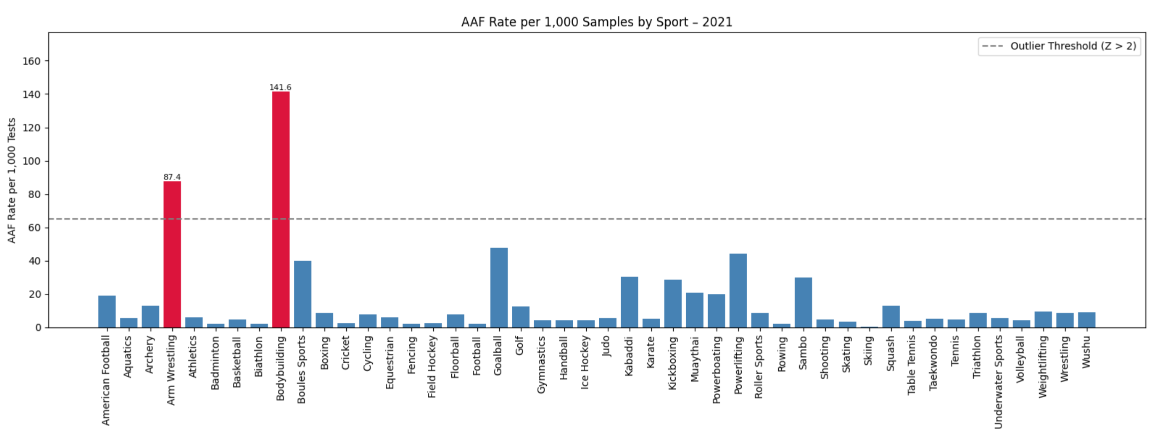

Figure 27:Sanctioned AAF rates per 1,000 samples by sport in 2021. Outliers (Z ≥ 2) are highlighted in red.

Total quantity AAFs per sport

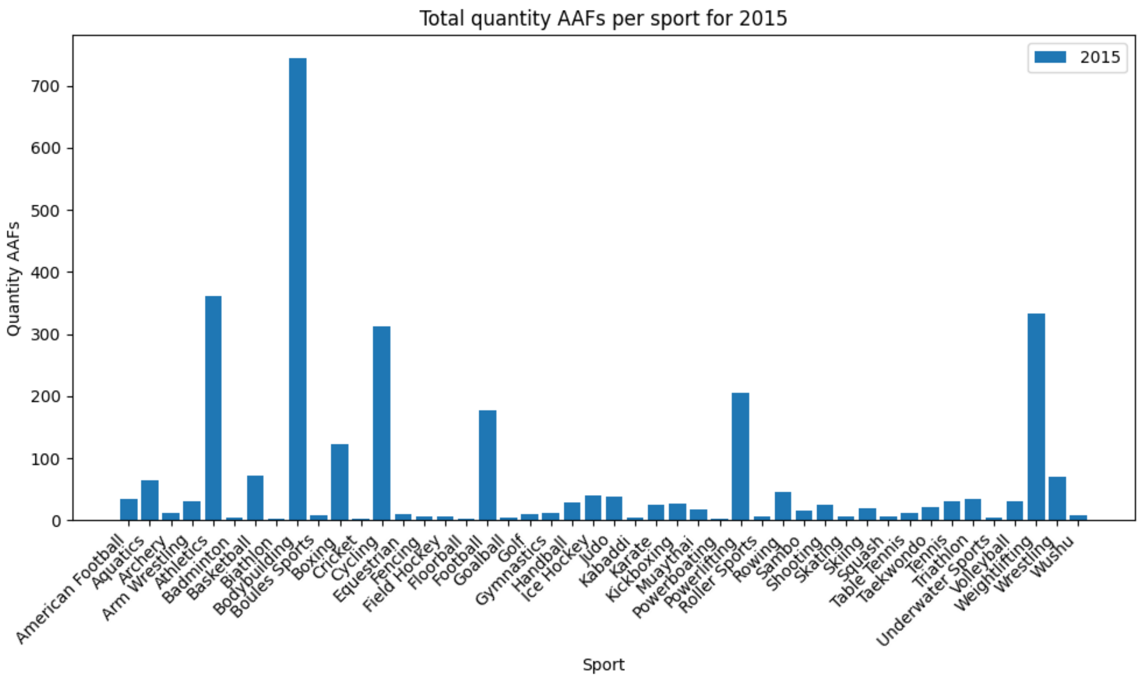

Figure 28: Total AAFs per sport in 2015 (regardless of sanction outcome), based on substance detection counts.

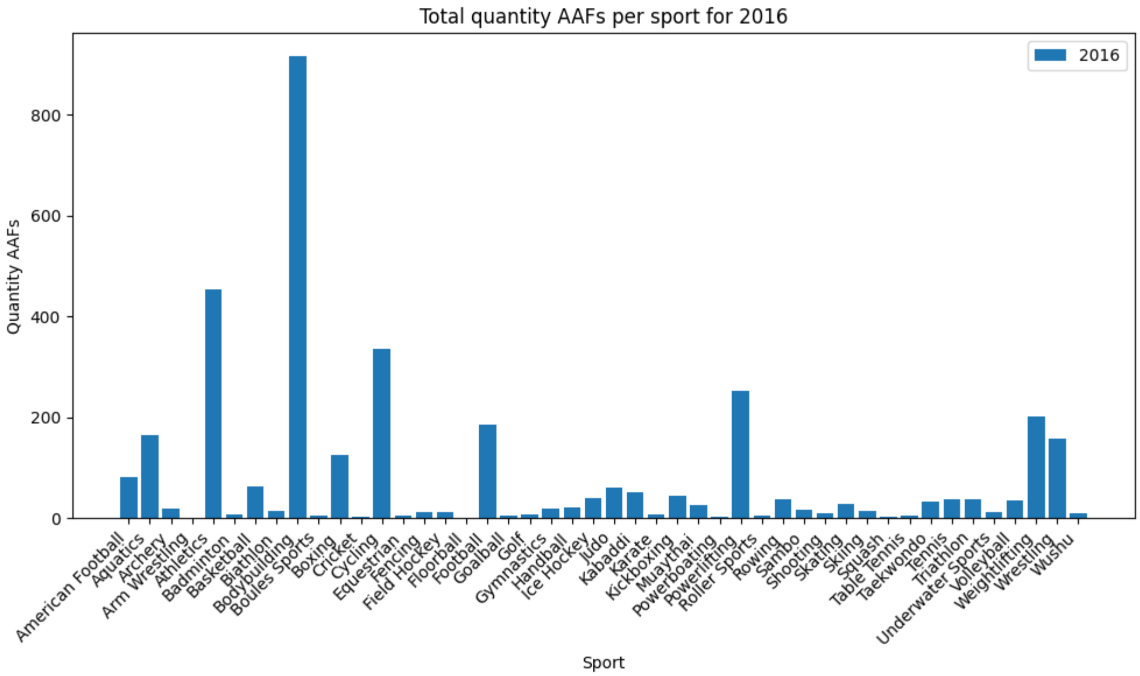

Figure 29: Total AAFs per sport in 2016 (regardless of sanction outcome), based on substance detection counts.

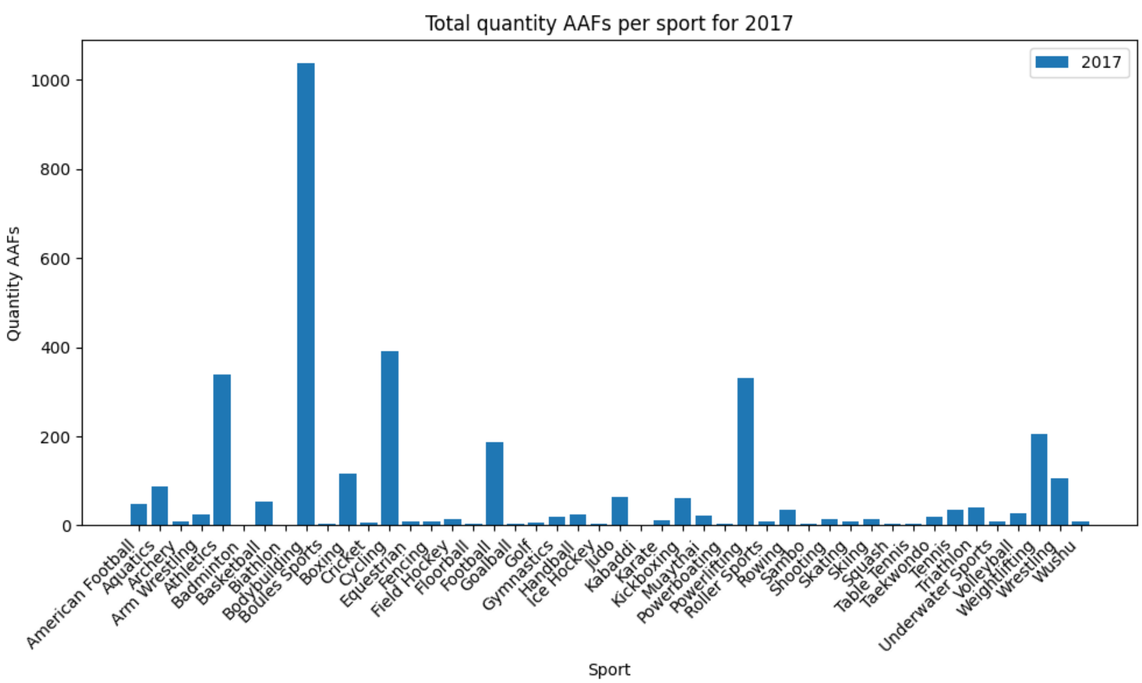

Figure 30: Total AAFs per sport in 2017 (regardless of sanction outcome), based on substance detection counts.

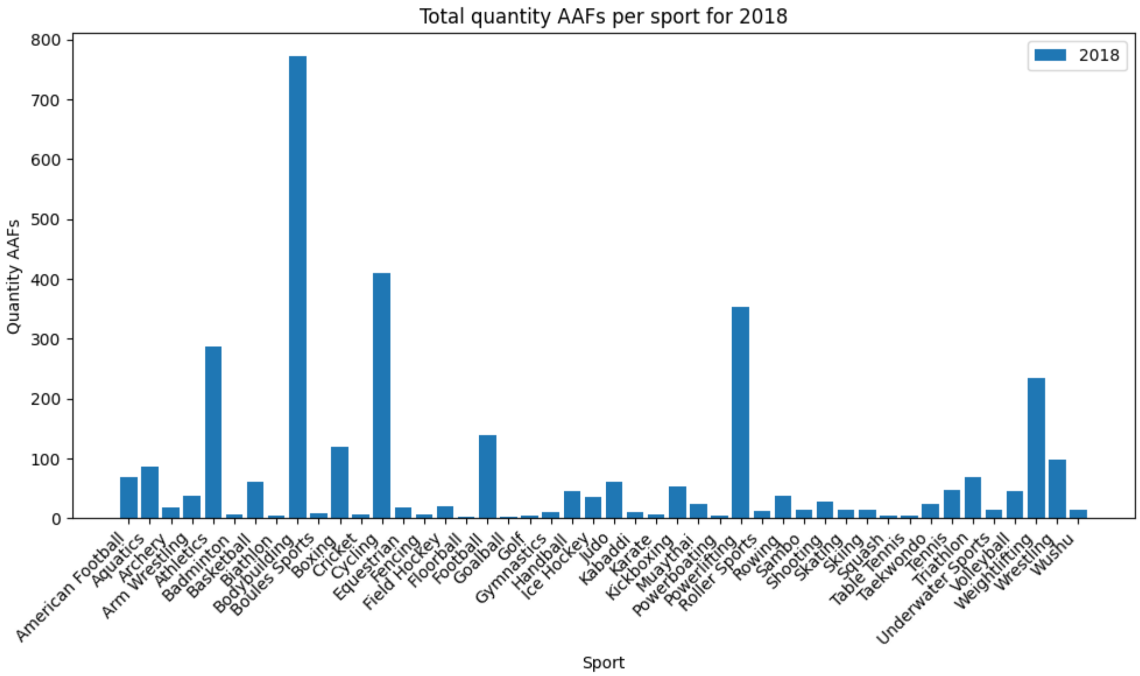

Figure 31: Total AAFs per sport in 2018 (regardless of sanction outcome), based on substance detection counts.

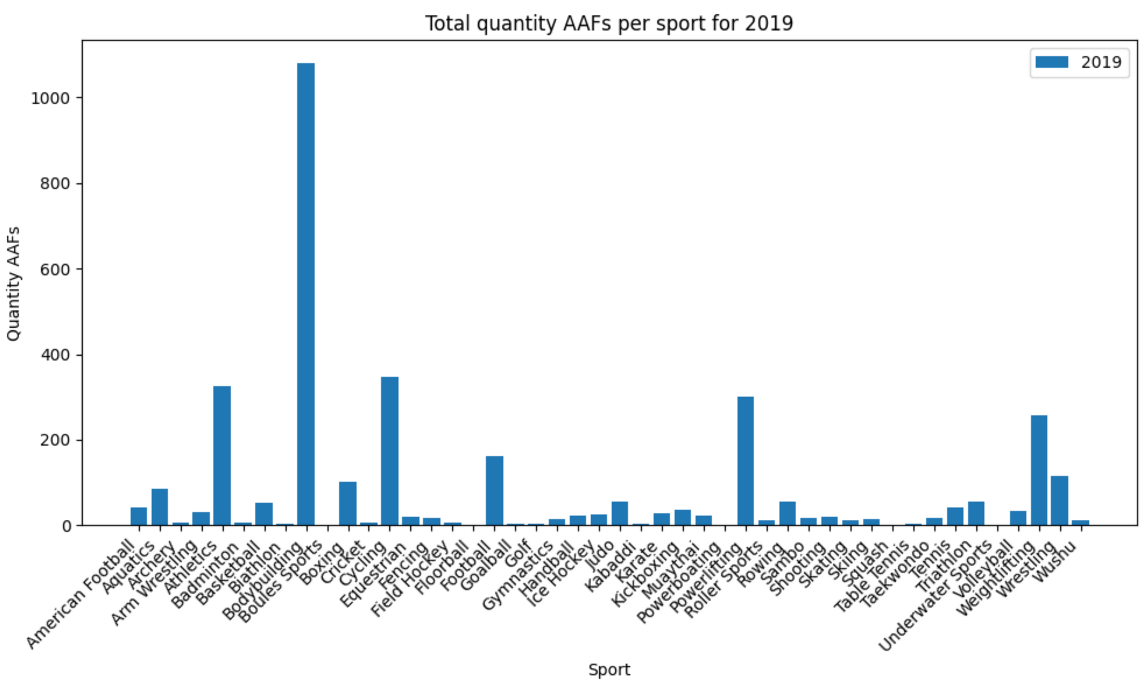

Figure 32: Total AAFs per sport in 2019 (regardless of sanction outcome), based on substance detection counts.

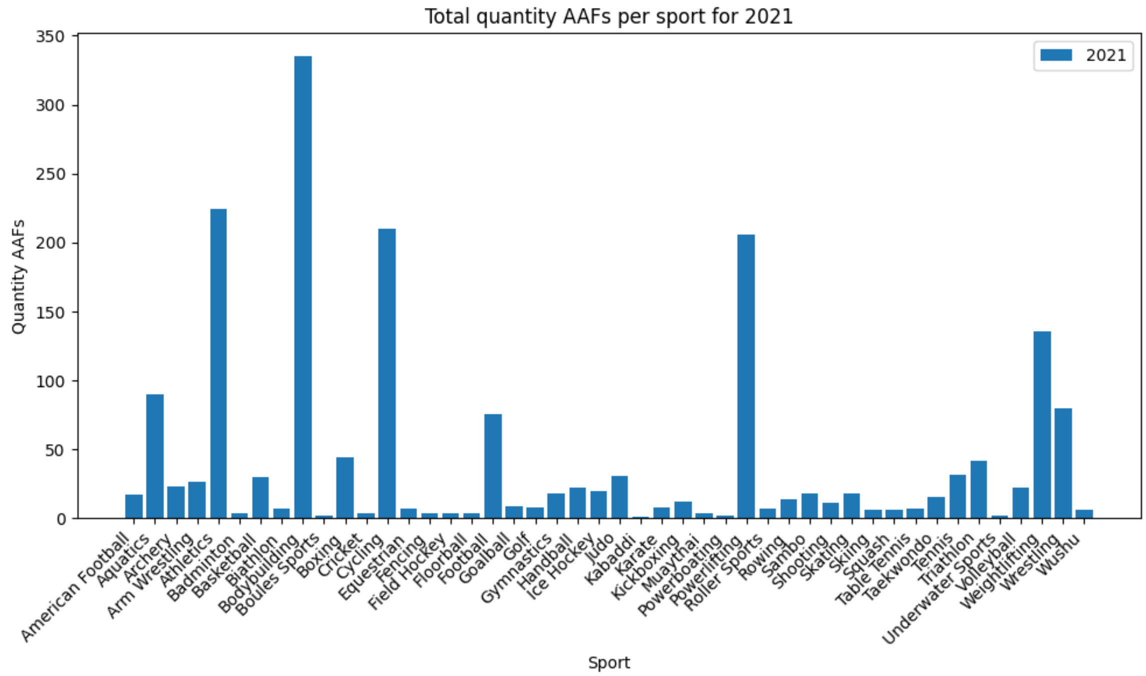

Figure 33: Total AAFs per sport in 2021 (regardless of sanction outcome), based on substance detection counts.

Heatmaps

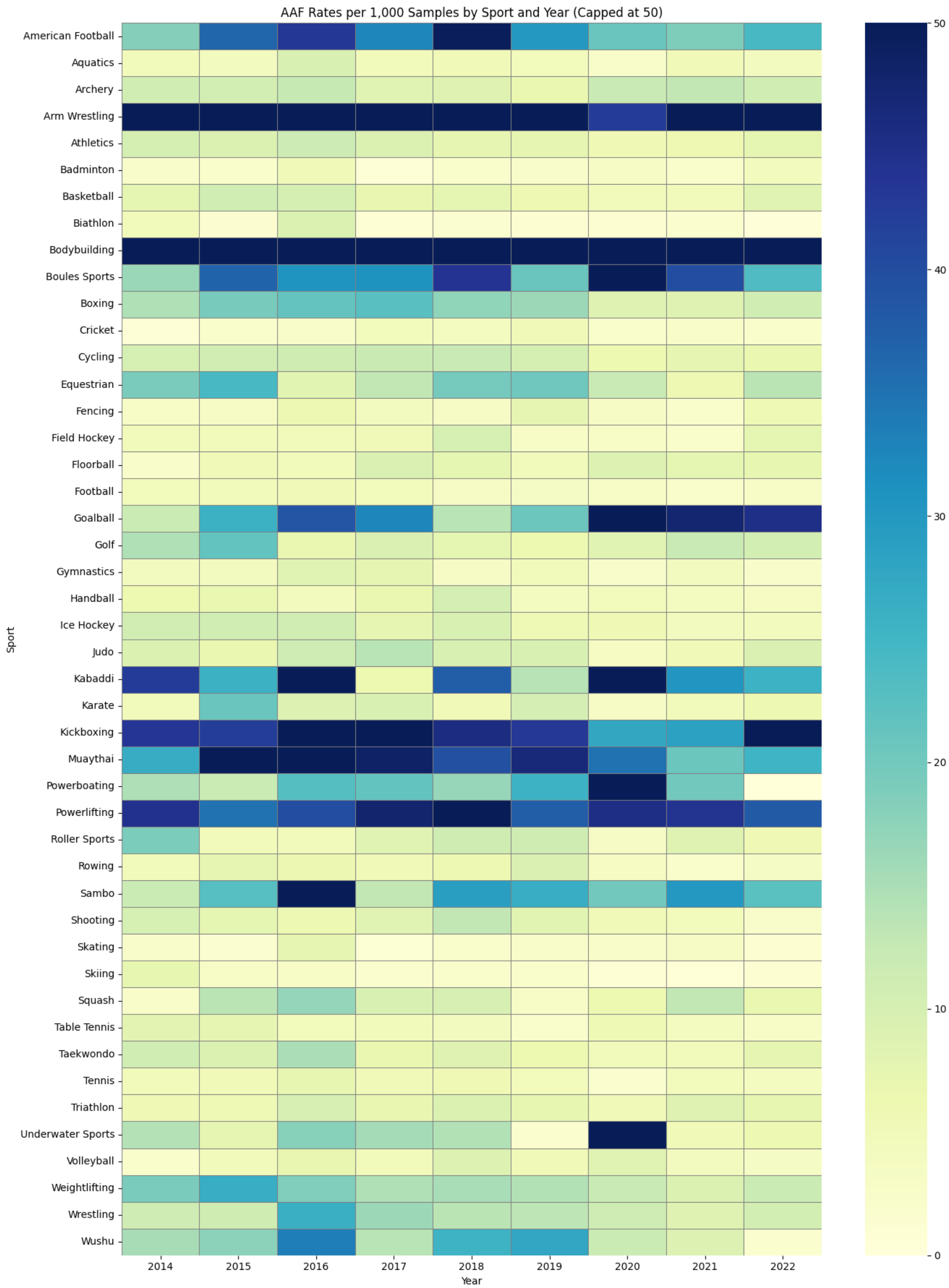

Figure 34: Raw AAF Rates per 1,000 Samples (Capped at 50)

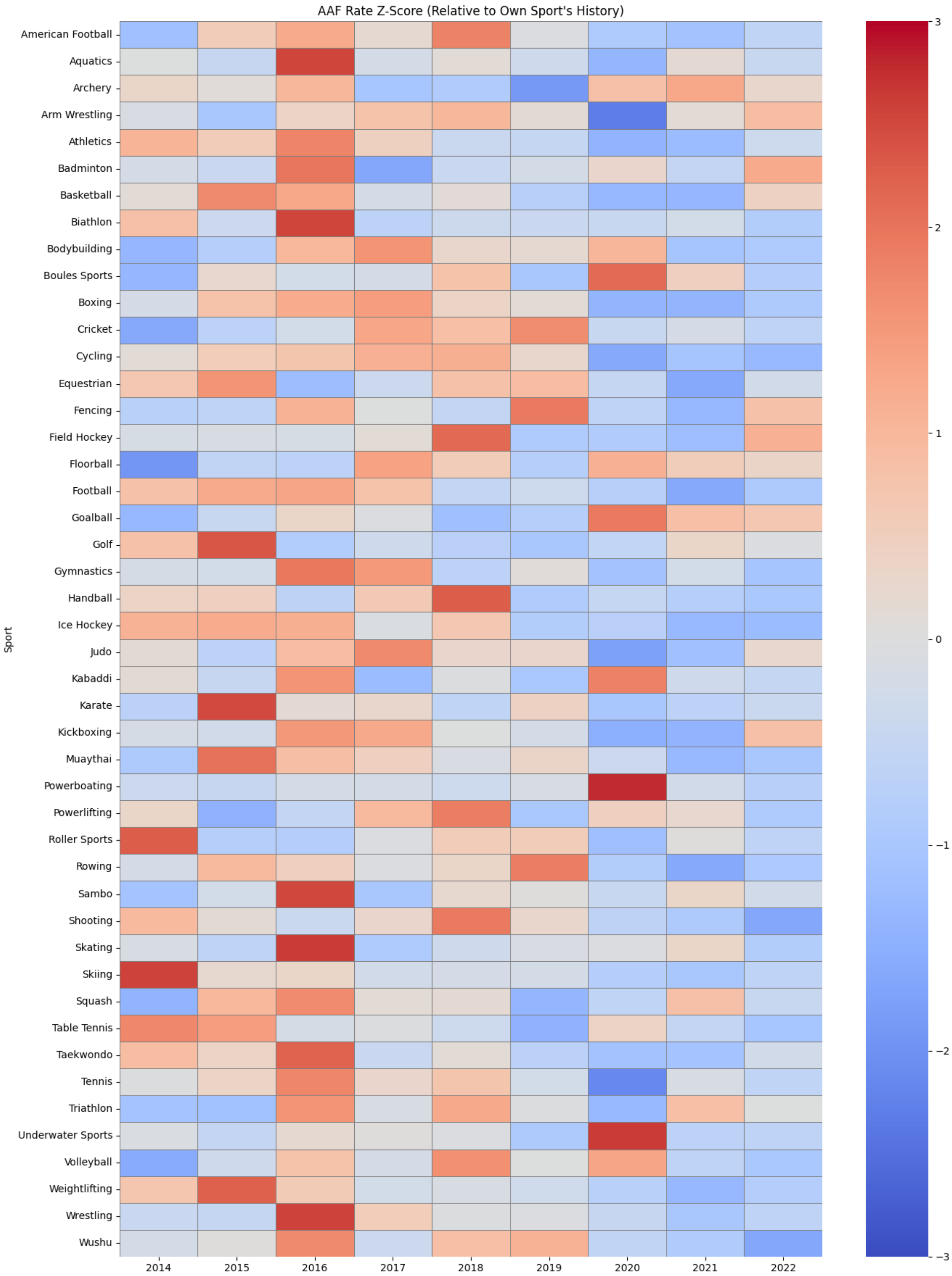

Figure 35: Z-Score of AAFs (Own history)

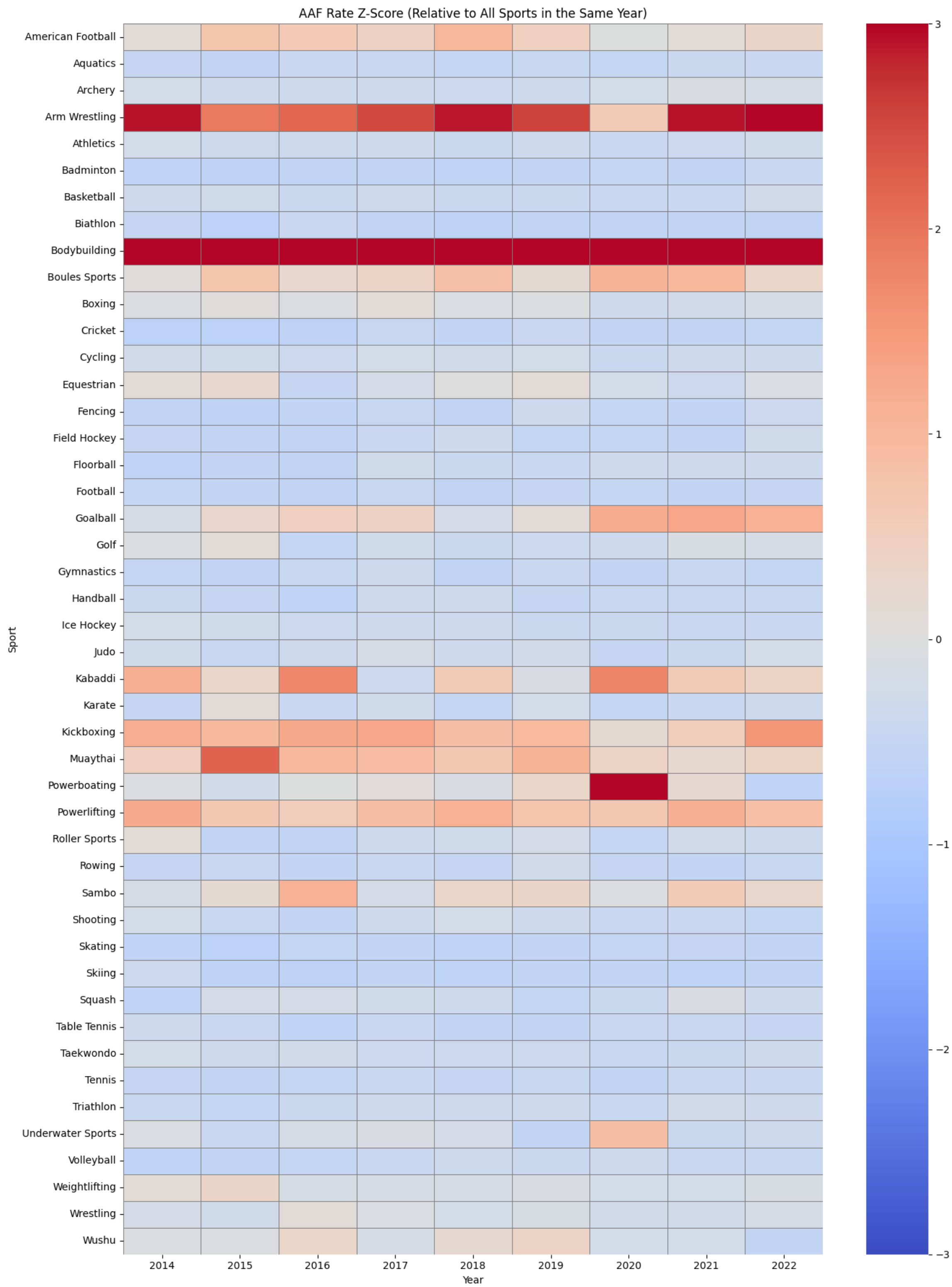

Figure 36: AAF Rate Z-Score (Relative to All Sports in the same Year)

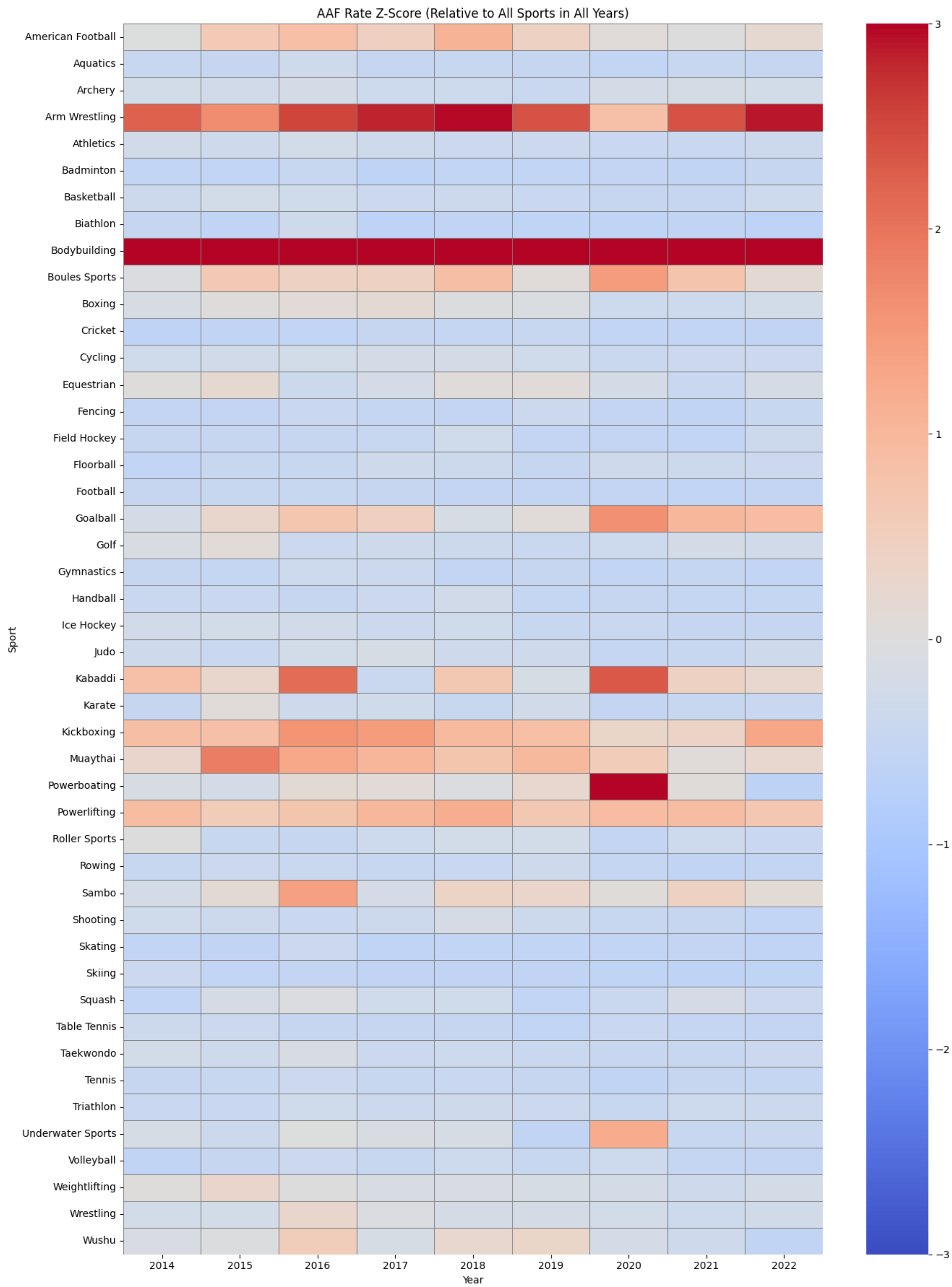

Figure 37: AAF Rate Z-Score (Relative to All Sports in All Years)

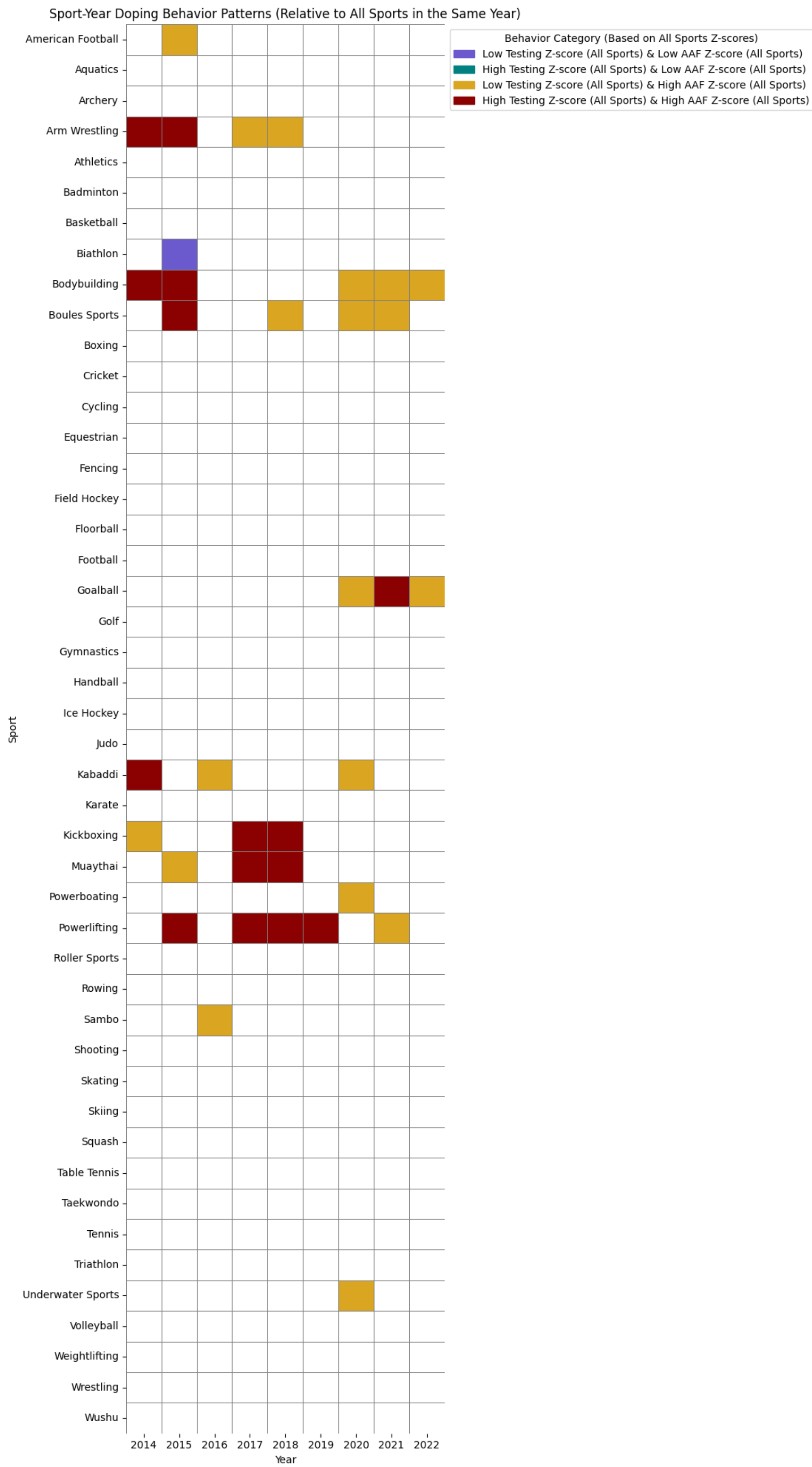

Figure 38: Sport-Year Doping Behavior Patterns (Relative to All Sports in the Same Year)

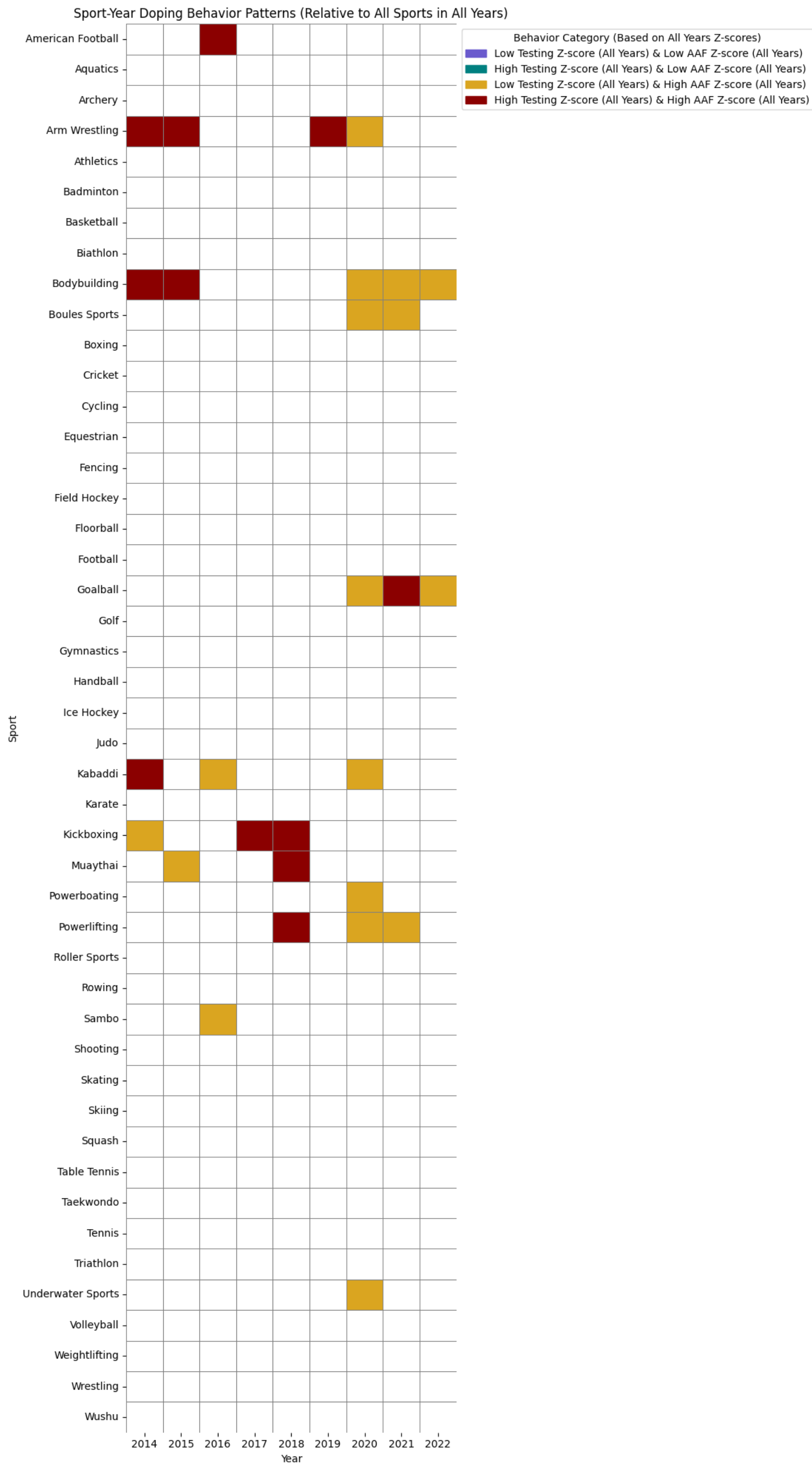

Figure 39: Sport-Year Doping Behavior Patterns (Relative to All Sports in All Years)