Formula 1 Driver Performance Index: Mining FastF1 Telemetry Through Principal Component Analysis

Katelyn Castillo, Christopher Nash Jasmin, Jhedson Angelo Petilo, Louie Sangalang

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Abstract
This study presents a novel data-driven methodology for evaluating Formula 1 driver performance through comprehensive telemetry analysis. We introduce the Driver Performance Index (DPI), a quantitative metric that decomposes driver capability into four fundamental components: consistency, style distinctiveness, technical execution, and raw pace. By processing high-dimensional telemetry data across qualifying and race conditions, our approach analyzes driver capabilities beyond traditional timing-based metrics. Analysis of current Formula 1 drivers demonstrates clear performance differentials, with Max Verstappen showing superior technical execution and pace across both session types. Notable findings include Oscar Piastri's distinctive driving style and strong technical components despite rookie status, and Lando Norris' improved race-day consistency compared to qualifying performance. Through Principal Component Analysis (PCA), we identify significant variations in driving style and technical approach, particularly evident in the McLaren intra-team comparison. This methodology addresses a fundamental challenge in F1's driver market: quantifying driver performance objectively while minimizing car performance and recency bias. Our findings suggest that comprehensive telemetry analysis can effectively distinguish driver capabilities from overall car performance, providing teams with a more nuanced understanding of driver potential.

Key words: Formula 1, Telemetry Analysis, Principal Component Analysis, Dimensionality Reduction, FastF1 API

1 Introduction

Formula 1 (F1) is the pinnacle of motorsport, featuring single-seater race cars capable of speeds exceeding 350 km/h and advanced engineering that pushes the boundaries of aerodynamics, materials science, and performance optimization. Governed by strict regulations, Formula 1 races, also called Grands Prix, are held on circuits worldwide and require teams to balance speed, reliability, and strategy. Each team fields two drivers competing for championship points across a series of races, with success often determined by fractions of a second.

When the cars are so close in performance, the skill of the driver becomes crucial. Specifically, drivers must choose the perfect path around the track (called the "racing line") that allows them to carry the most speed through corners while maintaining grip on the road. These split-second decisions by drivers often determine who wins and who loses, even when the cars have very similar capabilities.

Formula 1 has two championships running at the same time: one for individual drivers and one for teams (called constructors). This creates an interesting conflict - while drivers naturally want to win their own championship, they sometimes have to sacrifice their personal goals to help their teammate score points for the team championship. It's a constant balancing act between personal glory and team success.

1.1 2024 Season

The 2024 season started out as what seemed to be another Red Bull season given that Red Bull has dominated both the World Drivers' Championship and World Constructors' Championship. In 2022, Max Verstappen of Red Bull Racing won 15 out of 22 races, and in 2023 he surpassed this record by winning 19 out of 23 races [1]. The same story seemed to be playing out for this season, until McLaren turned up at the Miami Grand Prix with the fastest car thanks to their upgrades working well. Lando Norris' win in Miami at the beginning of May, followed by Charles Leclerc's win in Monaco three weeks later, marked the beginning of a very competitive and controversial season.

Teams sometimes favor one driver over another (called a "number one" driver), which is highly controversial in F1. This strategy means giving one driver better equipment, preferred race strategies, or even asking their teammate to move aside during races to help them win. When it became obvious that McLaren had the car to win both championships, fans of the sport expected Norris to be prioritized over his teammate Oscar Piastri. However, the team only officially announced Norris as their priority in September, a good four months of already having the fastest car [2].

Additionally, the three championship contenders (Verstappen, Norris, and Leclerc) have been compared to one another multiple times creating a lively debate between team principals, fans, and analysts alike on who is the better driver of the three. These comparisons are not new to the sport, or sports in general. While there is a way to quantitatively analyze driving style, race performance, consistency, etc. there are still other factors to consider. Telemetry data from cars can show precise differences in braking points, throttle application, and steering inputs through corners, and comparing this data across different teams becomes complex but still useful.

1.2 Driver Comparison

Comparing drivers within the team is a very complex task, what more comparing drivers across teams. It is not only a laborious task among fans, but it also causes heavy friction within teams when picking which driver to prioritize, and you do have to prioritize a driver in some instances. This season is a prime example of needing a quantitative way of comparing drivers, especially for McLaren who could have been a major contender in the drivers' championship had Norris been the clear number one driver from the beginning. Similarly, the driver market was very saturated this year with most teams changing their driver lineup and unable to decide which drivers to retain and which ones not to. Year on year, this is a problem for inter- and intra-team decisions: who are the best drivers on the grid?

As is common in sports, recency bias becomes a big factor in assessing driver performance even in F1 [3]. While fans, media, and even team bosses might focus heavily on the latest race results or memorable moments, telemetry data provides a more objective long-term view by tracking a driver's consistency in hitting braking points, managing tire wear, and optimizing corner exits across multiple races and seasons. This historical performance data helps cut through the noise of recent results and reveals patterns in a driver's technical abilities that might not be apparent to the naked eye. Analyzing telemetry data can help teams understand their own drivers better as well as how they stack up to other drivers on the grid.

2 Data Source

This analysis uses data from FastF1 API, which provides access to F1 lap timing, car telemetry and position, tyre data, weather data, the event schedule and session results [4]. Table 1 shows an overview of the available data from FastF1.

Data for each Formula 1 weekend is within the `Session` endpoint, which is divided into session types. A Formula 1 weekend generally has three free practice sessions, qualifying, and race. The data that was extracted for this analysis are only within qualifying and race sessions, and only for races in the 2024 season.

2.1 Laps

Once `Session` is instantiated, the `Laps` data for each session contains sector time, lap number, tyre freshness, number of laps done on tyre, and lap time. For the qualifying sessions, the following transformations were applied:

- Converted sector time to total seconds
- Added `LapEndDate` to extract accurate corresponding telemetry data
- Added `QualiSession` column to determine which qualifying session the lap was set (only fast laps are considered); drivers typically do a warm-up lap, fast lap, then cool down lap
- Added `LapRank` which is the driver's lap's rank at the time of setting it

Topic	Data	References
Event Schedule	event names, countries, locations, dates, scheduled starting times,...	events, get_event_schedule()
Results	driver names, team names, finishing and grid positions, points	SessionResults
Timing Data	sector times, lap times, pit stops, tyre data	laps, Laps
Track Status	flags, safety car	track_status
Session Status	started, finished, finalized	session_status
Race Control Messages	investigations, penalties	race_control_messages
Telemetry	speed, rpm, gear, position	Telemetry
Track Markers	corner numbers, sectors	get_circuit_info()

Table 1: Overview over the available data

- Added `DeltaFastestLap` which is the driver's lap's difference from the fastest lap at the time of setting it

For the race sessions, only the `LapEndDate` transformation was added. All laps are considered as there are no warm-up laps, fast laps, or cool down laps during the race.

2.2 Telemetry

Most of the information for the qualifying and race telemetry data is already given by the `get_car_data()` endpoint, and identifier columns such as `Round`, `Driver`, `LapNumber` was added to be able to merge with qualifying laps dataframe.

Each lap in F1 generates thousands of telemetry data points tracking driver performance in real-time, but the number varies depending on factors like lap length and car speed. To make fair comparisons across different drivers and laps, we standardized the data by converting each lap to exactly 300 data points, with 100 points for each sector of the track. This creates a consistent framework for analyzing driver performance regardless of when or where the data was collected.

3 Methodology

Our analysis focused on comparing the driving styles and performance characteristics of Formula 1 drivers using both telemetry data and results in Grand Prix weekends, specifically inter- (Verstappen, Norris, and Leclerc) and intra-team (Norris and Piastri) comparisons. The methodology employs multiple analytical approaches including preprocessing of raw telemetry data, distance matrix calculations, speed profile analysis, and Principal Component Analysis (PCA) to provide a comprehensive understanding of driving patterns.

As mentioned in the problem statement, the main point of contention is (1) comparing drivers across teams to determine their market value and what they can bring to the team and (2) determining the prioritization of drivers within the team. Our analysis framework addresses these challenges by using telemetry data to quantitatively assess driver performance beyond traditional metrics like race results and championship points. By analyzing detailed driving patterns through PCA and speed profiles, teams can better understand a driver's technical capabilities, consistency, and adaptability - crucial factors in both internal team dynamics and driver market valuations. This data-driven approach helps cut through subjective assessments and media narratives, providing teams with concrete evidence to make strategic decisions about driver lineups and resource allocation. While raw talent and race results remain important, understanding a driver's technical approach through telemetry analysis offers teams a more complete picture of their potential value and fit within the team's structure.

The analysis will be split between comparing the top three contenders in the 2024 World Drivers' Championship, namely Max Verstappen (Red Bull Racing), Lando Norris (McLaren), and Charles Leclerc (Ferrari), and their performances in qualifying and races. This will supposedly help teams decide on driver valuation. Conversely, the second part of the analysis will focus on comparing drivers from the same team, namely Lando Norris and Oscar Piastri from McLaren, to help identify driver prioritization quantitatively.

3.1 Telemetry Analyzer

Raw telemetry data was standardized to ensure consistent comparison across different laps and drivers. Each lap was resampled to exactly 300 data points, with 100 points per sector, regardless of the original number of measurements. Key telemetry features analyzed included RPM, Speed, Gear, Throttle, Brake, and Drag Reduction System (DRS) usage. The preprocessing pipeline involved:

- Filtering data by specific rounds and drivers
- Normalizing lap times to a 0-1 scale
- Calculating basic metrics per lap (duration, maximum speed, average speed, brake applications, DRS zones)

3.1.1 Distance Matrix

To quantify similarities between driving styles, we computed Euclidean distance matrices between average lap profiles for each driver. The process involved:

- Creating average telemetry profiles for each driver
- Computing pairwise distances between these profiles
- Generating separate matrices for each round and an aggregate matrix across all rounds, allowing us to measure how closely different drivers' approaches matched across various track conditions

3.1.2 Speed Profile

Speed profiles were analyzed to understand each driver's approach to different sections of the track. The analysis included:

- Plotting mean speed profiles with standard deviation bands
- Normalizing lap distances to allow direct comparison
- Generating separate visualizations for each round to track evolution of driving styles, allowing to identify where drivers gained or lost time relative to each other

3.1.3 Principal Component Analysis (PCA)

PCA was employed to reduce the dimensionality of the telemetry data while preserving the most important patterns in driving style and find underlying patterns in driving techniques that might not be apparent from raw telemetry data alone. The approach included:

- Standardizing the feature set using `StandardScaler`
- Determining optimal number of components using a variance threshold of 95
- Visualizing driver clusters in PCA space with confidence intervals
- Calculating centroids and spreads to quantify driving style consistency

3.2 Driver Performance Index

The F1 Driver Performance Index is a comprehensive metric that evaluates driver performance by combining telemetry data, lap metrics, and driving style analysis. The index is calculated using four main components:

1. Consistency **measures** the driver's ability to maintain consistent performance across laps and sectors.
2. Driving Style **evaluates** the uniqueness and consistency of a driver's approach using PCA-based analysis.
3. Technical Execution **assesses** the driver's technical proficiency through telemetry data analysis.
4. Pace Performance **evaluates** overall speed and race/qualifying performance.

Table 2 presents the comprehensive framework of the Formula 1 Driver Performance Index, which combines multiple performance metrics into a single, weighted score. The index is composed of four equally-weighted components (25% each). Each component utilizes specific metrics derived from various data sources, including timing data, telemetry, race control information, and race results. The Consistency component analyzes lap time variations and sector performance, while the Driving Style component employs Principal Component Analysis (PCA) to evaluate driving characteristics. Technical Execution incorporates multiple telemetry-based metrics such as throttle control and DRS usage, and the Pace component considers both relative speed and race position. All metrics are normalized using scaling techniques before being combined into their respective component scores. The final performance index is calculated as a weighted sum of these four components, providing a balanced assessment of a driver's overall performance.

All telemetry data is normalized prior to analysis, with

Component (25%)	Metrics	Calculation
Consistency	- Lap time standard deviation - Sector time consistency	1-mean(scaled_metrics) from Timing Data
Driving Style	- Style distinctiveness (PCA) - Style consistency	mean(scaled_distinct, scaled_consistency) from Telemetry
Technical Execution	- Throttle control - Brake efficiency - Gear changes - DRS usage	mean(scaled_metrics) from Telemetry and Race Control
Pace	- Relative pace - Grid/Race position	1-mean(scaled_metrics) from Results and Timing Data
Final Index = $\sum$(Component Score $\times$ 0.25)		

Table 2: Formula 1 Driver Performance Index Components

session-specific transformations for races vs. qualifying. MinMaxScaler is used throughout to ensure all metrics are on a comparable scale.

For now, equal weighting (25%) for all components is applied, but can be adjusted according to which parameter is more essential to the analyst. Results are relative to the specific session and driver group being analyzed as performance is normalized within the analyzed group, not against historical data.

4 Results

The analysis examines the relationship between drivers' qualifying performance and race outcomes across multiple seasons. By tracking metrics such as qualifying position, pole positions, and win-to-pole conversion rates, we can evaluate how effectively drivers translate their single-lap pace into race results. This data provides insights into which drivers consistently maximize their grid position on race day versus those who may excel in qualifying but struggle to maintain that advantage. The comparison between qualifying and race performance helps identify drivers who demonstrate complete race craft versus those who may be qualifying specialists.

Additionally, the analysis of telemetry data from multiple qualifying sessions reveals distinct patterns in driving styles when comparing inter- and intra-team drivers. By examining speed profiles, braking points, and throttle application across different tracks, we can quantify the technical differences that contribute to their performance. The PCA results show clear clustering in driving approaches, suggesting that each driver has a consistent and unique technical signature despite varying track conditions. Our distance matrix calculations further support these findings by measuring the similarity between drivers' approaches across different circuits. The following sections break down these results in detail, providing insights into both individual driver characteristics and comparative performance patterns that could influence team decisions and driver valuations.

4.1 Grand Prix Results Comparison

4.1.1 Qualifying Performance

Figure 1 shows the inter-team comparison between VER, NOR, and LEC, there are notable differences in their performance patterns. Verstappen (VER) shows remarkable Saturday performance with approximately 9 pole positions, despite having a better average qualifying position around 2.8. Leclerc (LEC) demonstrates a different pattern, maintaining a strong average qualifying position around 5th but securing fewer poles at about 2. Norris (NOR) shows impressive consistency with around 7 pole positions and an average qualifying position of about 3.5. Since this is on average, however, it does not completely show how most of these pole positions came after McLaren's Miami upgrade.

Looking at the McLaren teammates, the contrast between Norris and Piastri (PIA) is notable. While Piastri maintains a competitive average qualifying position around 5.5, he hasn't secured any pole positions according to the data. This suggests that while Piastri consistently performs well in qualifying sessions, Norris has been more successful in achieving the ultimate Saturday result of pole position.

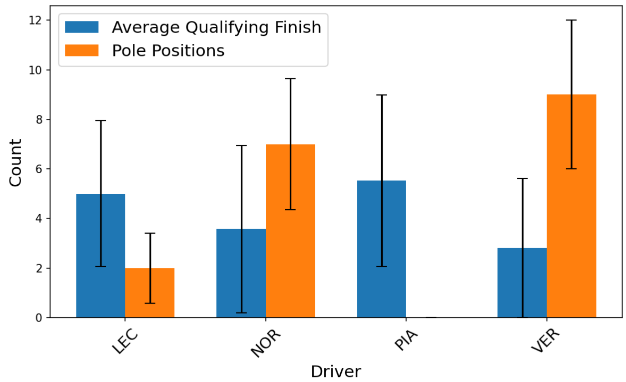

Figure 1: Qualifying Comparison

4.1.2 Qualifying vs Race Performance

Figure 2 shows the inter-team comparison between VER, NOR, and LEC, Verstappen shows the strongest qualifying performance with an average starting position around P2.8, yet his average finishing position is slightly lower at P3.6. Leclerc displays a different pattern, qualifying around P5 and finishing in similar positions around P4.8. Norris demonstrates good consistency, with both his average starting and finishing positions hovering around P3.5-4.0. Between Leclerc, Verstappen, and Norris, only Leclerc gains positions during a race albeit minimal; Verstappen and Norris typically lose positions during the race. This could be attributed to the Ferrari car's amazing race pace, though McLaren did have the better car for most of the season.

In the McLaren intra-team battle, there's a noticeable gap between Norris and Piastri. While Piastri qualifies on average around P5.5 and finishes around P4.9, Norris generally outperforms him in qualifying with an average of P3.6. However, interestingly, their race finishing positions are relatively close, suggesting that Piastri shows good race pace despite qualifying lower than his teammate. Piastri typically gains a position during a race, while Norris loses positions. This could indicate Piastri has better race pace than Norris.

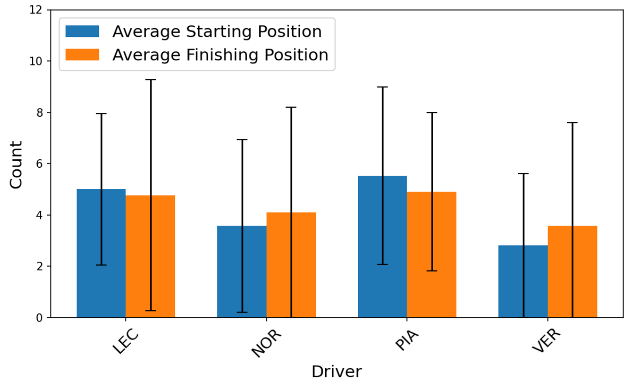

Figure 2: Qualifying vs Race Performance

4.1.3 *Pole Conversion*

Verstappen demonstrates strong overall performance with 9 poles and 8 wins, converting 5 of his pole positions into victories (55.56% conversion rate). This shows that while he's excellent at securing pole positions, he doesn't always maintain the lead from pole to finish.

Norris has secured 7 pole positions but only converted 2 of them into wins (28.57% conversion rate), with 3 wins total. This suggests that while he has strong qualifying pace, he faces more challenges maintaining position during races. Most of Norris' pole positions was never kept after the first lap as well, indicating issues in his launch starts.

Leclerc shows an interesting pattern with just 2 poles but 3 wins total, converting 1 of his poles into victory (50% conversion rate). This indicates that while he has fewer pole positions, he's been able to win races from other starting positions and converts his poles efficiently when he gets them.

Driver	Poles	Wins	Poles Converted	Conversion Rate (%)
VER	9.0	8	5.0	55.56
NOR	7.0	3	2.0	28.57
LEC	2.0	3	1.0	50.00

Table 3: Driver Pole Conversion

4.2 Telemetry Analysis Results

4.2.1 *Speed Profiles*

The qualifying speed profile analysis reveals intriguing patterns among four top drivers. The data, first visualized through a distance matrix heatmap, offers insights into the evolving dynamics of modern F1 qualifying sessions.

In Figure 3, the distance metrics between these three team leaders reveal distinct qualifying approaches. Verstappen and Norris show relatively close profiles (280.46), while both maintain larger distances to Leclerc (284.96 and 294.96 respectively). This suggests Ferrari's qualifying strategy under Leclerc differs significantly from both Red Bull and McLaren's approaches.

McLaren's teammates display an interesting dynamic with a distance of 264.96. Notably, Piastri's profile is closer to Verstappen's (257.61) than to his teammate Norris's. This indicates McLaren allows its drivers to develop distinct qualifying styles, with Piastri adopting an approach more similar to the current champion's aggressive style while Norris maintains his own established technique.

Overall, Piastri emerges as a particularly fascinating case study. The McLaren driver's speed profile shows remarkable adaptability, maintaining similar distances to all other drivers (ranging from 257 to 265). This consistency suggests Piastri has developed a versatile qualifying approach that incorporates elements from different driving styles, impressive for a relative newcomer to the sport.

The overall range of distances (257-295) demonstrates that while these drivers employ distinct qualifying strategies, they all remain competitive at the highest level, each finding their own path to optimal lap times. This balanced distribution of driving styles reflects the current state of F1, where multiple approaches to qualifying can yield success.

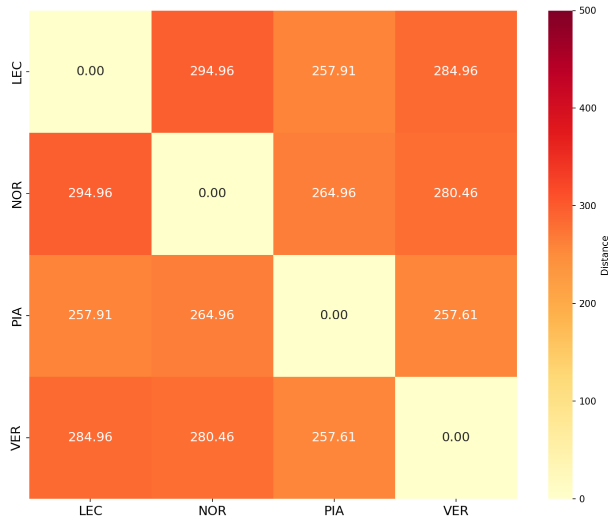

Figure 3: Average Qualifying Speed Distance Matrix

The heatmap in Figure 4 shows the race pace distance matrix between the same four drivers, revealing significantly different patterns from their qualifying profiles. The values are notably lower (78-120 range vs 257-295 in qualifying), suggesting race pace patterns are generally more similar across drivers. This makes sense as race conditions favor consistency and tire management over raw speed.

Verstappen shows the largest differences to both Leclerc (119.88) and Norris (94.53), suggesting his race pace management is quite distinct from Leclerc and Norris. Leclerc and Norris have relatively similar race patterns (86.47). Verstappen's consistently larger distances to others likely reflect his skill to bring the car to the front.

The McLaren teammates show the closest match in race pace (78.44) among all driver pairs. This is a stark contrast to their qualifying differences, suggesting McLaren has a clear race strategy that both drivers execute similarly. The similarity between teammates likely reflects McLaren's effective race strategy standardization and both drivers' strong race pace management

This race pace data provides an interesting contrast to qualifying, showing how driving styles converge more during actual race conditions, particularly within the same team.

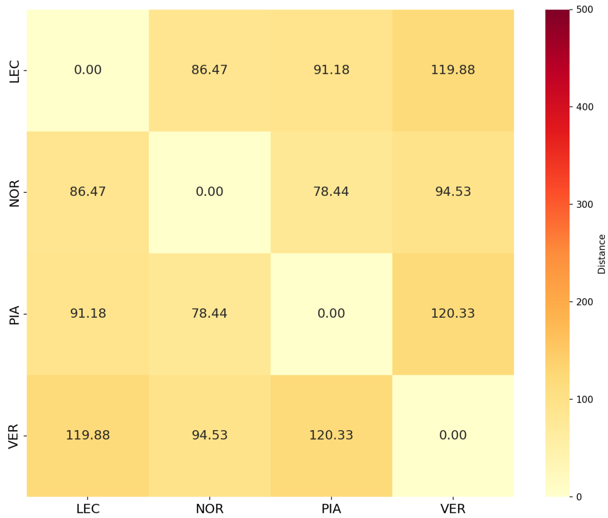

Figure 4: Average Race Speed Distance Matrix

4.2.2 PCA for Qualifying Sessions

Principal Component Analysis (PCA) transforms complex Formula 1 telemetry data into interpretable patterns. While F1 cars generate thousands of data points per lap across multiple channels (throttle, brakes, steering, speed, etc.), PCA reduces these variables into principal components that capture key variations in driving styles.

The first two components (PC1 and PC2) represent the most significant patterns in the data, with each component being a weighted combination of original variables. This transformation allows visualization of driving patterns, comparison between drivers, and analysis of qualifying versus race approaches, while preserving the most meaningful differences in driving techniques. The resulting visualizations transform detailed telemetry traces into more interpretable patterns, where each point represents a moment in time during a lap, and its position reflects how the various telemetry channels interact. This allows us to identify distinct driving styles, compare approaches between drivers, and analyze how these patterns shift between qualifying and race conditions. The percentage of variance explained by each principal component indicates how much of the original information is captured in these simplified representations, while maintaining the most meaningful differences in driving techniques.

The qualifying data reveals more diverse driving patterns, reflected in the higher variance percentages (14% for PC1, 9.7% for PC2) in Figure 5. During qualifying sessions, drivers demonstrate greater experimentation with their approaches, resulting in more dispersed data points across the PCA space. The plot shows multiple distinct clusters and a wider spread of points, suggesting that drivers are pushing different strategies and limits to find the fastest single lap. Notable clusters appear at various points including (-20, -20), (5, -20), and (5, -0), indicating common qualifying approaches or track sections where similar techniques are employed. The presence of clear voids in the extreme corners of the plot suggests certain combinations of driving characteristics are avoided during qualifying attempts, likely due to their inefficiency or risk level.

From an inter-team perspective, Verstappen, Norris, and Leclerc show distinct clustering patterns. Verstappen's data points are more widely dispersed across both PC1 and PC2, suggesting more adaptable driving approaches across different race conditions. Leclerc shows tighter clustering in certain regions, particularly in the positive PC2 direction, indicating a more consistent but potentially aggressive driving style. Norris's distribution falls somewhere between, showing moderate spread but with clear preferred regions in the plot.

Between the two McLaren drivers, there's a notable overlap in their distributions, suggesting similar driving styles as expected from teammates. However, Piastri shows a wider spread along both principal components, particularly visible in the clusters around PC1 values of 0-10. This could indicate less consistency or more experimentation with different driving approaches compared to Norris. A funnel pattern is visible where Piastri's points become more dispersed at higher PC1 values, suggesting increasing variability in driving style as overall performance improves.

There are noticeable voids in the center of the plot around (0,0), indicating that neutral driving styles are rare - drivers tend to commit to either more aggressive or conservative approaches during races.

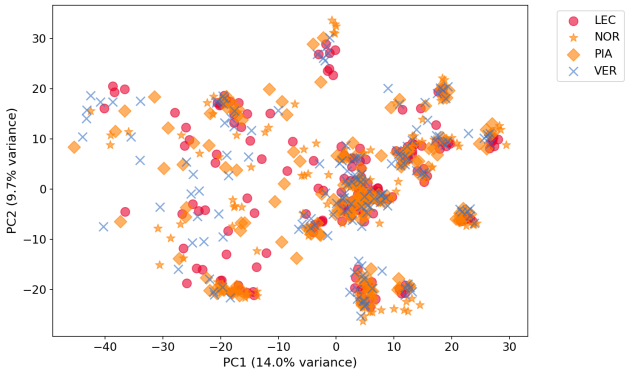

Figure 5: [Quali] Driver Performance Distribution

Looking more closely at Figure 6, an interesting asymmetry emerges in the error bars. While all drivers show similar variance along PC2 (vertical bars), there are notable differences in PC1 (horizontal bars). Verstappen shows the widest range along PC1, suggesting greater adaptability or inconsistency in overall race performance. Leclerc and Norris display more contained horizontal ranges, indicating more predictable performance patterns. Piastri's ranges closely mirror Norris', but with slightly larger error bars in both dimensions, which aligns with what we'd expect from a less experienced teammate. The centroids (intersection points) of all drivers cluster near the origin, suggesting that despite their different ranges, their average performances converge to similar baseline characteristics.

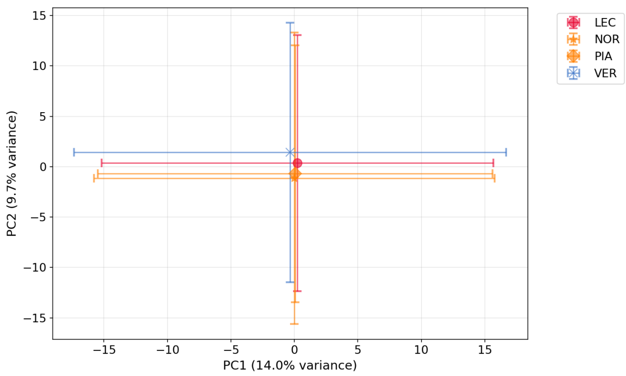

Figure 6: [Quali] Performance Variance Range

4.2.3 PCA for Race Sessions

Analyzing this race performance data reveals distinctly different patterns from qualifying. In Figure 7, PC1 (9.8% variance) likely represents race pace consistency, while PC2 (8.7% variance) could indicate overtaking or defensive performance characteristics.

Again, the top three championship contenders of Verstappen, Norris, and Leclerc show much more overlapping performance distributions during races compared to qualifying. This suggests that race conditions tend to equalize driver performances more than the raw speed shown in qualifying. Verstappen's points show a particularly dense concentration in the central region, indicating consistent race performance. Leclerc's wider vertical spread along PC2 hints at more variable race strategies or perhaps more aggressive overtaking attempts, while NOR shows a balanced distribution suggesting adaptable race craft.

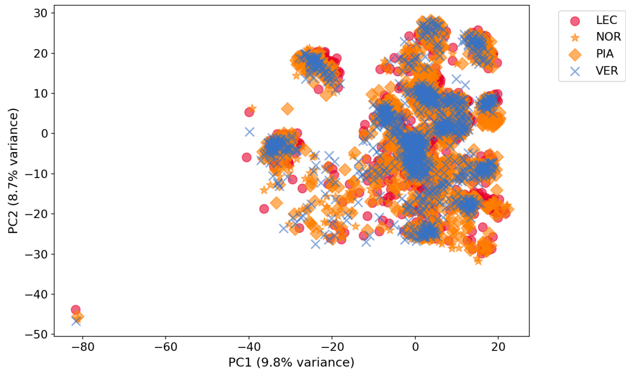

Figure 7: [Race] Driver Performance Distribution

The intra-team comparison between Norris and Piastri is particularly revealing for race conditions. Their significant overlap suggests similar race pace, but Piastri's broader spread into extreme PC2 values might indicate more variable risk-taking in wheel-to-wheel situations or tyre management.

Figure 8 shows remarkably uniform horizontal spreads, suggesting that over a race distance, all drivers operate within similar performance boundaries. This contrasts with qualifying's larger variations, as race conditions, fuel loads, and tire management naturally constrain performance extremes. The slightly larger vertical variance for Leclerc could indicate more strategic variability or perhaps more frequent involvement in battles for position during races.

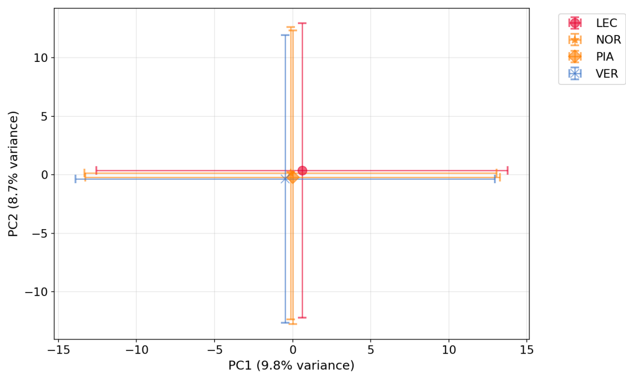

Figure 8: [Race] Performance Variance Range

The primary difference between qualifying and race sessions lies in the dispersion patterns. Qualifying data shows more experimental approaches and distinct clusters, reflecting the drivers' attempts to find the absolute limit for a single lap. In qualifying, the data showed wider individual variance (14.0% vs 9.8% in PC1), suggesting that raw speed differences between drivers are more pronounced in qualifying's single-lap format. This makes sense as qualifying is about pure speed without the complexities of race management, allowing unique driving styles to shine through more clearly.

In contrast, race data demonstrates more conservative, consistent patterns focused on long-run performance. Race data shows more clustered distributions around the center, indicating how factors like tire management, fuel loads, and traffic tend to normalize performance differences. The reduced variance percentages in both PCs (9.8% and 8.7% vs 14.0% and 9.7%) reflect this convergence of performance in race conditions. Ultimately, the qualifying sessions allow for more diverse driving styles (higher variance percentages), while race conditions appear to compress these differences into more uniform patterns (lower variance percentages).

Verstappen's data is particularly telling - while showing broad adaptability in qualifying, his race performance clusters more densely in the central region, suggesting superior race-craft in converting raw speed into consistent race pace. Leclerc's distribution shows the opposite pattern - more concentrated in qualifying but wider spread in races, possibly indicating stronger single-lap speed but more variable race performance due to aggressive strategies or tire management.

The intra-team comparison between Norris and Piastri shows smaller gaps in race conditions compared to qualifying, suggesting that race experience helps narrow the performance gap between teammates. The shared outlier points in races (-80 PC1) that weren't present in qualifying data indicate how external race factors can impact both drivers similarly, something that rarely happens in qualifying.

This analysis suggests that while drivers maintain their individual characteristics, the demands of racing versus qualifying create distinctly different patterns in their driving behaviors, with racing generally promoting more convergent driving styles among competitors.

4.3 2024 Driver Performance Index (DPI)

The qualifying performance breakdown reveals fascinating insights into both inter-team and intra-team dynamics as shown in Figure 9. Among the top contenders, Verstappen demonstrates superior overall performance, leading with exceptional consistency and technical execution that translates into dominant pace. Leclerc occupies a solid middle ground, balancing strong consistency with technical proficiency, though lacking Verstappen's outright pace advantage.

Within the McLaren garage, an interesting story unfolds. Piastri emerges ahead of his more experienced teammate Norris, showcasing impressive technical execution and pace. While Norris displays the most distinctive driving style among all drivers, as evidenced by his prominent style component, Piastri's more conventional approach appears to be yielding better overall results. This intra-team comparison is particularly noteworthy given Piastri's rookie status.

The overall performance hierarchy places Verstappen at the top, followed by Piastri, then Leclerc, with Norris rounding out the group. This ordering suggests that while raw experience plays a role, as seen in Verstappen's dominance, adaptability and technical execution can allow newer drivers like Piastri to challenge and even surpass more seasoned competitors in single-session performance.

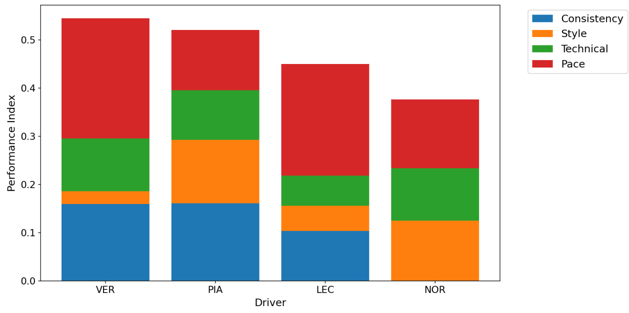

Figure 9: [Quali] Performance Index

The race performance breakdown reveals a different dynamic compared to qualifying as seen in Figure 10, though Verstappen maintains his overall supremacy with the highest performance index. His strength in the race comes from exceptional technical execution (large green segment) combined with superior pace (red segment), showcasing his ability to maintain high performance throughout longer stints.

Within McLaren, Piastri continues to impress with the second-highest overall performance, notably through a distinctive driving style (large orange segment) and strong technical components. However, Norris shows improved relative performance in race conditions compared to his qualifying position, with particularly strong consistency (large blue segment) suggesting better tyre management and race craft.

Leclerc's position reflects Ferrari's typical race-pace challenges, though he maintains competitive technical execution and consistency levels. The smaller pace component (red segment) compared to Verstappen highlights Red Bull's superior race management. Overall, the performance hierarchy in race conditions - Verstappen, Piastri, Leclerc, Norris - reflects both car capabilities and driver adaptability to longer-format racing, with consistency becoming a more prominent factor compared to qualifying performance.

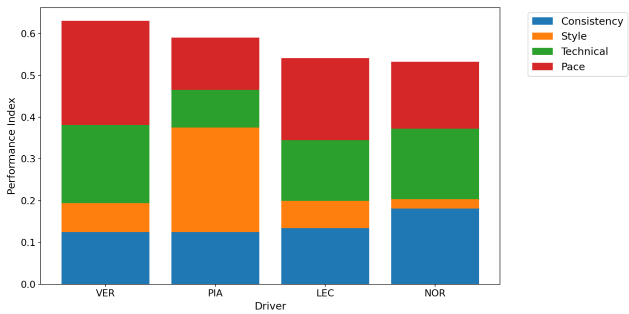

Figure 10: [Race] Performance Index

5 Conclusion

The fundamental challenge in Formula 1's driver market has always been quantifying driver performance objectively, particularly in distinguishing car performance from driver capability. Traditional metrics like qualifying gaps and race results often fall prey to recency bias and fail to account for the complex interplay of factors that determine true driver performance.

Consistency: Measures a driver's ability to replicate optimal performance across stints and varying conditions. This component particularly shines in race conditions, as evidenced by Norris's stronger race-day consistency compared to his qualifying performance.

Style Distinctiveness: Quantifies how a driver's approach differs from the mean. Piastri's prominent style component in race conditions suggests innovative line choice and unique car control techniques that could be particularly valuable for car development.

Technical Execution: Captures the efficiency of inputs (throttle, brake, steering) relative to outputs (lap time, tyre wear). Verstappen's commanding technical scores across both qualifying and race scenarios demonstrate why he's considered the benchmark.

Raw Pace: Represents pure speed potential when all other factors are optimized. The varying size of pace components between qualifying and race (particularly notable in Leclerc's case) highlights the different demands of single-lap versus race-distance performance.

The DPI's adaptability is particularly valuable for team decision-making. A team prioritizing car development might weight style distinctiveness more heavily, while one focused on immediate results might emphasize raw pace. Red Bull's driver choices have historically favored technical execution and consistency, aligning with their data-driven philosophy.

McLaren's current driver dynamic illustrates the DPI's practical application. While Norris traditionally carries the team's expectations, Piastri's strong technical execution and distinctive style suggest potential that pure results don't fully capture. This granular understanding helps teams make more informed decisions about driver hierarchy and development focus.

6 Recommendations

The implementation of the Driver Performance Index represents the foundation of a comprehensive driver analysis ecosystem. By expanding our data collection beyond traditional telemetry, we can create the Adaptability Index - a sophisticated addition to the DPI that evaluates driver performance under varying conditions. This framework analyzes cornering speed consistency, DRS utilization efficiency, and brake force optimization across different track conditions, providing deeper insights into a driver's true capabilities.

The correlation of traditional telemetry with advanced metrics reveals compelling patterns. Throttle control variability and brake pressure modulation, when mapped against tire degradation models, expose nuances in technical execution that timing screens cannot capture. This data becomes particularly valuable when cross-referenced with energy deployment strategies and race craft scenarios, offering a complete picture of driver adaptability.

Machine learning integration transforms this raw data into predictive insights. By training models on historical telemetry data, teams can forecast lap time performance based on evolving track conditions and setup adjustments. K-means clustering algorithms group drivers with similar adaptability patterns, establishing performance benchmarks and identifying areas for improvement. These predictions, combined with PCA-based analysis of driving styles, create a powerful tool for strategy optimization.

Practice sessions evolve from generic running to targeted component development. FP1 sessions focus on establishing technical baselines and adaptability metrics, while FP2 emphasizes race pace consistency with comprehensive tire modeling. FP3 becomes an opportunity for component-specific refinement based on machine learning insights from previous sessions.

The key to maximizing this framework's potential lies in real-time analysis and visualization. Interactive dashboards allowing real-time exploration of PCA scatter plots, variance retention graphs, and lap-time variability profiles provide immediate insights. Custom reporting templates for technical directors and strategists streamline decision-making, while "what-if" scenario analyses evaluate potential strategy adjustments. By adopting this technical framework, teams transform driver development from subjective assessment to data-driven optimization. The result is a comprehensive approach to talent identification and development that could revolutionize how teams approach driver selection and training in Formula 1's increasingly competitive landscape.

7 References

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