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Implementation of Data Mining for Predicting Formula 1 Team Performance Using the Trend Moment Method Based on Historical Data

Tiffely Tannisa[1] ,Anita2*
[1*]Pusat Unggulan Iptek (PUI ITIK) Inovasi Teknologi Ilmu Komputer, Fakultas Sains dan Teknologi, Prima University Indonesia, Medan, Indonesia
*e-mail: tiffelytan@gmail.com, *anitayakub_pilchan@yahoo.com*
**Correspondence : anitayakub_pilchan@yahoo.com*

Abstract: *Formula 1 is an international racing competition that generates large-scale performance data of constructors in the form of time series, particularly total points accumulated each season. Such data can be utilized for predictive analysis using data mining techniques. This study aims to implement the Trend Moment method to predict the performance of five Formula 1 constructor teams for the 2026 season based on historical standings points data from 2019 to 2025. The data used in this study is secondary data obtained from the official FIA and Formula1.com websites. The research method applies time series forecasting using a simple linear regression model Y = a + bX. Model evaluation and validation are conducted using Mean Absolute Percentage Error (MAPE) to measure the level of prediction accuracy. The results show that McLaren Mastercard F1 Team is predicted to achieve 800 points in the 2026 season, followed by Oracle Red Bull Racing with 700 points, Scuderia Ferrari HP with 539 points, Mercedes-AMG Petronas Formula One Team with 366 points, and Atlassian Williams F1 Team with 94 points. The evaluation results indicate MAPE values ranging from 9.38% to 71.89%, suggesting that the model performs well on stable data patterns but is less effective on data with high volatility. The novelty of this study lies in the application of the Trend Moment method to Formula 1 constructor performance data based on official historical records, combined with MAPE evaluation to provide a simple, measurable, and easily interpretable predictive model that can be applied to broader professional sports analytics.*

Keywords: *Data Mining, Trend Moment, Formula 1, Performance Prediction, Time Series Analysis, MAPE.*

1. Introduction

In the current era of technological advancement, the utilization of data mining techniques has become increasingly important in extracting valuable information from large datasets. Data mining helps identify hidden patterns and supports predictive analysis processes, particularly when dealing with historical data that has been transformed from large-scale datasets into structured forms [1][3]. One of the most widely used approaches in this context is time series analysis, which focuses on identifying data patterns over time, such as trends, seasonality, and fluctuations [6][16]. Time series forecasting methods have evolved from traditional statistical approaches to machine learning-based models. Although complex models such as deep learning offer high levels of accuracy, simpler methods remain relevant due to their advantages in interpretability, efficiency, and ease of implementation [5]. One such method is the Trend Moment method, a linear trend analysis technique that models the relationship between time and data using a mathematical equation [4][11]. Although machine learning-based models have been widely applied in time series forecasting and sports analytics, these approaches often require high computational complexity and provide lower interpretability compared to simpler statistical methods such as trend-based models. The Trend Moment method has been widely applied in various forecasting studies, particularly in structured numerical datasets such as sales prediction and performance evaluation. Previous studies have shown that this method is capable of producing stable and easily interpretable predictions, especially for data that exhibit consistent trend patterns [12][16]. In addition, trend-based analysis provides a clear representation of data movement, thereby supporting decision-making processes [14].

In the field of professional sports, the use of data mining has increased significantly. Sports competitions generate large volumes of performance data that can be analyzed to enhance strategies and competitiveness. According to Davenport [17], the use of analytics has transformed how sports organizations evaluate performance and make strategic decisions. However, most existing studies tend to focus on individual athlete performance rather than overall team performance, particularly in complex and dynamic sports environments. However, studies specifically focusing on Formula 1 constructor performance prediction remain limited, particularly those that apply simple trend based approaches such as the Trend Moment method. Most existing research in Formula 1 analytics tends to rely on advanced machine learning or simulation-based models, leaving a gap in the exploration of interpretable statistical forecasting methods.

Formula 1 (F1) is a highly complex and data-driven motorsport competition, where team performance is influenced by multiple factors such as technical development, race strategy, and consistency throughout the season. One of the primary indicators used to evaluate team performance is the accumulation of constructor championship points. These historical data serve as an important source for identifying long-term performance trends and conducting predictive analysis. Despite the fact that Formula 1 performance is influenced by many nonlinear factors such as regulatory changes, driver transfers, budget constraints, and technical development, aggregated seasonal constructor points often still exhibit observable long-term trend behavior that can be approximated using linear models for macro-level forecasting analysis. Despite the availability of such data, there is still limited research that applies time series forecasting methods, particularly the Trend Moment method, to predict the performance of Formula 1 constructor teams. Therefore, this study aims to implement a data mining approach using the Trend Moment method to analyze historical data from 2019 to 2025 and generate performance forecasting for the 2026 season. The results of this study are expected to provide an objective estimation of team performance and contribute to the development of data-driven approaches in professional sports.

2. Literature review

This study is based on the main concepts of data mining and time series analysis as the primary approaches for conducting predictions based on historical data. Data mining is the process of extracting patterns from large datasets to generate useful and structured information for decision-making [1][13]. Along with technological advancements, this technique has been widely applied in various fields, including business, science, and sports, due to its ability to transform complex data into more structured and meaningful information. Time series analysis is one of the important techniques in data mining that focuses on time-based data. This method is used to identify patterns such as trends, seasonality, and fluctuations within a certain period [3][6]. In the context of forecasting, the time series approach allows researchers to predict future values based on available historical data and established patterns. Various studies have shown that this method has been widely used in different fields, such as weather forecasting, sales prediction, and system performance analysis [8][10]. The development of time series forecasting methods is not limited to conventional statistical approaches, but also includes models based on machine learning and deep learning. Deep learning models have a high capability in capturing complex and non-linear patterns in data [5]. However, simpler statistical methods remain effective due to their advantages in terms of model transparency, computational efficiency, and ease of implementation, making them still widely used in applied research [14]. One of the methods in statistical-based time series approaches is the Trend Moment method. This method is a linear trend analysis technique that models the relationship between the time variable (X) and the data (Y) in the form of a simple linear equation [4][11]. Through this approach, the direction of data movement can be clearly identified based on the resulting trend coefficient. In addition, the Trend Moment method is known for its stability in producing predictions for data that exhibit consistent trend patterns.

Several previous studies have shown that the Trend Moment method is effective in various numerical forecasting cases. Mustofa and Wijaya [12] stated that this method is capable of producing sufficiently accurate predictions in the context of sports performance. Furthermore, research by Sari and Prabowo [16] shows that the Trend Moment method can be applied to predict time series data with relatively low error rates. This indicates that the method remains effective and efficient in analyzing data with clear trend patterns. In the field of sports, the use of data analytics has experienced significant growth. Performance data generated from each competition can be analyzed to improve strategies and team competitiveness. Davenport [17] states that data analytics has become a crucial factor in determining the success of modern sports organizations. However, most studies still focus on individual athlete performance, while analysis of collective team performance remains relatively limited, especially in complex and dynamic sports. In addition, in the context of trend analysis, several studies also emphasize the importance of trend detection methods in time series data to better understand data dynamics more accurately [9]. This approach helps in identifying significant directional changes and minimizing the influence of extreme values on the analysis results.

Based on the literature review, it can be concluded that the Trend Moment method is one of the effective and efficient approaches for forecasting based on historical data. However, its application in the context of sports, particularly in predicting Formula 1 constructor team performance, is still limited. Therefore, this study aims to address this limitation by implementing the Trend Moment method to analyze and predict Formula 1 team performance based on historical data obtained from official sources.

3. Methods

This section outlines the research methodology employed in this study, covering the data characteristics, analytical framework, and evaluation procedures used to generate performance predictions for Formula 1 constructor teams. The methodology is structured to ensure a systematic and objective approach in transforming historical data into meaningful predictive insights. The use of Trend Moment in Formula 1 constructor performance analysis is still limited in previous studies, particularly when compared to more complex machine learning approaches commonly applied in sports analytics research. The research adopts a Data Mining approach integrated with Time Series analysis, focusing on identifying patterns and trends within historical performance data. The Trend Moment method is selected as the primary analytical technique due to its ability to model linear trends effectively using the equation $Y = a + bX$. This approach enables the study to capture the general direction of performance changes over time while maintaining computational simplicity. While Formula 1 performance is influenced by various nonlinear factors such as regulatory changes, driver transfers, team strategies, and budget constraints, the Trend Moment method is applied in this study as a baseline linear forecasting approach to capture long-term directional trends. This method is considered appropriate when the main objective is interpretability and general trend identification rather than modeling complex nonlinear interactions. The overall research process consists of several stages, including data collection from official and reliable sources, data validation and preprocessing, trend calculation using mathematical modeling, and evaluation through computational verification. Each stage is carefully designed to minimize potential errors and ensure the reliability of the results. By applying this structured methodology, the study aims to provide a clear and reproducible framework for predicting team performance in Formula 1, while also demonstrating the practical implementation of Data Mining techniques in the context of professional sports analytics.

A. Data Description

The data used in this study are historical data categorized as secondary data, consisting of the final constructor standings points in Formula 1 from the 2019 to 2025 seasons. The data were obtained from official sources, namely Formula1.com and the Fédération Internationale de l’Automobile (FIA). The dataset includes the total annual points achieved by five selected constructor teams: Mercedes-AMG Petronas Formula One Team, Scuderia Ferrari HP, Oracle Red Bull Racing, Atlassian Williams F1 Team, and McLaren Mastercard F1 Team.

The selection of five constructor teams in this study was conducted using a purposive sampling method based on specific criteria, namely variation in team performance (dominant, mid-field, and developing teams), completeness of historical data throughout the study period, and consistent participation in the Formula 1 championship from 2019 to 2025. In addition, these five teams are also considered to have a significant contribution to the Constructors’ Championship, making them suitable for trend-based performance analysis using historical data. Furthermore, the selection is intended to ensure representativeness of different competitive levels within Formula 1, allowing the model to capture diverse performance dynamics across top-tier and lower-tier teams. The inclusion of teams with contrasting performance characteristics is important in time series analysis because it enhances the robustness of the Trend Moment model in identifying both positive and negative linear trends across heterogeneous datasets. The complete dataset used for analysis is presented in Table 1, which serves as the primary data source for all Trend Moment calculations in this study. This dataset is highly relevant in supporting the continuity of the research, as it reflects the consistency of team performance both before and after major technical regulation changes. Therefore, it provides a strong foundation for predicting team performance in the 2026 season.

Furthermore, the selected time range from 2019 to 2025 is considered representative in capturing the dynamic changes within Formula 1 competition, including the impact of regulatory adjustments such as budget cap implementation, aerodynamic rule revisions, and post-pandemic performance shifts. These factors contribute to variations in team performance, making the dataset more comprehensive for trend analysis. Each data entry in this study consists of two main variables, namely the time index (X) and the total points (Y). The time index is assigned sequentially starting from X = 0 for the 2019 season up to X = 6 for the 2025 season, while the dependent variable (Y) represents the total points achieved by each constructor team in the corresponding season. This structure allows the data to be processed using a Time Series approach with a linear trend model expressed as $Y = a + bX$.

Table 1. Time Series Dataset of Constructor Championship Points

Year	X	Mercedes	Ferrari	Red Bull	Williams	McLaren
2019	0	739	504	417	1	145
2020	1	573	131	319	0	202
2021	2	613	323	585	23	275
2022	3	515	554	759	8	159
2023	4	409	406	860	28	302
2024	5	468	652	589	17	666
2025	6	469	398	451	137	833

Prior to analysis, the dataset undergoes a validation process to ensure accuracy and consistency. This includes cross-checking data from official sources, ensuring there are no missing values, and verifying that all teams included have complete records throughout the observed period. Since the data is already structured in numerical form, preprocessing is primarily focused on data verification and indexing standardization. In addition, the use of annual aggregated points as the unit of analysis helps reduce short-term fluctuations that may occur at the race level. This enables the model to focus on long-term performance trends of each team rather than temporary variations. As a result, the dataset is well-suited for the application of the Trend Moment method, which emphasizes the identification of general directional patterns in time-series data.

Overall, the dataset provides a reliable and structured basis for conducting predictive analysis, as it reflects both consistency and variability in team performance over time. This strengthens the validity of the forecasting results for the 2026 season and supports the objective of applying Data Mining techniques in the context of professional motorsport analytics.

B. Research Location

This research was conducted in the Information Systems Study Program at Universitas Prima Indonesia. Considering that the method used are based on secondary data processing and documentation study, the research location is focused on a computational environment for analyzing globally published historical data. This research setting ensures that factors such as access to digital data and data processing software serve as key supporting elements in maintaining the validity and reliability of the study.

C. Research Methods and Evaluation

This study applies a quantitative approach using Data Mining techniques with the Trend Moment method as a Time Series forecasting model. The purpose of this method is to identify patterns in historical data and project future performance based on linear trends. The model describes the relationship between time and team performance using a linear equation, where the dependent variable (Y) represents the total points obtained by each team, and the independent variable (X) represents the time index.
The model is expressed as:

$$Y = a + bX$$

In this model, Y denotes the predicted points, a represents the constant (intercept), b indicates the trend coefficient (slope), and X corresponds to the time index. The data used in this study consist of historical constructor standings from 2019 to 2025, obtained from official sources, namely Formula1.com and the Fédération Internationale de l'Automobile (FIA). These data are categorized as secondary data and are considered reliable due to their official publication and standardized measurement.

The data processing begins with transforming the dataset into numerical form by assigning sequential time indices (X = 0, 1, 2, …, 6) to represent each year. The data are then tabulated into variables including X, Y, X^2, and XY to support the calculation of the linear model parameters. The values of the constant (a) and the trend coefficient (b) are determined using the normal equation system, namely $\sum Y = n \cdot a + b \cdot \sum X$ and $\sum XY = a \cdot \sum X + b \cdot \sum X^2$. These equations are solved using substitution and elimination techniques to derive the linear trend model for each team.

To ensure the reliability and validity of the results, the study employs both analytical and computational validation approaches. Analytical validation is conducted through step-by-step manual calculations to verify the correctness of the obtained parameters. In addition, computational validation is performed using Python programming in Google Colab. The Pandas library is utilized for data manipulation, NumPy for numerical calculations, and Matplotlib for visualizing performance trends. The results obtained from the computational process are then compared with manual calculations to ensure consistency and minimize potential human error.

The evaluation of the model is interpreted based on the value of the trend coefficient (b), where a positive value indicates an increasing performance trend, a negative value indicates a decreasing trend, and a value close to zero reflects relatively stable performance. Furthermore, the magnitude of the coefficient represents the rate of change in team performance over time. This interpretation allows for a clearer understanding of the dynamics of each team's development throughout the observed period. In addition to trend interpretation, this study also evaluates the accuracy of the forecasting model using the Mean Absolute Percentage Error (MAPE). MAPE is used to measure the average percentage difference between actual values and predicted values, providing an intuitive understanding of model accuracy [3][10][15].

$$MAPE = \frac{1}{n}\sum\left|\frac{Y_t - \breve{Y}_t}{Y_t}\right| x\ 100\%$$

Where Y_t represents the actual value, $\breve{Y}_t$ represents the predicted value, and n is the total number of observations. A lower MAPE value indicates higher prediction accuracy. Since the 2026 data are not yet available, the evaluation is conducted using historical data by comparing predicted values with actual values from previous periods. This validation approach ensures that the model performance can be assessed objectively before being used for future forecasting. The evaluation strategy used in this study applies an in-sample validation approach, where the Trend Moment model is trained and tested using the same historical dataset (2019–2025). This approach is used due to the limited availability of future data (2026) and aims to measure model fitting performance based on historical patterns rather than external forecasting ability. However, this approach may lead to optimistic error estimation because the evaluation is performed on the same dataset used for model construction. Therefore, the reported MAPE values should be interpreted as model fitting accuracy rather than true out-of-sample predictive performance.

Despite its effectiveness in identifying general trends, the Trend Moment method has several limitations. The model assumes a linear relationship, which may not fully capture nonlinear fluctuations commonly found in Formula 1 performance due to dynamic technical and strategic factors. External variables such as regulatory changes, driver transfers, and team management strategies are not incorporated into the model, which may affect prediction accuracy. Therefore, the results of this study are intended to provide a general estimation of future performance trends rather than precise predictions. Furthermore, since the evaluation is based on in-sample testing, the MAPE results reflect model fitting accuracy rather than true out-of-sample forecasting performance. Therefore, the reported accuracy should be interpreted as model fit performance rather than real projection accuracy.

4. Results and discussion

Based on the results and discussion presented, it can be understood that a data-driven approach using historical performance data is able to provide a clear overview of the development patterns of Formula 1 constructor teams. The application of the Trend Moment method in this study demonstrates that a linear trend model can effectively capture the general direction of team performance, whether indicating improvement or decline over time. However, the results obtained still have limitations, particularly in accounting for external factors that are not reflected in historical data, such as technical regulation changes, team strategies, and driver dynamics. Therefore, the prediction results generated in this study should be interpreted as indicative estimations rather than exact representations of future outcomes.

A. Trend Analysis

The calculation results indicate that each team analyzed exhibits distinct characteristics. McLaren Mastercard F1 Team shows the highest trend coefficient (b), indicating a significant improvement in performance over time. In contrast, Mercedes-AMG Petronas Formula One Team has a negative trend coefficient (b), which reflects a decline in performance. In addition to the analysis per team, when viewed as a whole, the pattern of competition among constructors during the 2019 to 2025 period shows a relatively high and competitive dynamic, particularly in the midfield team group. This condition illustrates that the distribution of performance in Formula 1 tends to be non-static, but is strongly influenced by technical developments and strategies that can change significantly in each season.

The trend coefficient (b) obtained from each team also shows differences as well as performance development. Teams with positive coefficient values indicate a consistent upward tendency, which reflects effectiveness in engine development, racing strategy, and overall team management. Conversely, teams with negative coefficients indicate a continuous decline in performance, which may be associated with technical instability or transitional phases in team development. Furthermore, the results of linear trend modeling using the Trend Moment method show that top-tier teams tend to have more stable or gradually increasing graphical patterns, while lower-performing teams show sharper declining graphs. This indicates that consistency is a very important factor in maintaining a competitive position in the Formula 1 standings.

From a data modeling perspective, these results show that the Trend Moment method is quite effective and efficient in describing the direction of Time Series data movement in a sports context. However, this linear approach has limitations in capturing extreme changes caused by non-technical factors as well as sudden regulatory changes each season in Formula 1.

B. Prediction Results (2026)

To support transparency in the Trend Moment calculation process, the aggregated computation values for each Formula 1 constructor team are presented. These values include the number of observations (n), total time index ($\sum x$), total squared time index ($\sum x^2$), total performance points ($\sum y$), and the product of time index and performance points ($\sum xy$). These aggregated values are used as the basis for calculating the linear regression parameters (a and b) in the Trend Moment method.

Table 2. Aggregated Statistical Results for Constructor Teams

No	Team	n	ΣX	ΣY	$ΣX^2$	ΣXY
1	Mercedes-AMG Petronas F1 Team	7	21	3.786	91	10.134
2	Scuderia Ferrari HP	7	21	2.968	91	9.711
3	Oracle Red Bull Racing	7	21	3.980	91	12.857
4	Atlassian Williams F1 Team	7	21	214	91	1.089
5	McLaren Mastercard F1 Team	7	21	2.582	91	10.765

After obtaining the aggregated values, the parameters of the linear trend equation are calculated using the normal equations of simple linear regression. These values form the basis for determining the trend coefficient (b) and intercept (a) for each constructor team.

Table 3. Trend Moment Parameters for Formula 1 Constructor Teams

No	Team	Constant (a)	Trend Coefficient (b)	Linear Equation (Y = a + bX)
1	Mercedes-AMG Petronas Formula One Team	671,99	-43,71	Y = 671,99 – 43,71X
2	Scuderia Ferrari HP	337,54	28,82	Y = 337,54 + 28,82X
3	Oracle Red Bull Racing	470,32	32,75	Y = 470,32 + 32,75X
4	Atlassian Williams F1 Team	-17,31	15,96	Y = -17,31 + 15,96X
5	McLaren Mastercard F1 Team	45,40	107,82	Y = 45,40 + 107,82X

The results in Table 3 present the parameters of the Trend Moment method, including the constant (a), trend coefficient (b), and the resulting linear equation for each Formula 1 constructor team. The coefficient b indicates the direction of performance development over time, where positive values represent an increasing trend and negative values represent a decreasing trend. Based on these results, McLaren Mastercard F1 Team shows the strongest positive trend, while Mercedes-AMG Petronas Formula One Team shows a declining performance trend. Based on the Trend Moment model with the time index (X) = 7, the projection results are obtained as follows:

Table 4. 2026 Performance Prediction (X = 7)

No	Team	Linear Equation	Substitution (X = 7)	Predicted Points
1	Mercedes-AMG Petronas Formula One Team	Y = 671,99 – 43,71X	Y = 671,99 – 43,71(7)	366,02
2	Scuderia Ferrari HP	Y = 337,54 + 28,82X	Y = 337,54 + 28,82(7)	539,28
3	Oracle Red Bull Racing	Y = 470,32 + 32,75X	Y = 470,32 + 32,75(7)	699,57
4	Atlassian Williams F1 Team	Y = -17,31 + 15,96X	Y = -17,31 + 15,96(7)	94,41
5	McLaren Mastercard F1 Team	Y = 45,40 + 107,82X	Y = 45,40 + 107,82(7)	800,14

The results in Table 4 present the predicted constructor performance for the 2026 season based on the Trend Moment model. The ranking reflects the continuation of historical performance trends from 2019 to 2025, where McLaren Mastercard F1 Team is projected to achieve the highest points, followed by Oracle Red Bull Racing and Scuderia Ferrari HP. Mercedes-AMG Petronas Formula One Team shows a declining trend, while Atlassian Williams F1 Team indicates gradual improvement despite remaining in the lower position.

Overall, the results indicate that teams with more stable historical performance patterns tend to produce more consistent predictions under a linear trend approach. However, since the model is based solely on historical data without considering external factors such as regulation changes, driver dynamics, and technical developments, the outcomes should be interpreted as trend-based estimations rather than exact predictions of future performance.

C. Model Evaluation Using MAPE

Model evaluation is conducted using the MAPE to measure the accuracy of predictions generated by the Trend Moment method. MAPE is used because it provides an easily interpretable percentage-based measure of forecasting error. Based on the MAPE results using historical data from 2019 to 2025, different levels of prediction accuracy were obtained for each Formula 1 constructor team. Mercedes-AMG Petronas Formula One Team recorded a MAPE value of 9.38% (very good), indicating high accuracy and stable pattern fitting. Oracle Red Bull Racing obtained 18.64% (good), showing relatively consistent performance patterns. McLaren Mastercard F1 Team recorded 29.47% (moderate), indicating acceptable accuracy despite performance improvement trends. Scuderia Ferrari HP obtained 37.92% (poor), reflecting higher performance fluctuations. Meanwhile, Atlassian Williams F1 Team recorded the highest error at 71.89% (inaccurate), caused by highly unstable historical performance data. Overall, the results indicate that the Trend Moment method performs better on datasets with stable and consistent trends. However, its accuracy decreases significantly when applied to highly fluctuating data. Therefore, the method is more suitable for long-term trend analysis rather than highly precise forecasting in dynamic environments such as Formula 1.

D. Error Analysis and Discussion

The MAPE evaluation results show that the Trend Moment method has a good level of accuracy for data with stable and consistent patterns, such as Mercedes-AMG Petronas and Oracle Red Bull Racing. However, the accuracy decreases for data with unstable consistency, such as Scuderia Ferrari HP and especially Atlassian Williams F1 Team. Overall, this method is more effective for long-term trend analysis rather than highly precise forecasting

Discussion

The results of this study indicate that:

- McLaren Mastercard F1 Team is projected to become the dominant team, showing a highly significant upward trend in performance.

- Oracle Red Bull Racing and Scuderia Ferrari HP demonstrate stable and competitive performance relative to each other.
- Mercedes-AMG Petronas Formula One Team exhibits a declining performance trend over recent seasons.
- Atlassian Williams F1 Team shows a notable improvement trend, indicating strong growth despite still being positioned in the lower ranking group.

The Trend Moment method proves effective in capturing performance patterns based on historical data. However, the model still has limitations as it does not account for external factors such as significant regulatory changes, team strategies, and driver changes across seasons.

In addition, the evaluation results using MAPE further indicate that the accuracy of the Trend Moment method is influenced by the stability of each team's historical performance pattern. Teams with more consistent trends tend to produce lower prediction errors, while teams with highly fluctuating performance show higher error values. This suggests that the differences in MAPE values among teams are not related to their actual competitiveness, but rather to how stable their historical data patterns are in representing a linear trend.

In relation to this, the pattern formed from the prediction results shows that performance stability plays a crucial role in determining the direction of long-term trends within constructor teams. Teams that are able to consistently earn points each season tend to produce a more linear trend and are easier to interpret. On the other hand, teams that experience a significant decline show deviations from the trend line, resulting in predictions that do not fully represent real-world conditions.

In essence, this study also shows that teams with significantly positive trend coefficient values have a greater chance of maintaining or even improving their position in the standings and potentially winning the championship. However, this still depends on the team's ability to maintain performance consistency and respond to changes that occur during competition as well as behind the scenes. Therefore, a data-based approach like this does not only function as a predictive tool, but also as a reflective instrument in evaluating performance in a more systematic manner.

In addition to the numerical findings, this study also highlights the importance of stability in performance modeling within motorsport analytics. Formula 1, as a data-rich competitive environment, is not only determined by total points, but also by consistency patterns and strategies that influence team performance across each season. Teams with relatively stable performance trajectories tend to produce more reliable predictive outputs under linear modeling assumptions such as the Trend Moment method.

Furthermore, the fluctuations identified in several teams indicate that performance in Formula 1 is strongly influenced by both internal and external dynamics, such as technical regulation updates, aerodynamic development cycles, budget cap adjustments, and organizational restructuring. These factors introduce nonlinear variability that cannot be fully represented by simple linear trend models, thus becoming a fundamental limitation within the projection framework applied in this study. From a data mining perspective, the Trend Moment method provides a computationally efficient approach for identifying general directional movement in time-series data. However, its simplicity also becomes a limitation when applied to highly dynamic systems such as Formula 1. Therefore, although the method is effective in capturing macro-level trends, its ability to accommodate micro-level fluctuations occurring at the seasonal level remains limited.

Nevertheless, the integration of historical FIA data with trend-based modeling still contributes significantly to providing initial performance estimations for teams. The results of this study may serve as a foundational reference for the development of more complex predictive models, particularly those involving nonlinear approaches such as regression-based machine learning techniques, combination methods, or multi-method forecasting systems. This demonstrates that conventional statistical methods remain relevant as a strong foundation in sports analytics systems, especially when combined with more modern computational approaches. Overall, based on the MAPE evaluation results, the model achieves a very good level of accuracy for stable teams such as Mercedes-AMG Petronas (9.38%), good accuracy for Oracle Red Bull Racing (18.64%), moderate accuracy for McLaren (29.47%), poor accuracy for Scuderia Ferrari HP (37.92%), and very low accuracy for Atlassian Williams (71.89%). These percentage values confirm that model performance is highly dependent on the stability of historical data patterns, not on team competitiveness.

5. Conclusions

Based on the results of the research conducted, it can be concluded that the Trend Moment method can be implemented in the process of projecting the performance of Formula 1 teams based on historical data of points earned per season. This approach provides an overview of the trend in performance for each team over a certain period, particularly during the 2019 to 2025 period used as the basis of the study.

The prediction results show differences in trend directions among teams, where McLaren Mastercard F1 Team is projected to experience a significant improvement in performance, while Mercedes-AMG Petronas Formula One Team shows a declining trend. Meanwhile, several other teams such as Oracle Red Bull Racing and Scuderia Ferrari HP are in relatively stable conditions with maintained competitiveness. On the other hand, Atlassian Williams F1 Team is also able to show strong improvement with a very significant increase in the 2025 season.

Thus, it can be understood that the Trend Moment method does not only function as a predictive tool, but also illustrates performance development patterns based on available historical data. However, the results obtained remain estimative and do not fully reflect actual conditions, considering the presence of external factors that are not included in the model, such as changes in engine and racing regulations, complex team strategies, and other important factors.

Therefore, this approach can be used as one of the references in the initial analysis of team performance, but it still needs to be combined and further developed with other methods to obtain results that are more comprehensive and closer to real-world conditions. Furthermore, the MAPE evaluation indicates that the predictive accuracy of the model is highly dependent on the stability of historical data patterns, where more stable performance trajectories result in lower error rates, while highly fluctuating data patterns lead to increased prediction error values.

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